INFERENTIAL MEASUREMENT AND CONTROL OF BALLAST WATER TREATMENT SYSTEM

BY

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Dedicated to my Family

ABSTRACT

As a result of interaction with the surrounding environment, shipping has become one of the vectors of bio-invasion across the globe. Ballast water is one of the means of bio-invasion from shipping through which microorganisms break through natural barriers and establish in a new location. Shipboard treatment systems are predominately considered as mitigating measures for bio-invasion via a ballast water system. Currently shipboard performance monitoring of ballast water treatment systems, and thus assessment of discharge quality of ballast water as required by the Convention, depends on off-line laboratory assays with long delay analysis. Lack of online measurement sensors to assess the viability of microorganisms after treatment has made monitoring and thus control of ballast water treatment systems difficult.

In this study, a methodology was developed, through a mathematical algorithm, to provide an inferential model-based measurement system in order to monitor and thus control non-observable ballast water systems. In the developed inferential measurement the primary output of the treatment system is inferred by using easy to measure secondary output variables and a model relating these two outputs.

Data-driven modeling techniques, including Artificial Neural Networks (ANN), were used to develop an estimator for the small scale UV treatment system based on the data obtained from conducted experiments. The results from ANN showed more accuracy in term of Root Mean Squared Error (RMSE) and Linear Correlation Coefficient (LCC) when compared to the other techniques. The same methodology was implemented to a larger scale treatment system comprising micro-filter and UV reactor. A software-based inferential measurement for online monitoring of the treatment system was then developed.

Following monitoring, inferential control of the treatment setup was also accomplished using direct inverse control strategy. A software-based “Decision Making Tool” consisted of two intelligent inverse models, which were used to control treatment flow rate and maintain the effective average UV dose. The results from this study showed that software-based estimation of treatment technologies can provide online measurement and control for ballast water system.

DECLARATION

No portion of the work presented in this thesis has been submitted in support of an application for another degree or qualification of this or any other university of other institute of learning.

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Abbreviations

ANN	Artificial Neural Networks
AOT	Advanced Oxidation Technology
BW	Ballast Water
BWE	Ballast Water Exchange
CEM	Concept Exploration Method
CCA	Canonical Correlation Analysis
DAQ	Data Acquisition
DNV	Det Norske Veritas
EKF	Extended Kalman Filter
GA	Genetic Algorithm
HAB	Harmful Algal Blooms
IMO	International Maritime Organisation
JAMS	Japanese Association of Marine Safety
LCC	Linear Correlation Coefficient
LP-HI	Low Pressure High Intensity
LP-LI	Low Pressure Low Intensity
MAE	Mean Absolute Error
MEPC	Marine Environmental Protection Committee
MLR	Multiple Linear Regression
MMR	Multivariate Multiple Regression
MNLR	Multi Non Linear Regression
MP-HI	Medium Pressure High Intensity
MPSS	Multi Point Source Summation
MSE	Maximum Squared Error
NIS	Non Indigenous Species
NMSE	Normalised Mean Squared Error
PC	Principal Component
PCA	Principal Component Analysis
PCR	Principal Component Regression
PLS	Partial Least Squares
PLSR	Partial Least Squares Regression
PSP	Paralytic Shellfish Poisoning
RMSE	Root Mean Squared Error

SA	Simulated Annealing
SD	Standard Deviation
UNEP	United Nation Environmental Program
UV	Ultraviolet
UVT	Ultraviolet Transmission
VLCC	Very Large Crude oil Carrier

Chapter 1 Introduction

1.1 Introduction

Ever since human beings believed in their ability to understand, explore and exploit the world and its resources they have endeavoured to expand the knowledge of scientific principles. These principles have been engineered creatively to find suitable solutions to problems or improvise the status quo. The intentional outcome of engineering solutions, in the form of design or development, should and will favour the defined objectives and goals. However, this may develop an overlapping area with unintentional consequences if it interacts with other surrounding systems.

Shipping is a good example of the interactions between different disciplines. Cost efficient transportation of goods across the globe has made shipping the most wanted means of transport. As a consequence over 80% of worldwide cargo is being transported by ships (Anil *et al.*, 2002; Gomes, C. F. S., 2003). Ships are designed to operate safely and economically for a specific mission. The interaction of ship, as a complex mobile structure, with her surrounding environment has turned shipping into one of the major pollution contributors. Currently, pollution prevention measures as enforced by the IMO Conventions are considered at the design stage. Despite these preventive measures, ships can still contribute to environmental pollution either unintentionally or accidentally.

Invasions of marine species to new environments are often aided by human activities among which the shipping industry is one of the major, but unintentional, vectors. Ships can provide suitable habitats for transportation of marine species in the form of attaching to the ship's hull/sea chest and also being transported, at different life cycle stage, through ballast water. (Bax et al., 2003; Anil, A. C., 2006). Research on the subject showed that shipping, on average, is responsible for 25% and 52% of introductions of Non-indigenous species (NIS) into European waters (Stretaris et al, 2005) and coastal waters in the North America (Fofonoff et al, 2003) respectively. According to the International Maritime Organisation (IMO) the importance of fouling organisms to ship's hulls due to changes in maritime conditions, such as faster ships, lower port / anchorage stay and more efficient antifouling coatings, has decreased. On

the contrary, cleaner ballast water, increased ship's transit speeds and improved management of ports have made ballast tanks of commercial ships a hospitable means of transport throughout the world (Bax *et al.*, 2003).

Ships load seawater as ballast to provide stability and manoeuvrability, when she is empty or partially loaded. The loaded seawater (ballast water) will subsequently be discharged at the loading port to retain ship's stability (Gollasch et al., 2000; Wonham et al., 2001; Drake et al., 2002; Lowis et al., 2003). The transportation of seawater from one geographical location (discharge port) to another (loading port) provides a platform for the translocation of marine microorganisms. Due to the pumping effect, ballast tanks hostile conditions, length of the journey and different environmental conditions of new habitat, not every boarded microorganism can survive to the end of the journey. Nevertheless, there are some viruses and microorganisms that could benefit from free transportation and pass natural barriers by ships' ballast tanks and establish a new life in the receiving location (Bax et al., 2003; Drake et al., 2002; Hallegraeff, G. M., 1998; Faimali et al., 2006).

The introduction of non indigenous species to the foreign environment, through ballast water, has brought ecological, economical and public health impacts (Mack et al. 2000; Carlton 2001; GEOHAB, 2001; Anil, A. C., 2006). Global Ballast Water Management Programme (GloBallast) announced that the invasion of marine species has been one of the four greatest threats to the world's oceans. It was further stated that unlike the other form of pollutions, e.g. oil spills; the impacts of invasions are often irreversible. To stop the threat or minimise its consequences to some manageable level, shipboard treatment systems are predominately considered as mitigating measures for bio-invasion via a ballast water system. Much research has been carried out on treatment technologies and they are categorised into primary and secondary (main) treatment systems. Secondary treatment technologies are further sub-classed into physical and chemical technologies (Lloyds Register, 2010). The author, however, believes that in order to include more mitigating options, the concept of "*Preventive* and *Cure measures*" can be considered. The concept for preventive measures is to exclude entry of marine species to ships, while the "*cure concept*" is to treat them during uptake of ballast and/or at transit and /or during discharge.

The *preventive concept* may include, but is not limited to, new ship's design with zero

ballast requirement or reception of clean/treated ballast water from shore or mechanical separation (e.g. filters) that ensures removal of microorganisms down to viruses and bacteria. In the *cure concept* the boarded microorganisms are either inactivated or expelled from the ship using available time in the ballast voyage. *Preventive concept* is mostly suitable for new ships' designs or new ports infrastructures and this concept needs to be further researched. However, the methodologies in the c*ure concept* can be retro-fitted in the existing ships with some modifications in ship's ballast water system.

The effectiveness of treatment systems, as current predominant control measures, can be assured when there is a communication between the treatment system and inactivation process of microorganisms. The behaviour of any process is indicated by the primary/quality output variables, which in turn depends on the operating conditions and the process adjustments (Tham, M. T., 2000). Unfortunately, more often than not these variables are either difficult, too expensive, or even impossible to measure (Tham, M. T., 2000; Assis et al., 2000; Bolf et al., 2008)

The behaviour of biological processes is often highly nonlinear and complex (Assis et al., 2000). Similarly, the inactivation process of microorganisms in the ballast water treatment system is considered nonlinear. There is also no online measurement device to assess the viability of microorganisms after treatment, meaning the output variable can only be measured through off-line laboratory assays with long delay analysis. This indicates that there is no immediate observation in the treatment system and hence monitoring and controlling of the system becomes difficult. This thesis aims to develop a methodology, through a mathematical algorithm, to turn a non-observable system such as a ballast water treatment system into an observable system for which monitoring and control can be provided.

1.2 Thesis Layout

This thesis is divided into six main chapters including this one as introduction to the thesis and final chapter as all conclusion. The brief contents of other chapters are described below:

A system is considered observable if the behaviour of the entire system can be determined, in a finite time, by using the output of the system or otherwise it is non-observable (Kalman, R. E., 1960; Chen, C. T., 1984). In a non-observable system,

either the output of the system is not measurable within defined finite time or behaviour of the system is unknown or the states of input variables are uncertain or combination of all the above. Ship's ballast water treatment systems are practical examples of non-observable systems: uncertainties in the input to the system, output cannot be immediately measured and there is no mathematical model to represent the inactivation process of microorganisms. Chapter 2 addresses the interaction of a ship's ballast system with the surrounding environment and reviews how these non-observable interacting systems could contribute unintentionally to environmental pollution. The chapter also includes mitigating measures to stop bio-invasions and reviews the observability of ballast water treatment systems.

Observability plays a prominent role in optimal control of the dynamic system. It is difficult, if not impossible, to optimally operate and control a non-observable system (Nešić, D., 1998). For such dynamic systems (non-observable), any changes in the immeasurable variables can present operational problems and as a consequence output from the system deviate from desired point. There are well-known techniques such as Leunberger observer (Luenberger, 1966) or the Kalman filter (Kalman and Bucy, 1961) or modern intelligent algorithms that can reconstruct the immeasurable variables of a dynamic system. In chapter three, different techniques are reviewed and a methodology to turn a non-observable system into observable one is developed. This chapter also includes a case study to validate the developed methodology and provide an inferential model-based measurement system to monitor the performance of small scale UV treatment system. The procedure of building an inferential measurement system essentially consists of a model. Series of treatment experiments conducted to generate required data and different data-driven modeling techniques, including Artificial Neural Networks (ANN), are applied. The testing procedure and biological results of experiments as well as comparisons on the accuracy of developed models are also presented in chapter three.

Monitoring of a process, e.g. ballast water treatment system, can be used to improve the performance and ultimately control the process. The main goal for a ballast water treatment system is to stop bio-invasions by ballast water. The performance and discharge quality of treatment system is currently determined by off-line laboratory analysis. It is vitally important to estimate the output of the system online in order to monitor its performance when immediate measurement is not possible. After successful development of an inferential measurement system for small scale UV reactor, the same

methodology was implemented to larger scale treatment system comprising of micro-filter and UV reactor. Series of experiments were conducted on treatment setup at two different locations. Chapter four describes tests and sampling procedures of a large scale treatment setup. Biological results are also presented and discussed in this chapter. In order to develop mathematical models for each involved technologies, multilayer feed-forward neural networks was applied using off-line data from experiments. A software-based inferential measurement for online monitoring of the treatment system is then developed by combining both (mathematical and biological) models together. The development procedure of inferential measurement for the ballast water treatment setup is presented and discussed next in chapter four.

In chapter five an optimisation program was developed for the operation of UV reactor. In this light, various optimisation methods are reviewed and discussed. Three optimisation algorithms (UV reactor mathematical model coupled with direct search, single output and multi-output ANN algorithms) are developed to solve the single objective optimisation problem for the operation of UV reactor. The results in terms of accuracy and computational time are compared and presented in this chapter. Following development of an inferential measurement in chapter four, control of the treatment setup is the next step. A control system can be defined as an interconnection of subsystems, which will provide a desired system response to input. It consists of a sensor for controlled variables, a process under control, a controller and an actuator (Dorf, R.C. & Bishop, R. H., 2005). Using inferential measurement, monitoring and control of ballast water treatment system is also proposed using direct inverse control strategy. A software-based "Decision Making Tool", which consists of two intelligent inverse models (biological and optimisation), was used to provide setpoint for flow control system. In order to demonstrate the application of inferential control concept for ballast water treatment setup, a wet test was designed and results are presented next in chapter five.

In the final chapter the overall conclusions of the work performed followed by recommendations for further research to continue this research are presented.

Chapter 2 Review of Ship's Ballast Water Interaction with Environment

Summary

The main goal in his chapter is to review the consequence of interaction of ship's ballast system with surrounding environment, concerned regulations and possible mitigating measures.

Chapter 2's objectives may be briefly summarised as:

- *To review bio-invasion as consequence of interaction of ship's ballast system with surrounding environment,*
- *To review the international regulation adopted for the ballast water management,*
- *To categorise and review the technologies to stop bio-invasion.*

2.1 Introduction

Interaction of two systems may develop an overlapping area where monitoring and controlling of it becomes difficult as output variables of such interaction cannot be measured. Shipping industry is an excellent practical example of interacting systems. Ships are complex mobile structures consisting of various interrelating systems working in unison to accomplish the specific mission profile. Ship can successfully perform her mission profile when the communications between interacting systems are well established. The problem may, however, occur when any of the ship's systems interacts with the other system outside the ship's boundary, e.g. environment, for which proper communications do not exist. Ship's ballast water system is an example of such interaction. This system is used to retain the stability of ships and ensure safe movement of ships across oceans and seas while its interaction with marine environment causes the microorganisms to break through the natural barriers such as lands or changes in water temperatures or salinities. Lack of engineering mechanisms to relate ship's ballast system to the translocation of microorganisms has introduces shipping as the main contributor of marine bio-invasion. Bio-invasion, in this regards, may be defined as introduction of non-indigenous species (NIS) into a new ecosystem, whereby a threat and undesirable imbalances in the ecosystem will be developed (Anil *et al.*, 2002).

According to UNEP, introduction of NIS is considered as a second major threat for biodiversity (UNEP, 2002).

2.2 Ship's Ballast Water System and Bio-invasion

For a ship to remain safe in an adverse weather conditions and to operate efficiently and successfully when in the unloaded condition, ballast must be taken on board. In the past, ships carried solid ballast in the form of rocks, roof tiles and many other heavy materials, but from the 19th century the method of ballasting changed from solid ballast to the water ballast, thereby reducing the time required to ballast and de-ballast.

Ballast water is a necessary feature of commercial shipping. Correct ballasting, that is pumping the correct amount and achieving an even load distribution associated with the ballast, fulfils the following functions:

- Reduces stresses of the ship's hull;
- Ensures transverse stability of the ship;
- Improves propulsive efficiency by submerging the propeller fully into water;
- Improves manoeuvrability of ships by submerging the rudder fully into water;
- Restores the stability as fresh water and fuel are being consumed during the voyage.

Ship's ballast system has been designed, to allow safe operations and movements in the seas and ballast system design includes, but not limited to, the number of tanks, capacity of them and their locations, pumping rate and the piping system. This makes different ships to have different ballast tanks configurations and systems. With the possible measurements of some parameters, the ballasting/deballasting (ballast system) can be manipulated to ensure the stability, reduce shearing force and bending moments and maintain minimum design draft of the ship.

On the other hand, the coastal ecosystem consisting of marine creatures is the other system, which unintentionally interacts with the ballast water system. The greatest number of marine creatures, due to the penetration of sunlight to the seabed and abundance of food and nutrition, live in coastal water. Most of these creatures stay put and their natural dispersal discouraged by natural barriers such as lands and by changes in water temperature and salinities. As a consequence, unique coastal ecosystem is formed where balances are established over millions of years. However, this balance has been drastically changed when two systems interact with each other.

The process of breaking the natural barriers by microorganisms is started when ballast water is taken onboard a vessel to achieve the required safe operating conditions during a specific voyage or part of a voyage. Once the ship arrives at her destination the ballast water is pumped out of the tanks and into the harbour. The transportation of seawater from one geographical location (discharge port) to another (loading port) provides a platform for the marine microorganisms to break through natural barriers. All boarded microorganisms cannot survive to the end of their journey due to the pumping effect, ballast tanks hostile conditions, length of the journey and different environmental conditions of new habitat. There are some viruses and microorganisms, nevertheless, could benefit from free transportation to establish new life in the receiving location.

The processes of ballasting and de-ballasting, which facilitate transportation of living organisms outside their historic range, have been identified as one of the four greatest threats to the world's oceans. Major ocean's threats include unsustainable fishing, invasive organisms via shipping, climate change and pollution such as untreated sewage, fertilizers, garbage, pesticides and industrial chemicals. Cleaner ballast tanks, increased ship's transit speeds and improved management of ports from environmentally aspect have made ballast tanks of commercial ships hospitable means of transport throughout the world (Bax *et al.*, 2003). As a result ship ballast tanks are estimated to carry more than 10,000 different species around the world (Bax *et al.*, 2003; Carlton, 1999; Gollasch, 1997). Much research has been carried out on the microorganisms carried out by ship's ballast tanks and some examples are brought in the next subsection.

2.2.1 Microorganisms Carried in Ballast Water

Small planktonic organisms can be readily pumped in and out of ballast tanks. Plankton can be categorised as *holoplankton*, *meroplankton* or *tychoplankton*. *Holoplankton*s spend their entire lives drifting in water column, and include various bacteria, protozoans, unicellular plants (phytoplankton), and small animals (zooplankton). The latter primarily consists of copepods, mysid shrimp, arrow worms and comb jellies in salt water and copepods, water fleas and rotifers in fresh water. *Meroplankton* spend only part of their live cycle drifting in the plankton, and include the larvae or eggs of various worms, clams, snails, crabs, starfish, sea squirts, fish and other organisms. *Tychoplankton* are organisms that normally live on the bottom but have been

temporarily suspended in the water column. Certain other organisms that in a strict sense are not planktonic may be associated with planktonic hosts, such as certain viruses and parasitic nematodes and flatworms. In addition, some organisms that are non-planktonic may be carried into ballast tanks attached to or clinging to bits of wood or other floating debris, and small fish or shrimp may swim in through Ballast intake ports. Some examples of bio-invasion are presented below.

The Chinese mitten crab

The Chinese mitten crab *Eriocheir sinensi* (Figure 2-1) first found as NIS in German waterways in 1912 and has since spread through much of Europe (Clark *et al.*, 1998). First introduction of Chinese mitten crab in British water (Thames at Chelsea) dated back to 1935 (Ingle, 1986). This species may have introduced via ballast water at larvae stage or ship's hull (Eno, 1997). They spend most of their life in fresh water and migrate to the sea for reproducing. When populations are high, adult mitten crabs burrow in the banks of rivers and levees, thus increasing erosion and threat to flooding control structures (Eno, 1997).

Figure 2-1: Chinese Mitten Crab, *Eriocheir sinensis* (Ray, 2005)

European green crab

Carcinus maenas, the European green crab (Figure 2-2), is native to northern Europe. They are usually a dark green colour and now found in South Africa, Japan, and Australia. It was introduced to the east coast of North America sometime in the 1800's (Scattergood, 1952) and since then invaded the west coast. One or combination of different vectors including ballast water, packing material for oyster, live bail, etc. may be responsible for its introduction (Cohen *et al.*, 1995). Expansion along the west coast is attributed by currents (Yamada *et al.*, 2001). Decrease in population of soft clams (*Mya arenaria*) in New England (Glude, 1955), *Nutricola spp.* in Central California (Grosholz *et al.*, 2000), and the venerid clam *Katelysia scalarum* in Tasmania (Walton

et al., 2002; Ross *et al.*, 2004) are all believed to be the results of introduction of *C. maenas*.

Figure 2-2: The European Green Crab, *Carcinus maenas* (Ray, 2005)

Mussels

Perna viridis, the Asian green mussel, is native to the tropical area and its populations distributed between the South China Sea and the Persian Gulf (Figure 2-3). Its first appearance, in the western hemisphere, was in Trinidad in 1990 (Agard *et al.*, 1992), then in Venezuela (Rylander *et al.*, 1996) and in Tampa Bay, Florida in 1999 (Benson *et al.*, 2001; Ingrao *et al.*, 2001). It is believed that the introduction of Asian green mussel to the Caribbean has been through ballast water and subsequent dispersal is attributed to either ballast water or prevailing current (Ray, 2005). Like the freshwater zebra mussel (*Dreissena polymorpha*), the green mussel attaches to any hard structure. It has caused clogging of inlet water pipe of local power plants at Tampa Bay (USGS, 2001).

Figure 2-3: The Green Mussel, Perna viridis (Ray, 2005)

Perna perna, the brown mussel (Figure 2-4), is native of South Africa and has successfully invaded South America from Uruguay to the Caribbean probably via ballast water (Gulf States Marine Commission, 2003). Similar to the green mussel, it can attach to any hard surface such as jetties, navigational buoys, and oil platforms (Hicks & Tunnell, 1995).

Figure 2-4: The Brown Mussel, Perna perna (Ray, 2005)

Musculista senhousia, the Asian date mussel (Figure 2-5), is native to intertidal and subtidal sediments from Siberia to the Red Sea. It has been introduced to Australia, New Zealand, the eastern Mediterranean, and southern France presumably via ballast water (Crooks, 1996 and references therein). This species forms dense beds that significantly alter nearby sediments and thereby may interfere with the recolonisation of sediments employed for beneficial use project (Crooks, 1998; Crooks & Khim, 1999).

Figure 2-5: The Asian Date Mussel *Musculista senhousia* (Ray, 2005)

The zebra mussel, *Dreissena polymorpha*, native to European water was first detected in North America in Lake St Clair, Michigan, in 1988. This species is believed to have been introduced in 1983 or 1984 from transoceanic ships that discharged freshwater ballast containing planktonic larvae or young adults (Ahlstedt, 1994). It has now spread, infesting more than 40% of the United States waterways and fouls the cooling water intakes of the industry. (Globallast, 2001).

Figure 2-6: Black-stripped mussel, Mytilopsis sallei (Ray, 2005)

Figure 2-7: Zebra mussel, Dreissena polymorpha (Ray, 2005)

Black-stripped mussel (Figure 2-6), *Mytilopsis sallei*, has been reported from Mumbai and Visakhapatnam (Karande & Menon, 1975; Raju *et al.*, 1988). This species is native

to tropical and subtropical Atlantic waters and is invaded the Indian waters sometime during 1960s. It has also spread to Hong Kong and invaded Australian waters.

Whelk

Rapana venosa, the veined rapa whelk (Figure 2-8), is native to the Japanese water and found in Chesapeake Bay in 1998 (Mann & Harding, 2000). It is known as an invasive species in the Black, Adriatic and Aegean Seas and believed to have entered via ballast water.

Figure 2-8: The Veined Rapa Whelk, Rapana venosa (Ray 2005)

American jack knife clam

Figure 2-9 shows American Jack knife clam, *Ensis americanus*, native to the Atlantic coast of North America, which was detected in 1989 on Holme Beach, Norfolk (Howlett, 1990). Introduction of this species to European water was assumed to be via Tanker ballast water and its spread within European waters has been by pelagic larvae (Cosel *et al.*, 1982).

Figure 2-9: American jack knife clam, *Ensis americanus* (Source: www.europe-aliens.org, Sergej Olenin)

Comb jellyfish

Mnemiopsis leidyi, an opaque comb jellyfish (Figure 2-10), about 10 centimetres long, entered the Black Sea in early 1980s by ship's ballast water from the United States. *M. leidyi*, encountered no predators in the Black Sea but plenty food. It ate the eggs and larvae of various fish that led to a collapse of the fishing industry (Shiganova, 1998).

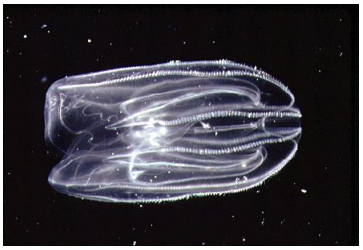

Figure 2-10: An Opaque Comb jelly fish, *Mnemiopsis leidyi* (Source: the Internet)

Bacteria

Vibrio cholerae 01 and 0139 are the cause for the human epidemic cholera, and can be transported through ballast water (Ruiz *et al.*, 2000). As the bacteria are capable of forming associations with plankton, their survival in the ballast water tanks are much easier.

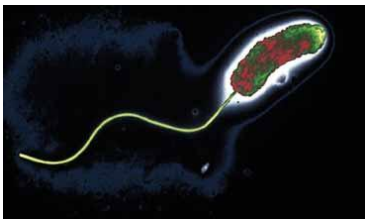

Figure 2-11: *Vibrio cholerae* (Source: the Internet)

Table A1 (in Appendix A) lists viruses, bacteria and species previously detected and isolated from ballast tanks of ships calling various ports around the world.

The interaction of ship's ballast water and marine environment has developed an undesirable and non-observable system of translocation of NIS across the globe. This is undesirable because ships are not designed and meant for such purpose and is non-observable due to:

- Uncertainty in the input i.e. number, types, sizes and live/dead status of microorganisms entering the ships are unknown,
- Lack of biological model to correlate the survivability of microorganisms during the transit,
- Uncertainty in the distribution of microorganisms inside the ballast tanks,
- Uncertainty in the output i.e. number, types, sizes and live/dead status of microorganisms exiting the ships are unknown,
- Lack of reliable sensors, which can detect the important variables.

The result of such non-observable system, which cannot be monitored and controlled, has created environmental and economical impacts. Some of the potential impacts are

presented in the next section.

2.2.2 The potential impact of NIS

It is now undoubtedly clear that ballast water operations are responsible for introduction of many NIS around the globe. The vast majority of these species will neither survive the journey nor adapt to the new environment outside their historical habitats after introduction (Hooff, 2008). Upon introduction, some NIS may become established, but with no detectable impact. In some other cases, however, the introduced NIS become invasive species and pose a threat for new ecosystem and often have direct / indirect impacts on socio-cultural, economical and human related health (Mack et al. 2000; Carlton 2001). Some well studied cases are brought in the following.

The impact of HAB (harmful algal blooms, Figures 2-12 & 2-13) on human health, fishery resources, and marine ecosystems is well recognized during the past two decades. Many causes, both natural and anthropogenic, have been attributed to the geographic spread of HAB. Ballast water has also been identified as one of the responsible vectors. In the 1970s, the PSP (paralytic shellfish poisoning), a toxin syndrome caused by consumption of seafood contaminated by certain HAB species, was mostly recorded in the northern hemisphere. Since then, there has been a cumulative global increase in the recorded distribution of the causative organisms and the confirmed appearance of PSP toxins in shellfish at levels above the regulatory limit for human consumption (GEOHAB, 2001).

Figure 2-12 Harmful algal bloom in Lake Erie, USA, taken on Sept. 15, 2006. (Source: www.noaanews.noaa.gov)

Figure 2-13: Red algal bloom at Leigh, near Cape Rodney, New Zealand. (Source: NIWA; photo by M. Godfrey).

Introduction of zebra mussels (*Dreissena polymorpha*) and the closely related quagga mussel (*Dreissena rostriformis bugensis*) into the Great lakes in the late 1980's most likely through ship's ballast water arriving from Europe had immediate economic

impact. High fertility and rapid dispersal of both species resulted in their expansion throughout the great lakes, Ohio River and Mississippi River regions during 1990's and caused biofouling of industrial and municipal water intake pipes. The annual cost of controlling and damage to infrastructure was estimated $1.1billion (Pimentel et al., 2005).

Other case study is the decline of native fisheries production caused by introduction of comb jellyfish, *Mnemiopsis leidyi*, into Black Sea (Shiganova, 1998). As a consequence of *M. Leidyi* establishment in the Black sea, the fish catch fell by 90% in six years (Pearce, 1995).

To control such disastrous impact of translocation of NIS, measures should be adopted to stop bio-invasion or minimise it to a manageable level. These measures are either *preventive* or *cure* strategies and there should be a frame of reference to compare the output of these strategies against it. In the next two sections, international regulation for the standard of ballast water discharge and various mitigating methodologies are presented.

2.3 International Regulation

In response to ecological, economical and public health impact of bio-invasion caused by ballast water, the International Maritime Organisation (IMO) through its Marine Environmental Protection Committee (MEPC) has developed international legislation to prevent transportation and subsequent spread of aquatic organisms in ships ballast water.

In February 2004, the international community established baseline global ballast water management standards to prevent the spread of aquatic invasive species through ballast water. In the same year, the IMO adopted a new International Convention for the Control and Management of Ships' Ballast Water and Sediments. The IMO Ballast Convention will enter into force 12 months after ratification by 30 states, representing 35 percent of world merchant shipping tonnage. The Convention (IMO, 2004) is divided into Articles; and an Annex which includes technical standards and requirements for the control and management of ships' ballast water and sediments.

According to the regulation B of the Convention ships are required to have onboard and

implement a Ballast Water Management Plan approved by the Administration (Regulation B-1). The Ballast Water Management Plan is specific to each ship and includes a detailed description of the actions to be taken to implement the Ballast Water Management requirements and supplemental Ballast Water Management practices. In addition ships must also have a Ballast Water Record Book (Regulation B-2) to record when ballast water is taken on board; circulated or treated for Ballast Water Management purposes; and discharged into the sea. It should also record when Ballast Water is discharged to a reception facility and accidental or other exceptional discharges of Ballast Water.

The specific requirements for ballast water management are contained in regulation B-3 Ballast Water Management for Ships:
Ships constructed before 2009 with a ballast water capacity of between 1500 and 5000 cubic metres must conduct ballast water management that at least meets the ballast water exchange standards or the ballast water performance standards until 2014, after which time it shall at least meet the ballast water performance standard.
Ships constructed before 2009 with a ballast water capacity of less than 1500 or greater than 5000 cubic metres must conduct ballast water management that at least meets the ballast water exchange standards or the ballast water performance standards until 2016, after which time it shall at least meet the ballast water performance standard. Ships constructed in or after 2009 with ballast water capacity of less than 5000 cubic metres must conduct ballast water management that at least meets the ballast water performance standard.

Ships constructed in or after 2009 but before 2012, with a ballast water capacity of 5000 cubic metres or more shall conduct ballast water management that at least meets the standard described in regulation D-1 or D-2 until 2016 and at least the ballast water performance standard after 2016.

Ships constructed in or after 2012, with a ballast water capacity of 5000 cubic metres or more shall conduct ballast water management that at least meets the ballast water performance standard.

Table 2-1 summarizes the application dates depending on the ratification date of the

Convention. It can be seen the first deadline for the fitting of ballast water treatment facilities on new built ships under the forthcoming Convention is for ships constructed during 2009 with ballast capacity of less than 5000 cubic meters. The enforcement of the first deadline was discussed and suggested to be postponed in MEPC 56/23 due to delays with ratification of the Convention and in the development of type-approved ballast water management systems. In this respect shipowners will not be required to have systems installed on their vessels constructed during 2009 with a ballast capacity of less than 5,000 cubic metres until the second annual survey, but before January 2012.

Table 2-1: Summary of Regulation B3

	Construction Date	**Ballast water Capacity**	**Standard Applied**	**Application Date**
Existing Ships	Before 2009	Cap. < 1500 m^3	D-1 or D-2	Until 2016
		1500m^3 ≤Cap. ≤5000m^3	D-1 or D-2	Until 2014
	Before 2012	Cap.> 5000m^3	D-1 or D-2	On or after 2009
New Ships	On or after 2009	Cap.< 1500 m^3	D-2	On or after 2009
		1500m^3 ≤Cap. ≤5000m^3	D-2	On or after 2009
	On or after 2012	Cap.> 5000m^3	D-2	On or after 2012

In the regulation B3 reference is made to two standards, D1 and D2, which any ballast water management system should meet their requirements when applicable. The first standard, so called Ballast Water Exchange (D1), set out as interim measure to provide ship operator with guidelines of ballast water exchange in deep water and the second standard (D2) set a line for the biological quality of discharged ballast water, when a shipboard treatment system is installed. These standards are as follows:

- **D1 Standard:** Ships performing Ballast Water exchange shall do so with an efficiency of 95 per cent volumetric exchange of Ballast Water. For ships exchanging ballast water by the pumping-through method, pumping through three times the volume of each ballast water tank shall be considered to meet the standard described. Pumping through less than three times the volume may be accepted provided the ship can demonstrate that at least 95 percent volumetric exchange is met. The operation of ballast water exchange by ships should be conducted according to the regulation (B4) of the Convention. In this regulation all ships performing ballast water exchange should:

  - whenever possible, conduct ballast water exchange at least 200 nautical miles

from the nearest land and in water at least 200 metres in depth, taking into account Guidelines developed by IMO;

- in cases where the ship is unable to conduct ballast water exchange as above, this should be as far from the nearest land as possible, and in all cases at least 50 nautical miles from the nearest land and in water at least 200 metres in depth.

D2 Standard: Ships conducting ballast water management shall discharge less than 10 viable organisms per cubic metre greater than or equal to 50 micrometres in minimum dimension and less than 10 viable organisms per millilitre less than 50 micrometres in minimum dimension and greater than or equal to 10 micrometres in minimum dimension; and discharge of the indicator microbes shall not exceed the specified concentrations.

The indicator microbes, as a human health standard, include, but are not be limited to:

a) Toxicogenic *Vibrio cholerae* (O1 and O139) with less than 1 colony forming unit (cfu) per 100 millilitres or less than 1 cfu per 1 gram (wet weight) zooplankton samples ;

b) *Escherichia coli* less than 250 cfu per 100 millilitres;

c) Intestinal Enterococci less than 100 cfu per 100 millilitres.

Ballast Water Management systems must be approved by the Administration in accordance with IMO Guidelines (Regulation D-3 Approval requirements for Ballast Water Management systems). These include systems which make use of chemicals or biocides; make use of organisms or biological mechanisms; or which alter the chemical or physical characteristics of the Ballast Water.

In support of the Convention, fourteen guidelines were developed to minimise the risk of transferring harmful aquatic organisms in ship's ballast water and sediments. These guidelines provide Flag Administrations and Port State Authorities with guidance on procedures and principles. The two most significant guidelines are G8 and G9, which provide guidelines for approval of ballast water management systems and procedure for approval of ballast water management systems that make use of active substances respectively.

2.4 Control Measures for Bio-invasion

To control bio-invasion through ship's ballast systems the strategy of either *prevention* or *cure* concepts should be adopted. Prevention is always better than cure and hence it is advisable to focus on preventive measures. However, maturity of these concepts and adaptabilities of the technologies on the existing ship and current port infrastructures and facilities are important points to contemplate. Effectiveness, feasibility, capital and operational costs, habitability, ability to monitor and controllability are the considerations for the shipping industry to accept these measures.

2.4.1 Preventive Concept

The idea is to prevent boarding of microorganisms into the ship either by designing a new ship with ballast-free concepts or receiving microorganisms-free seawater from shore/ports or mechanical separation (e.g. filters) that ensures separation of microorganisms down to viruses and bacteria.

2.4.1.1 Ballast-Free Ship

One way to mitigate the translocation of non-indigenous species is "ballast-free ship" concept. It is intended for new building and involves redesigning of ship's ballast system (Figure 2-14) so that seawater constantly passes through entire length of the parallel body of the ship. In this concept, ballast tanks are replaced by ballast trunks beneath cargo space and allowed to be flooded during ballast condition. Therefore due to the motion of ship, a slow and continuous flow of local seawater moves through open trunks (Parsons and Kotonis, 2007). During cargo loading, these trunks can be isolated from the sea by valves and seawater can then be discharged using ballast pumps (Parsons and Kotonis, 2007). When ship is loading cargo, valves isolate these ballast trunks from sea and seawater in these trunks are pumped out by conventional ballast pumps (Parsons and Kotonis, 2007). Computer modelling and scale model tests showed that this idea is technically and economically possible when the ship is operating at nominal speed (Parsons and Kotonis, 2007). This concept may not be suitable for all types of ship as the entire ship design needs to be redeveloped to support proposed concept. It is worthwhile to mention that the biological performance of this concept for the discharge of fouling and non-fouling NIS must be approved.

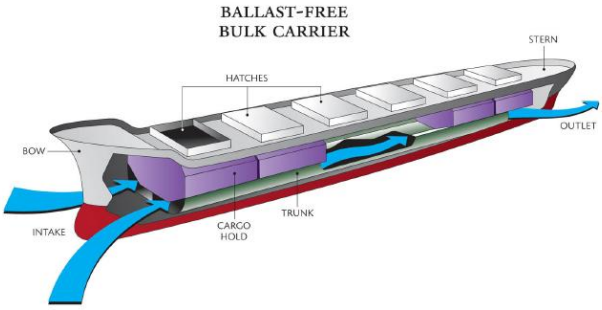

Figure 2-14: Operation principle of the "ballast-free ship" concept (Gregg et al., 2009)

The other example of ballast free ship is an innovative concept for a very large crude oil carrier (VLCC) that eliminates the requirement for ballast tanks. Det Norske Veritas (DNV) has claimed that a tanker with this design would prevent the spread of invasive species. According to DNV, this design is called "Triality" due to three main objectives of creating an environmental friendly VLCC, using well known technology and being financially competitive. There is a drastically hull design difference between this concept and conventional VLCC design. Key elements of the concept are a more V-shaped hull and cargo tanks with five longitudinal rows rather than the three rows in typical of conventional tankers. With a more V-shaped hull, the mean draft of Triality design is about 23 feet in unloaded condition as compared to 10-13 feet for the conventional ship. This higher mean draft would provide full propeller immersion and sufficient forward draft to avoid bottom slamming during unloaded condition (Siuru, B., 2011).

2.4.1.2 Microorganisms-Free Ballast

Author believes other preventive measure can be microorganisms-free ballast. Unlike ballast-free ship, the ballast tanks configurations remain unchanged and boarding of microorganisms is stopped by providing treated ballast water from ports. In this way ship receives treated ballast water (microorganisms-free) from port in a more or less similar way that she takes fuel bunker. It is noteworthy to say that similar to fuel bunkering, there should be a provision for receiving treated ballast from ports. It should also be noted that since ships do not have any measures to control the translocation of NIS in this method, then all the commercial ports should have the facility at sufficient size and capacity compatible to their operations (number, types and sizes of ships calling them). Much technical and economical study is required to ensure feasibility of this method.

2.4.1.3 Separation

In the separation methodology, technology is used onboard the ship to physically remove microorganisms during uptake of ballast. Researches and studies (Parsons and Harkins, 2002; Waite et al., 2003; Velduis et al., 2006) showed that neither of treatment systems assigned in this category can meet D2 standard of the Ballast water Convention. It is, though, possible to use separation technology with an infinitesimal porosity to remove bacteria, but currently the required operational energy and footprint may be limitations for installation of such technology. Nonetheless, performance of each individual, if known, can be used as supplementary treatment technology. In the following a brief description of experimented separation technologies will be reviewed.

I. Filtration

Filtration technology consists of techniques such as sand filtration, membrane filtration and screen filtration. In principle both sand and membrane filtrations may make the removal of microorganisms of sizes less than 1 micron possible, however such techniques may not be viable for ballast water treatment due to relatively lower permeability when compared to screen filtration. In the ballast water treatment process maintaining ballasting / deballasting flow rate for the intended period of time is one of the key issues. As a consequence, the filtration process suitable and currently being used in ballast water treatment systems are generally discs or fixed screen with automatic backwashing. Since the standards set for the discharge of ballast water are based on the sizes of microorganisms in minimum dimensions, filtration with appropriate mesh size has the capability of removing materials above specific size. The effectiveness of filtration process is the balance between flow rate, operating pressure and cleaning frequency. In a test to investigate the effectiveness of an automatic backwash screen filtration by the Great Lake Ballast Technology Demonstration Project on a dry bulk carrier two filter units (pre-filter unit of 250 micron and various filter units from 25 to 150 micron) connected in series and the biological effectiveness of two smallest filters showed 95-99 percent removal of macro-zooplankton and 70-80 percent removal of micro-zooplankton and phytoplankton (Parsons et al., 1999). Authors also conducted series of tests to investigate the biological effectiveness of automatic backwashing filter with 40 micron weaved mesh and observed more or less similar results.

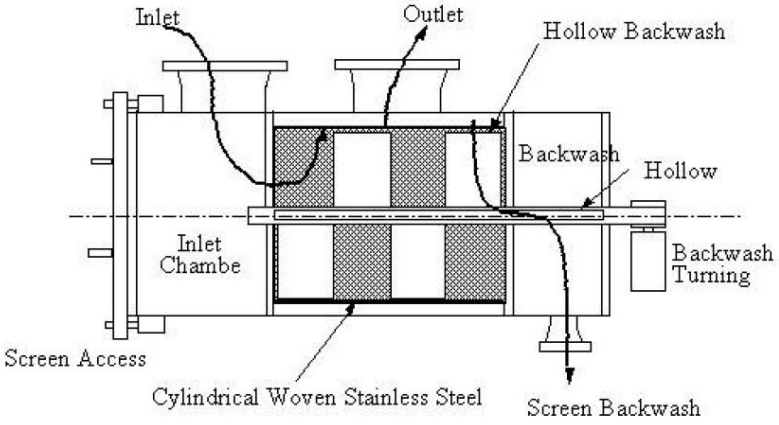

Figure 2-15: Automatic backwashing filter (Parsons et al., 2002)

II. Hydrocyclone

An alternative technology to filtration is hydrocyclone, which enhance sedimentation by using high velocity water. In cyclonic separation technology, water at extremely high flow rates creates centrifugal force capable of separating solids and large organisms. As ballast water enters the specially designed separator, a cyclonic flow is produced inside it. The centrifugal force then drives the solid particles and large organisms toward the outer wall and allowing the cleaner ballast water to move through the centre of separator. Similar to automatic filtration, separated solid particles and organisms are continuously being discharged during operation to the location of origin. The main advantage of hydrocyclones over automatic filters is the lesser pumping pressure requirement, hence very unlikely to upgrade existing ship's ballast pumps. Additionally there are no movable parts and no filter elements or screens to clean in the hydrocyclones, which eliminates the necessity of back washing operation. Consequently, the system requires little or no maintenance when compared to automatic filtration.

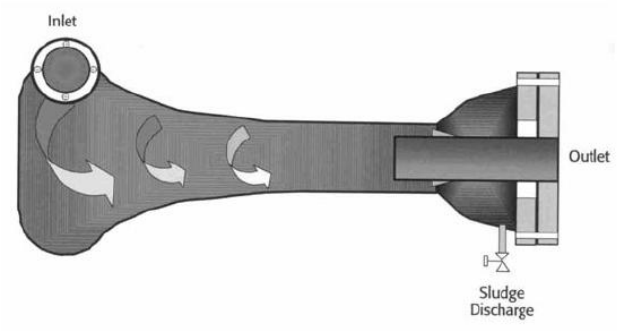

Figure 2-16: Typical Cyclonic Separator - Hydrocyclone (Glosten-Herbert-Hyde Marine., 2002)

The over-riding goal in hydrocyclone technology, as far as biological effectiveness is

concerned, is the removal capability of the system at rated flow rate. The effectiveness of separation depends on the specific gravity of the particles, the particle size and the flow rate. Therefore, conventional cyclonic separators are limited to the particles with a specific gravity greater than surrounding water and not as much effective for many types of organisms such as bacteria, pathogens, most zooplankton and phytoplankton (Cangelosi et al., 2001).

III. Membrane/Media filter

Membrane/Media filters can separate submicron (less than 1 μm) microorganisms and particles from ballast water and have removed so in other water treatment processes. Such technology need to be specifically designed in order to cope with the flow requirement of ballast water operations, while considering space restriction and power consumption at reasonable level for given applications (Lloyd's Register, 2010; Kazumi, 2007). Recent research on using compressible element such as crumb rubber in filter technology showed potential to treat ballast water and requires less space than conventional media filter (Tang et al., 2006a; 2006b). Elasticity of compressible media reduces the porosity of filter media during compression and the media porosity can be adjusted depending on compression of filter media. Tang et al. (2006b) investigated the effectiveness of crumb rubber filter for the removal of turbidity, particles, phytoplankton and zooplankton. The results indicated that crumb rubber filtration removed up to 48% of turbidity, 46% of overall particles, 70% of phytoplankton and 45% of zooplankton. In their experiments, the researchers conducted three design (media size, filter depth and filtration rate) parameters and operational (high, medium and low) factors and found media size had higher removal efficiency of all targeted matters, but at the expense of higher head losses.

2.4.2 Cure Concept

In this concept, the idea is to inactivate or expel boarded microorganisms during uptake of the ballast, using available transit time in the ballast leg of the voyage. The strategies for this concept may include, but not limited to, Ballast Water Exchange (BWE) in the open ocean, delivering ballast water to port reception facility and treatment of ballast water.

2.4.2.1 Ballast Water Exchange (BWE)

BWE is the most current shipboard practice procedure, which relied on the replacing

ballast water taken onboard in port area with Open Ocean water prior to discharge at the next port of call. There are two basic methods of conducting BWE procedure: Empty-refill and flow-through methods. The former one involves discharging the ballast water completely and refilling the tanks, while in the latter method oceanic water is continually pumped into ballast tanks and allowed to be overflowed until exchange is gradually accomplished. The shortcomings of BWE are: safe conductance depends on the weather and sea surface conditions, it is not 100% effective and if conducted at the wrong time and locations, then it can result in a greater diversity of microorganisms in the ballast water (Gregg et al., 2009 and the references therein). Rigby et al. (1993) studied the effectiveness of BWE onboard the bulk carrier and found that 37, 13 and 5% of the original water remained in the ballast tanks for the exchange of one, two and three ballast tanks volumes respectively. It is very important to mention that the effectiveness in removing microorganisms through BWE is a complex issue and depends on several factors, including nature and behaviour of microorganisms, the design and structural configuration of tanks, mixing within the tanks and the types and behaviour of sediments. There are some discrepancies reported in microorganisms removal through BWE and are attributed to the age and design of the ships. These factors reflect the complexity of flow patterns and behaviour of microorganisms in the tanks (Gregg et al., 2009 and the references therein).

2.4.2.2 Port Reception

In this methodology, similar to microorganisms-free method, ports should be facilitated to receive the untreated ballast water from ships at such a rate and volume that guarantee safe cargo operations of ships. The size and capacity of port reception facility depends on the number and types of ships calling them. Similarly, ports must be physically able to expand in order to accommodate such reception facilities and ship's ballast system has to be modified to allow for shore connection, this methodology needs to be researched for feasibility and cost effectiveness as compared to other methods. A prominent advantage of this method is no need for onboard ship treatment system and no changes in shipboard ballast operation.

2.4.2.3 Treatment System

The technologies selected, tested and eventually used for treatment of ballast water are generally inspired from municipal and other industrial applications. Key factors such as required space, biological effectiveness, safety and associated costs (constructional,

installation and operational) restricted the use of some of treatment technologies.

Generic approach to categorize ballast water treatment system in the literatures is to divide them into solid-liquid separation (primary treatment) and disinfection (secondary / main treatment). The latter can then be subdivided into chemical and physical inactivation of the microorganisms. However, in this thesis, separation technologies is classed as *preventive* concept and in this section the main focus is placed on the performance of so called main treatment system. In the treatment method inactivation/killing of microorganisms are carried out using one or more of following methods:

- By irradiation of ultraviolet light or cavitation or ultrasound or asphyxiating
- By injection / addition of various effective chemical

These technologies are thus subcategorized into two main groups of physical and chemical disinfection technologies. In the latter a form of active substance, either stored or generated onboard the ship by involved technology, is added to ballast water for treatment. Active substances of any form, when added for intended purpose, may be present in the discharged ballast water at a concentration harmful for receiving environment. It means that the discharged ballast water is still toxic and may impose unacceptable harm to the organisms in the discharged location. Therefore the active substances or preparation as well as the discharged ballast water should be subjected to toxicity testing, according to the IMO Convention guideline (IMO, 2005b), in order to protect the environment of the discharged location and human health as consequences of toxic discharge. In the following each individual secondary treatment technology will be reviewed.

I. Physical disinfection

Technologies including UV irradiation, deoxygenating, cavitation, heat, ultrasound and lazer, to date, are considered as physical disinfection treatment technologies.

a) UV irradiation

Ultraviolet (UV) rays are an invisible form of light between the X-ray portion of the spectrum and the visible portion. UV wavelengths range between 100 and 400 nm. For the past several decades, UV rays shorter than 300 nm have been known to destroy bacteria and viruses. The most recent research has found that wavelengths between 200 and 280 nm (UV-C) are the optimal range, with 254 nm being the most effective for

inactivation of microorganisms. UV lights can be produced by various lamps, but generally three types of Low Pressure Low Intensity (LP-LI), Low Pressure High Intensity (LP-HI) and Medium Pressure High Intensity (MP-HI) are used in some applications like drinking water. The lamps in the reactor are either fixed vertically (perpendicular to the flow) in the reactor, or horizontally (parallel to the flow) or diagonally to the flow direction (USEPA, 2006). The lamp placement in the reactor influences the dose delivery. Most of the UV systems currently produced for disinfection of wastewater application have their lamps fixed in a position that the flow lines are running parallel to the lamp axes (Christopher P. Martin et al., 2004). Some manufacturing companies, however, claim that the vertical arrays (perpendicular to the flow) are more efficient and it is less probable that the exiting water has not received adequate dose (Infilco Degremont, Inc., 1996; Christopher P. Martin et al., 2004).

The inlet and outlet configuration of UV reactors can have significant influence on the hydrodynamics of UV reactor and thus UV dose delivery. For instance, perpendicular inlet and outlet to the flow direction within the reactor promotes short-circuiting, eddies and dead zones in the reactor. In contrast to perpendicular inlet and outlet configuration, straight inlet and outlet configurations with smooth gradual changes in cross sectional area will improve the flow characteristics for optimal dose delivery (USEPA, 2006).

In general, UV radiation of microorganisms causes chemical bonds to form in cellular DNA. The exposure thus interrupts normal DNA replication and organisms are killed or rendered inactive. UV disinfection of water is currently used in the drinking water, waste water and aquaculture industries. In ballast water treatment, like other water disinfection processes, UV needs to dose target microorganisms adequately in flowing ballast water through a treatment chamber (Christopher P. Martin et al., 2004; USEPA, 2006).

The biological effectiveness of UV, however, is affected by the UV Transmittance (UVT) of the ballast water. UVT measures the ability of a medium to transmit UV light. It represents the percentage of UV energy in the water available for disinfection of microorganisms after a specified distance of UV light penetration (e.g. 1 cm). This would indicate that lesser amount of UV light reaches the targeted microorganisms free-floating at the longer distance away from UV irradiation source than nearer ones. UVT

is often represented as a percentage and is related to the UV absorbance by the following equation:

$$\%UVT = 100 \times 10^{-A} \quad (2.1)$$

where A (absorbance) is calculated as follows:

$$A = \log(I_o/I) \quad (2.2)$$

I_o = Intensity of reference beam

I = Intensity of sample beam

Number of studies carried out on the performance of UV irradiation. Sutherland et al. (2001) found the reduction in the growth rate and relative abundances of three phytoplankton species; whereas Waite et al. (2003) claimed that the exposure of a natural phytoplankton assemblage to the UV irradiation at the UV dose of 60 $mJcm^{-2}$ did not show a statistically significant effect and in the case of larger organisms, the treatment at the noted UV dose showed mortality of zooplankton in the sample. In all testing conditions at various level of turbidity, the UV treatment unit, however, reduced bacteria population significantly. In another experiment performed by Oemcke et al. (2004), the efficacy of UV in killing zoospores of the seaweed, a marine bacterium, and cysts of dinoflagellate determined in two laboratories. The results showed significant kill rate of 99% of seaweed zoospores and 99.9% of the marine bacterium were achieved at the UV dose of 60 and 37.5 $mJcm^{-2}$ respectively. Contrary to the above results, the maximum kill rate of 40% was only achieved when cysts of dinoflagellate were exposed to the UV dose ranging from 50-350$mJcm^{-2}$. Oemcke et al. (2004) confirmed ineffectiveness of UV irradiation even at high UV dose of 1,600$mJcm^{-2}$ on the cysts of dinoflagellate. The results showed survivability of dinoflagellate (maximum kill rate of 70%) as determined by hatching the exposed cysts.

b) UV + TiO_2

Alfa Laval developed a ballast water treatment system based on advanced oxidation technology (AOT) inspired from the self cleaning windows of skyscrapers. In the self cleaning windows AOT reaction occurs, when sunlight strikes titanium dioxide and prevents the growth of organisms. Alfa Laval in its system, so called PureBallast, employs one or more AOT units, which contain titanium dioxide catalysts. Once light hits these catalysts, they generate radicals with short lifetime of a few milliseconds as claimed. Unlike UV treatment, which destroys the DNA of organisms, the generated

radicals efficiently break down the cell membrane. This ballast water treatment system has been tested and received type approval in 2008 (Lloyd's Register, 2010).

c) Deoxygenating

In this treatment technology, killing / inactivation of organisms are accomplished by removing dissolved oxygen from the ballast water. This can be done by purging oxygen from ballast tanks by continuous supply of nitrogen (Tamburri et al., 2002) or by using of a venturi oxygen stripping system (Tamburri et al., 2006) or by adding nutrients to stimulate the growth of bacteria (McCollin et al., 2007). In the nitrogen treatment method, Tamburri et al (2002) conducted laboratory experiments to test the oxygen tolerance of larvae from three taxonomically diverse invaders and observed significant mortality in them. In their report it was also claimed the system may be cost effective due to reduced rate of corrosion in ballast tanks. In the second option to remove oxygen from ballast water, Tamburri et al (2006) designed a shipboard system to mix combustion products of marine diesel engine (oxygen stripping gas) with ballast water using a venturi jet pump installed in ballast line. It is also stated that the oxygen stripping gas in this system would reduce the ballast tank corrosion as well as number of live invading organisms in accordance with IMO biological standard. Biological results of deoxygenating using venturi oxygen striping system, in case of organisms greater than 50 μm (Zooplankton), showed significant mortality after holding organisms in treated condition for four to five days (Tamburri, 2006). However, total abundances of organisms between 10 and 50 μm (phytoplankton) in the two shipboard tests were reduced from 1000 ~ 3500 cells/ml to 593 cell/ml (± 234 SD) and 443 cell/ml (± 218 SD). The biological results of VOS system for phytoplankton is significantly above the standard set by IMO Convention. In the third option, a nutrient solution added to ballast water tank to encourage the growth of bacteria and hence increasing the oxygen consumption within ballast water. As a consequence of removed oxygen from ballast water in tank, a hostile environment is created for aerobic organisms. McCallin et al, (2007) performed shipboard experiment using this method to deprive ballast water organisms from oxygen. The biological results of targeted zooplankton in this experiment (copods and nauplii) showed IMO compliance, whereas the results for phytoplankton were inconclusive.

d) Heat Treatment

In this process, heat energy would be used to raise the ballast water temperature high

enough to kill invasive organisms. Heat energy source may vary from ship to ship and depends on the targeted temperature. It can be obtained from steam generated from waste heat recovery plant or main propulsion engine cooling water. The biological effectiveness of a heat treatment system depends on the required temperature at which the organisms should be subjected (thermal threshold) and time of exposure to that temperature. Hence, the efficiency of a system depends on the ability of the equipment to raise the ballast water temperature to the thermal threshold of organisms. In 1999, Rigby et al. conducted a shipboard experiment to assess the effectiveness of heat treatment on ballast water management. In this experiment (Figure 2-17), ballast water uptake was continuously heated by engine cooling water and flushed through ballast tank until temperature of ballast water in tank reached 38 °C. From the onboard microscopic observation of samples taken from treated ballast tank, Rigby et al. concluded that heat treatment of ballast water to the temperature of 38 °C and sufficient time to accomplish heating operation for all ballast tanks would kill plankton (mainly chaetognaths and copepods) and major portion of phytoplankton. It was also stated that only very limited original phytoplankton (mainly dinoflagellates) could survive after the heat treatment.

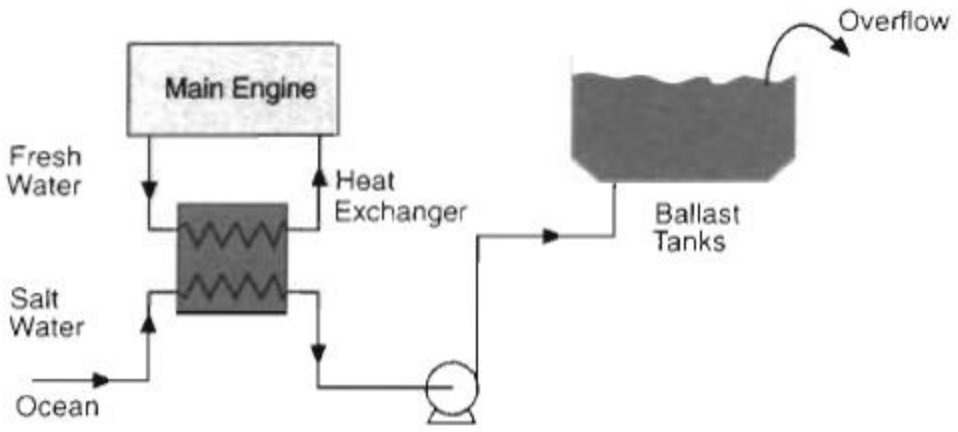

Figure 2-17: Circuit diagram of heat treatment system on MV Iron Whyalla (Rigby et al., 1999)

In other shipboard experiment, Quilez-Badia, G. et al. (2007) carried out a short-time high temperature heat treatment technique on ballast water. In their heat treatment system, which actually conducted before adoption of IMO Convention, ballast water from three tanks was subjected for a few seconds to high temperatures ranging from 55 °C to 80 °C in two stages. The ballast water was initially preheated to the temperature of 40 - 45 °C and then to the required temperature, for particular tests, using steam from ship (Figure 2-18). Treated ballast water was cooled down to the temperature of 22 – 27

°C prior to discharge. The researchers concluded that the treatment was effective in some of the tests for the zooplankton, in all the tests for the phytoplankton; and probably on most occasions for the bacteria.

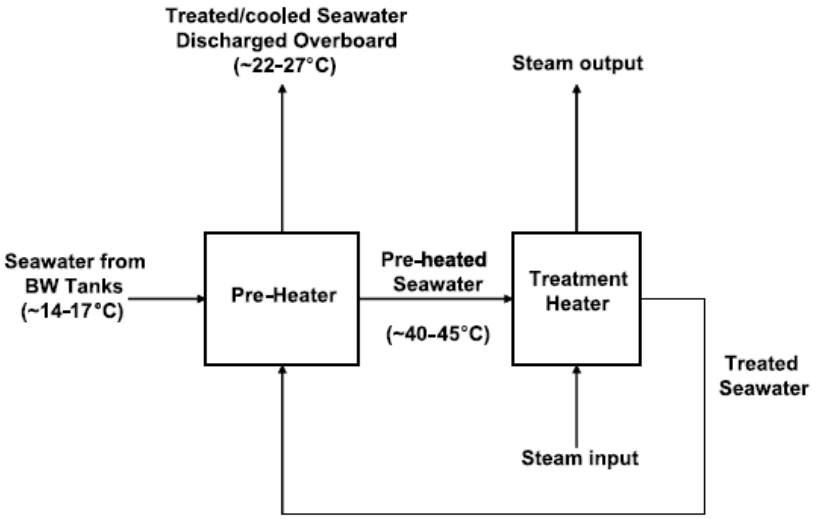

Figure 2-18: Simplified circuit diagram of heat treatment system (Quilez-Badia, G. et al., 2007)

e) Ultrasound

Ultrasound (sonic spectrum ranging from 20 kHz and 10 MHz) can be generated by a transducer. In this process, transducer converts mechanical or electrical energy into high frequency vibration. The effect of high frequency vibrations on the liquid will results in cavitation, which can be defined as formation and subsequent collapse of vapour filled bubbles. As a result, cavitation act on the surface of organisms and cause the rupture of cell membrane through the collapse of generated micro-bubbles and upon subsequent collision with other organisms and particulate matter further mortality can be obtained (Buchholz et al., 1998). Ultrasound technology has been used in water treatment and food industries to control parasites such as *Giardia* and *Cryptosporidium*. In other research using this technology, low mortality rate of below 40% for zooplankton (*Artemia*) and 71% for phytoplankton at the flow rate of 400 l/h was found (Sassi, J. et al., 2005).

f) Cavitation

Hydrodynamic cavitation is another way forward for creation, growth and subsequent violent collapse of vapour or vapour-gas filled micro-bubbles. Laboratory scale tests have been carried out to assess this technology as ballast water treatment system. This process similar to ultrasound treatment needs better understanding before serving as viable single treatment technology. However, some systems use these techniques

(Hydrodynamic cavitation and Ultrasound) with chemical to achieve required biological effectiveness (Lloyds, 2010).

g) Laser Technology

Utilizing laser technology as a potential for controlling of biofouling and reduction of spread of invasive species has been inspired from its ability to sterilize surgical equipment. Low power pulsed Laser irradiation, at laboratory scale, was used by Nandakumar et al. (2008) to examine the biological effectiveness of laser on planktonic organisms in a flowing water system. In the experiments, the researchers expose three plantonic organisms (*Skeletonema Costatum, Chaetoceros gracilis* and *Heterocapsa circularisquama*) to the low power pulsed laser irradiation at 532 nm with a fluence of 0.1 J cm^{-2}. The experiments conducted at two flow rates of 4.6 and 9.0 l h^{-1} and the mortality recorded was >90% for *S. costatum* and *H. circularisqama* and >70% for *C. gracilis*. The observed results led the researchers to suggest that there is a potential for laser technology to act as ballast water treatment.

II. Chemical disinfection

Technologies including Chlorination, Ozonation, Hydrogen peroxide, Peracetic acid, Vitamin K (SeaKleen) and Chlorine Dioxide, to date, are considered as chemical disinfection treatment technologies and have been employed in the ballast water treatment systems.

a) Chlorination

Chlorine has historically been used as disinfectant in drinking water, irrigation and swimming pool facilities. Chlorine kills pathogens such as bacteria and viruses by breaking the chemical bonds in their molecules. When enzymes in bacteria come in contact with chlorine, one or more of the hydrogen atoms in the molecule are replaced by chlorine. This causes the entire molecule to change shape or fall apart. When enzymes do not function properly, a cell or bacterium will die. Chlorine is effective for the inactivation of vegetative bacteria and many viruses, and can be used, at high dose, for bacterial spores, mycobacteria and protozoa (Korich *et al.*, 1990; Sobsey, 1989; Jarroll, 1988). It is, however, ineffective for the killing of *Gymnodinium catenatum* cysts (Bolch & Hallegraeff, 1993). When chlorine is added to seawater (ballast water), it reacts with bromide ions, range of inorganic cations, ammonia and various organic compounds, which could be present in seawater. Chlorine used in these reactions can no longer be considered as disinfectant. The amount of chlorine used during these

processes is referred to "chlorine enquiry" of water. Therefore for effective disinfection, higher dose has to be applied. Chlorine enquiry is determined by the amount of organic matter in the water, the pH of the water, contact time and temperature.

Chlorine for disinfection can be generated onboard to eliminate the chance of onboard storage, Seawater or any water containing NaCl can be used to generate a disinfecting solution such as hypochlorous acid or hypochlorite ion, which contains chlorine. The process is based on the electrolysis of NaCl in sea/saline water as it flows through electrolytic cell. Chlorine generated at the anode side of cell chemically reacts to form sodium hypochlorite and hypochlorous acid. Reactions are shown below:

$$Cl^- \rightarrow Cl_2\,(aq) + 2e^- \quad Eo \;\; 1.396\ V \qquad (2.3)$$

$$Cl_2 + 2H2O \rightarrow 2HOCl + 2H^+ \qquad (2.4)$$

$$HOCl \rightarrow OCl^- + H^+ \qquad (2.5)$$

The disinfection effectiveness of hypochlorous acid (HOCl) is higher than hypochlorite ion (OCl^-) and the proportion of each in the produced disinfectant solution is determined by the pH and the temperature. At lower pHs, most of the chlorine is in the form of hypochlorous acid while at higher pHs, most of the chlorine will be in the ion form (Matousek, R. C. et al., 2006).

Electrolytically generated chlorine was chosen as a potential treatment option for ship's ballast water. This treatment system had previously shown good results when used to disinfect river water prior to application in a citrus orchard (Grech and Rijkenberg, 1992). Matousek, R. C. et al. (2006) performed mesocosm-scale testing by adding sodium hypochlorite, electrolytically generated from seawater with and without using filtration, to assess the viability of this technology as ballast water treatment system. The results from this study showed that the hypochlorite level of greater than 3.0 ppm with or without filtration was able to reduce the bacteria by more than 99.999% and both phytoplankton and mesozooplankton by more than 99%. In this study, filtration was effective when initial concentration of hypochlorite was less than 1.5 ppm.

b) Ozone

Another type of oxidizing biocide used to treat potable and a variety of industrial process water is ozone (O_3). It is continuously created and destroyed by the action of

ultraviolet sunlight. Ozone can also be artificially produced when oxygen (O_2) molecules are broken into oxygen atom by an energy source and subsequently recombined with an oxygen molecule. Ozone is an unstable gas and decomposes to elemental oxygen in a short time; therefore it needs to be generated onsite and fed immediately into chamber containing the water that needs disinfection (USEPA, 1999).

Ozone is a very strong oxidant causing direct oxidation and destruction of the cell walls of organisms. Ozone decomposes in water to form the free radicals such as hydrogen peroxy (HO_2) and hydroxyl (OH). These radicals have great oxidizing capacity and disinfection capability (USEPA, 1999). Similar to chlorination, susceptibility of the target organisms, dosage and contact time are important and playing a key role in disinfection effectiveness of ozone. It was reported to control most vertebrate species, unicellular, and some benthic organisms a dosage of 0.4 ppm is sufficient, whereas higher dosage of 10 ppm is needed to control more resistant cysts (Laughton et al., 2001). Preliminary results of other study on ozone, conducted onboard a double hull tanker, showed mortality rates of 99.9% for the bacteria and over 90% for zooplankton after five and ten hours of contact time respectively (Cooper, 2002). Other studies, at laboratory scale, to assess the potential of ozonation for disinfection of ballast water, indicated that to achieve 4-log reduction of *Bacillus subtilis* pores, dosages of 9 mg L^{-1} (at pH 7) and 14 mg L^{-1} (at pH 8.2) for 24 hours of contact time is required (Oemcke and van Leeuwen, 2004). In a similar experiment, Oemcke and van Leeuwen (2005) applied high ozone doses of 5 to 11 mg L^{-1} and contact time of 6 hours to achieve 4-log reduction of the *Amphidinium* sp. The researchers, however, drew the conclusion that "Ozonation is likely to be a difficult technology to implement for organisms with high dose requirement in combination with characteristics of ballast tanks, which contain areas of sediments high in detritus and areas of corrosion" (Oemcke and van Leeuwen, 2005).

In another shipboard experiment, using a prototype ozone treatment installed on an oil tanker, S/t Tonsina, ozone gas diffused into a ballast tank for 5 to 10 hours and inactivation rates of 99.99 % of the culturable bacteria, > 99 % for dinoflagellates and 96 % for zooplankton were observed (Herwig et al., 2006).

c) Peracetic acid and peraclean

Peracetic acid has shown effectiveness in controlling the coliform bacteria in sewage

sludge and bacteria spores at the concentrations of 6–8 and 300 ppm respectively (Baldry and French 1989; Sagripanti and Bonifacino 1996). Due to the fact of its effectiveness and lack of undesirable by-products, peracetic acid can be considered as a potential for the treatment of ballast water. Having said that, peracetic is very dependant to the pH of the water and found to be little to no effective for the pH value above 8 (Sagripanti and Bonifacino 1996). This finding together with the pH of seawater may limit usage of peracetic as biocide for ballast water treatment. However a commercially available biocide, Peraclean® Ocean, comprising of peracetic and hydrogen peroxide has been developed and reported to be effective in the killing of marine organisms. It has shown effectiveness over a broad range of microorganisms such as bacteria, spores, phytoplankton, aquatic invertebrates and fish eggs at 50-400 ppm and contact times of 2- 72 h (Fuchs et al. 2001; Fuchs and de Wilde 2004). Unlike peracetic acid, Peraclean® is very active at pH values of 5-7 and also shows good activity up to a pH of 9 (Fuchs et al. 2001). Lab-scale testing has shown that the product could effectively inactivate cysts of marine dinoflagellates *Gymnodinium catenatum, Alexandrium catenella* and *Protoceratium reticulatum* at 400 ppm, control the growth of *Escherichia coli*, *Staphylococcus aureus*, *Listeria innocua* and *Vibrio alginolyticus* at 125–250 ppm and eliminate vegetative dinoflagellate cells at the concentration of 100 ppm (Gregg and Hallegraeff, 2007). Veldhuis et al. (2006) in a full scale land based ballast water treatment system assessed the effectiveness of Peraclean® Ocean. It was applied to estuarine water at a concentration of 150 ppm and resulted in the total inactivation of all zooplankton and phytoplankton. In this experiment bacterial growth decreased at the present of H_2O_2, but rapid bacterial regrowth was observed after 6 to 10 days suggesting that full bacterial disinfection was not achieved (Veldhuis et al. 2006).

d) SeaKleen

Another commercially available biocide developed by Garnett, Inc. Atlanta is SeaKlean. It is the mixture of naphthoquinones, menadione (a water-soluble form of Vitamin K_3) and its bisulphate and has been effective in inactivation of a broad range of fresh water and marine organisms (Sano et al., 2004; Railkow et al., 2006). Laboratory scale testing of SeaKleen® proved to be effective on killing of aquatic algal species (*Chlorella* sp., *Isochrysis galbana*, *Neochloris* sp., *Tetraselmis suecica*), vegetative dinoflagellates (*Alexandrium catenella*, *A. tamarense*, *Gymnodinium catenatum*, *Karenia brevis*, *K. brevisulcata*, *Karlodinium veneficum*, *Prorocentrum minimum*, *Protoceratium reticulatum*, *Scrippsiella trochoidea*), dinoflagellate temporary cysts (*Glenodinium*

foliaceum), raphidophytes (*Chattonella marina*) and zooplankton (*Crassostrea virginica* larvae, *Cyprinodon variegates*, *Dreissena polymorpha* larvae, *Leptocheirus plumulous*, *Mytilus galloprovincialis*) at concentrations ranging from 0.5 to 2 ppm (Wright and Dawson 2001; Cutler et al. 2004; Gregg and Hallegraeff 2007). In shipboard tests, when ballast tanks were dosed by SeaKleen® at the concentration of 2 ppm, mortality rate of 99 and 100% of zooplankton after 24 and 48 hours of exposure time were resulted (Wright and Dawson, 2001). SeaKleen® showed even better results when tested against phytoplankton. Wright and Dawson (2001) assessed the effectiveness of SeaKleen® on vegetative microalgae and found they can be controlled at the concentration range of 0.5–2 ppm and exposure time of 2–24 hours. Similarly, in another experiment conducted by Gregg and Hallegraeff (2007), the researchers observed no viable vegetative microalgal cells at the concentration of 2 ppm following an exposure of 48 hours. There are, however, some disagreements for the effectiveness of this biocide over elimination of bacteria. According to Wright and Dawson (2001), SeaKleen® is highly effective against bacteria and can eliminate *Escherichia coli* and *Vibrio fisheri* at a concentration of 1 ppm. Conversely, Gregg and Hallegraeff (2007) found in their experiments that concentrations of 50-200 ppm is required for inhibiting regrowth of *E. coli*, *Listeria innocua*, *Staphylococcus aureus* and *Vibrio alginolyticus*. Inconsistencies also exist in regards to the degradability of SeaKleen®. In Wright et al. (2007a) studies a half life of 18-30 h for SeaKleen® was documented, whereas in other experiment, SeaKleen® in dark condition and in seawater without organisms degraded to 21% of the initial concentration after 28 days. Gregg and Hallegraeff (2007) in their study found no significant degradation of 4 ppm SeaKleen® after 15 weeks and concluded that degradation of this product was not influenced by ballast tank sediment, biological matter or light conditions. Faimali et al. (2006) also reported that under light condition the rate of degradation of SeaKleen® did not improve.

e) Acrolein

Acrolein® is another broad-spectrum biocide, which is used extensively in the petroleum industry to reduce bacteria in produced fluids and control submerged plants and algae in irrigation canals. In laboratory scale experiments on marine organisms, Acrolein® showed that vegetative dinoflagellates and marine bacteria can be controlled at concentrations of 1-6 ppm after contact times of 24 and 72 h (Penkala et al. 2004). Results from a 5 days shipboard trial showed 99.99% reduction of bacteria for a period of 2 days and inhibited bacterial regrowth for 3 days when ballast tanks were dosed at

the concentration of 9 and 15 ppm respectively. However, at lower concentration of 1 and 3 ppm, Acrolein® was reported ineffective (Penkala et al. 2004). This would manifest itself in higher concentration for treatment in ballast tanks when compared to laboratory scale results. Much research are needed to assess the ability of Acrolein® in inactivation of ballast water organisms, before considering it as potential biocide for ballast water treatment.

f) Hydroxyl Radical Treatment

Onboard generation of hydroxyl^{-} and oxygen radicals and subsequent addition to ballast water is one of proposed treatment options for controlling organisms in the ballast water. The hydroxyl radicals are produced from the positive ions O_2^+ and N_2^+ reacting with water and found effective in killing unicellular algae, protozoans and bacteria within 2.67–8 seconds at the concentration of 0.63 mg L^{-1} (Bai et al. 2005; Qiong et al. 2009; Zhang et al. 2006).

The effectiveness of this biocide on cysts and spores has not been documented and it decomposes rapidly (nanoseconds) into water, oxygen and carbon dioxide, which makes it environment friendly technique (Gregg et al., 2009).

g) Hydrogen Peroxide

Hydrogen peroxide is an oxidative biocide and can be considered as potential biocide for the treatment of ballast water. It has limited risk to humans and decomposes rapidly into oxygen and water (Gregg et al., 2009). Required concentration for the killing of marine organisms varies from 3 ppm for vegetative dinoflagellate cells of *Karenia mikimotoi* to over 140,000 ppm for *B. subtilis* spores (Ichikawa et al. 1993; Sagripanti and Bonifacino 1996). There are discrepancies in the required concentration for elimination of dinoflagellate cysts among researchers and the effective dose varies from 100 to 10000 ppm (Bolch and Hallegraeff 1993; Ichikawa et al. 1993; Montani et al. 1995; Hallegraeff et al. 1997). This inconsistency may be due to different densities of targeted organisms or exposure time or pH of seawater (Kuzirian et al. 2001) or elevated temperature as Mesbahi (2004) suggests. Hazard concerns about onboard storing, handling and distribution of large volume of hydrogen peroxide in addition to the required high dose may exclude hydrogen peroxide as potential biocide for ballast water treatment. Nevertheless, the PeroxEgen™ on-board hydrogen peroxide water treatment system has claimed effective control of ballast water organisms by injection

of hydrogen peroxide, produced *in-situ*, at the concentration of less than 100 ppm (Eltron Water Systems 2007).

h) Glutaraldehyde

Glutaraldehyde is an organic biocide, which successfully control the marine bacterium *Vibrio fischeri* at a concentration of 8- 14 ppm, but needs to be dosed at much higher concentration of 20000 ppm in order to inactivate *B. subtilis* spores (Sano et al. 2003; Sagripanti and Bonifacino 1996). Sano et al. (2003) conducted experiment to assess biocidal effectiveness of glutaraldehyde against number of non-indigenous species invaded into the Laurentian Great Lakes from NOBOB (No Ballast On Board) vessels and recommended 500 mg L^{-1} of glutaraldehyde and the exposure time of 24 hours would be effective for 90% mortality of organisms. Glutaraldehyde has been proposed as a treatment option for vessels with little or no ballast for the control of organisms present in the ballast tank sediment (Sano et al. 2003, 2004), but high required concentration and associated cost might be limiting factors.

i) Chlorine Dioxide

Chlorine dioxide (ClO_2) is another disinfectant, though more expensive than chlorination, but could be considered as ballast water treatment due to its advantages. Chlorine dioxide does not react with organic material; maintain its biocidal effect within wider range of pH than chlorine and does not produce free available chlorine or chlorinated byproducts, hence more environment friendly (Muntisov et al. 1993; Junli et al. 1997; Vianna da Silva and da Costa Fernandes 2004). The results of studies for marine systems indicate that it is more effective in eliminating vegetative bacteria and viruses than chlorine (Hillman et al. 2004; Gregg and Hallegraeff 2007). The effectiveness of ClO_2 against seawater organisms showed that at the concentration of 25 ppm and exposure time of 2 hours, vegetative cells of the dinoflagellates *Alexandrium catenella*, *Gymnodinium catenatum*, *Protoceratium reticulatum* and *Scrippsiella trochoidea* are eliminated; whilst higher dose of 50 ppm followed by two weeks exposure time was needed to inactivate resting cysts of *G. catenatum* and *P. reticulatum* (Gregg and Hallegraeff 2007).

The Ecochlor® Ballast Water Treatment System generates chlorine dioxide, which could then be injected into ballast water for disinfection. In both laboratory and shipboard experiments, generated ClO_2 at the concentration of 5 ppm found to be

effective in eliminating bacterial and planktonic populations. In shipboard test, however, some recovery of bacteria and phytoplankton was observed after 5 days (Swanson and Perlich 2006). Degradability of ClO_2 was also tested during shipboard trial and observed no active residual ClO_2 in the ballast water at the time of discharge. Furthermore, corrosion tests were conducted for the product and no adverse effect was observed for the period of 28-32 days (MEPC 2008). More tests and investigations are required to assess the effectiveness of biocide against organisms in ballast water tank sediment and corrosion impacts.

III. Multi-Components Treatment Systems

The Ballast Water Management Convention requires a system to meet the performance standard D-2 and upon successful fulfilment of the provisions, a type approval certificate will be issued for the system. The Convention has not limited the use of combination of treatment options. As a result, there are number of treatment systems under commercial development in various stages of testing, which combined different technologies to mitigate the invasion of non-indigenous species according to the Convention. Some of these systems are discussed below.

a) Mechanical Treatment and Ozone Disinfection

Mitsui engineering and Shipbuilding Co. Ltd in conjunction with the Japanese Association of marine Safety (JAMS) have developed a hybrid system consists of four treatment processes of pretreatment, disinfection (ozone), gas/liquid separation and discharge unit during deballasting. In this system, a specially designed pipe creates cavitation and subsequent injection of ozone enhances the killing effect. Separation unit prevents gaseous ozone entering the ballast tanks and the purpose of discharge unit is to decompose any remaining oxidant in the ballast water during discharge. The land based systems were tested at various flow rates from 20 to 150m^3h^{-1} and documented that the effectiveness of the special pipe (elimination of 85% for phytoplankton and 100% for zooplankton at 150m^3h^{-1}) was increased with higher flow rate (Kikunchi et al., 2004).

b) Filtration, Cavitation, Electrochemical Disinfection and De-oxygenation

The Oceansaver®, Norwegian company, is another multi-components treatment system comprising mechanical filtration (50μm self cleaning), a hydrodynamic cavitation chamber, an electrochemical disinfection unit and a nitrogen super-saturation generator (Anderson, 2007). The system has been tested and in operation on several vessels and obtained both final and type approval from IMO. The manufacturer suggests that the

system can be operated in different combination depending on the biological quality of ballast water (Gregg et al., 2009).

c) Cyclonic Separation, Filtration and Chemical Biocide Treatment

SEDNA® is a modular system, manufactured by Hanmann AG and Degussa AG of Germany, consisting of a two step separation and subsequent biocide treatment by Peraclean®. In the physical separation, ballast water is primarily treated by a number of hydrocyclone and then passed through a self cleaning 50 μm filter. The superiority of SEDNA®, as claimed by the manufacturers, is due to its performance not limited to sediment load, salinity, temperature or voyage length and the chemical is fully degradable after 24 hours retention (HSB, 2006; Lloyd's register, 2010). SEDNA® ballast water treatment system using Peraclean® has received both Basic and Final Approval by IMO as well as type Approval by the relevant national regulatory authority (MEPC 2007c).

d) Mechanical Separation and Electrochlorination

Other option for multi-components ballast water treatment system is to combine mechanical separation either by hydrocyclone or filtration and electrochlorination. The advantage for such system is onboard generation of chlorine based biocide (sodium hypochlorite or hypochlorous acid), which eliminate storage of biocide product onboard the ship. A two-stage system has been developed by Greenship Ltd of Netherlands consists of a hydrocyclone for removing sediments and larger organisms during uptake and an electrolytic cells that produces sodium hypochlorite for disinfection. Effectiveness of system at laboratory scale experiments with flow rate of 50 m^3h^{-1} suggest 100% removal of particles greater than 20 μm, and 80% of the particles greater than 10 μm (MEPC 2007a). Results of land based tests on natural seawater at the flow rate of 100 m^3h^{-1} showed the system is capable of removing of 100% of organisms >50 μm, 98-100% of organisms 10-50 μm and eliminated 99.9-100% of aerobic heterotrophic bacteria including *E. coli* and Enterococcae (MEPC 2007a). This system obtained Basic Approval from IMO in 2008 (Lloyd's register, 2010; Gregg et al., 2009).

Severn Trent De Nora developed a similar ballast water treatment system, BalPure®, but used combination of filtration and electrochlorination (Lloyd's Register, 2010).

e) Mechanical Separation and UV Irradiation

Another viable two-stage ballast water treatment system can be a combination of

mechanical separation and UV irradiation. UV is well known to be effective against a wide range of microorganisms, but rely on the UV transmission to provide required dose. Therefore an efficient mechanical separation not only removes sediments and particles but reduces the biological work load for subsequent UV treatment. Optimarin AS has developed a ballast water treatment system comprising filter as pre treatment technology and UV and received both land based and shipboard system Approval from IMO in 2008 and 2009 respectively (Lloyd's Register, 2010).

f) Filtration and Free Radical Treatment

RWO GmbH Marine Water Technology together with Veolia Water Solutions and Technologies have developed a two-stage ballast water treatment system, CleanBallast, comprising mechanical separation and electrochemical treatment. The working principle of the treatment system is to pass ballast water through self-cleaning disc filters for removal of sediments and larger particles followed by addition of active substances (free hydroxyl^{-} and oxygen radicals and small amount of hypochlorous acid) produced in-situ by the Ectosys® electrochemical treatment cell (MEPC, 2007b; Gregg et al., 2009). This system has been tested in river, brackish and seawater at four different locations and claimed to meet the D-2 performance standard of the Convention, but limited data is available (MEPC, 2006; NAG Marine, 2007).

2.5 Challenges in Ballast Water Treatment System

Review of control measures showed that shipboard treatment systems are currently feasible solution for both existing and new ships. Studies showed 12 type approved treatment systems have entered the market by the end 2010 (Lloyd's Register, 2010). However, some challenges, such as unified method to up-scale existing systems for higher flow rate demand, online measurement of the performance of treatment systems and sampling regime that is representative of discharged ballast water, need to be attempted. Lack of online and accurate measurement device to assess the quality output of ballast water treatment system is common problem to all of them. This, in fact, depends on the off-line laboratory assays with long delay analysis. In this study online measurement that provides observability for ballast water treatment system has been considered.

Measurement devices are developed to measure and display the data proportional to certain variables of interest and hence provide observability. Unfortunately, there are

some situations in real systems that it is difficult or too expensive or impossible to measure these variables and in some cases where online measurement is possible, sensors do not provide the exact data or may be corrupted by the noise (Marquez, H. J., 2001). Under these situations, the systems are either non-observable or lack of robust observation will invariably lead to deviations from true status of the system. Observability in ballast water treatment system, similar to any other engineering system, can lead to monitoring, optimisation and controlling of the system. Ballast water treatment systems are non-observable due to the following reasons:

- Lack of reliable online sensor to measure the output of treatment system i.e. number, types, sizes and live/dead status of microorganisms exiting treatment systems,
- Need for laboratory assay and expertise with long delay analysis to measure the output of treatment system,
- Lack of biological model to correlate the survivability of microorganisms to the performance of treatment system,
- Nonlinear and time varying nature of inactivation process of microorganisms,
- Possible nonlinear nature of treatment system.

Therefore, it is difficult, if not impossible, to monitor and thus control the ballast water treatment system and maintain the quality throughout the course of treatment.This highlights the need for the methodology based on which observability is developed for a nonlinear-nonobservable system such as ballast water treatment system. It should, however, be mentioned that monitoring and hence control strategy for a ballast water treatment system has been developed throughout the course of this thesis.

2.6 Conclusion

Interaction of two systems may develop an overlapping area where monitoring is difficult. The consequence of such interacting systems may lead to unintentional penalties. Interaction of ship's ballast system with the surrounding marine ecosystem has facilitated microorganisms to break through natural barriers and being introduced into new environment. Introduction of Non Indigenous Species, so called bio-invasion, is considered as a second major threat for marine biodiversity.

Bio-invasion is an irreversible pollution and has been announced as one of the four greatest threats to the world oceans. IMO Convention has been adopted to

stop/minimise the bio-invasion and much research conducted to support development of controlling measures in response to the Convention.

Control measures, under the classification of *preventive* and *cure* concepts, were discussed in this chapter. Currently ballast water treatment system is a feasible solution for both existing and new built ships to provide compliance with the standard set in the Convention. Lloyd's Register (2010), reported availability of 12 type approved treatment systems in the market for shipboard installation.

The behaviour of inactivation processes of microorganisms during treatment process is often highly nonlinear and complex. Lack of biological model for the inactivation of microorganisms and unavailability of reliable online sensors to measure the output variables of ballast water treatment systems have turned ballast water treatment system into non-observable system. Hence it becomes difficult to monitor and control the actual performance of ballast water treatment systems. In the next chapter methods providing observation for non-observable systems are reviewed in order to develop a methodology for a complicated non-observable system.

In this thesis combination micro-filter and UV reactor has been chosen for the experiments and development of monitoring and control of the ballast water treatment system. The main reason is UV irradiation for disinfection does not produce active substances and hence it is possible to treat ballast water both during uptake and discharge. Micro-filter also helps physical removal of larger microorganisms and other suspended substances and leave smaller microorganisms, in size, for effective UV disinfection.

Chapter 3 Observability for Non-Observable Systems

Summary

The main goal of this chapter is to review and investigate different methodologies for providing observability for the systems whose state variables and/or output variables cannot be measured. In this light some of data-driven modelling techniques are also reviewed and tried for the development of an inferential measurement system.

Chapter 3's objectives may be briefly summarised as:

- *To review different methodologies by which state variables of non-observable systems can be estimated,*
- *To investigate observability methodology for non-linear systems,*
- *To develop an inferential measurement for the systems whose output variables cannot be measured online and needs laboratory assays with long delays analysis,*
- *To verify the developed methodology for the inferential measurement system through a case study.*

3.1 Introduction

Observability represents one of the fundamental requirements of modern control system theory (Nešić, D., 1998). In theory, observability is defined as the possibility of determination of the current state of the system, in a finite time, only from the outputs. In a less formal manner, Observability means determination of behavior of the system from the system's outputs. Chen, C. T. (1984) states: "if a dynamical equation is observable, all the modes of equation can be observed at the output". However, this concept is defined under the assumption that complete knowledge (i.e. matrices **A**, **B**, **C** and **E** from equations 3.1a and 3.1b) of a dynamical equation are known (Chen, C. T., 1984).

$$\dot{\mathbf{x}} = \mathbf{A}(t)\mathbf{x}(t) + \mathbf{B}(t)\mathbf{u}(t) \qquad (3.1a)$$

$$\mathbf{y} = \mathbf{C}(t)\mathbf{x}(t) + \mathbf{E}(t)\mathbf{u}(t) \qquad (3.1b)$$

where **x**(t) is state variables, **y** is the output and **u**(t) is the input.

The dynamical equation is completely observable, if the knowledge of input, $\mathbf{u}_{(t0,\, t1)}$ and the output $\mathbf{y}_{(t0,\, t1)}$ over the finite time interval of (t_0, t_1) suffice to determine the state $\mathbf{x}_0$ at time t_0. Otherwise the dynamical equation, representing the system, is non-observable at t_0 (Chen, C. T., 1984).

Observability plays an important role in realisation theory, i.e. optimal control theory, fault detections and system monitoring (Nešić, D., 1998; Marquez, H. J., 2001). It is very often necessary to manipulate the state vector, **x**, when dealing with dynamic system in real time. The ability to control a system or a process at their optimal states is of considerable interest for many disciplines since it can reduce design, operation/production costs while maintaining/improving the quality. Unfortunately, more often than not **x** is either difficult or too expensive or even impossible to measure reliably. Such systems in which the state variables cannot be measured reliably is said to be non-observable. A system may be considered as non-observable due to:

- Significant uncertainties,
- Lack of measurable devices/sensors to detect the important state variables,
- Non-linearity and time varying nature of the system, and
- Slow response of the process.

An observable system may become non-observable in the area where it interacts with the other system. Non-observable interacting systems may create unintentional consequences, e.g. pollution, that cannot be easily monitored and controlled. There are some techniques available that unmeasured variables of a system can be reconstructed. Some of these techniques are presented in the next sections.

3.2 Kalman Filtering

The Kalman filter is the state estimator for a linear system when model for the system as well as certain stochastic properties of measurement and disturbance noises are available (Assis, A. J. and Filho, R. M., 2000). The Kalman filter tries to estimate the state $x \in \Re^n$ of a discrete-time controlled process (Equation 3.3) with a measurement $z \in \Re^m$ given in Equation 3.3 (Welch, G. and Bishop, G., 2006).

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \tag{3.2}$$

$$z_k = Hx_k + v_k \tag{3.3}$$

The variables w_k and v_k are the process and measurement noise respectively. They are assumed to be independent of each other and with normal probability distributions. Although, the process noise covariance, *Q*, and measurement noise covariance, *R*, may change with time, but in this process it is assumed to be constant. The $n \times n$ matrix *A* relates the state variables at the previous time (*k-1*) to the state variables at the current

time (k) and assumed to be constant. The $n \times l$ matrix B relates the control input $u \in \Re^l$ to the state variables x and $m \times n$ matrix H in the measurement equation (3.3) relates the state variables to the measurement z_k. Similarly both matrices B and H are assumed to be constant despite the fact that they may change in practice.

The Kalman filter estimates a process in a form of feedback control, which means it first estimates the process state and then obtains feedback in the form of measurement. Hence, there are two groups of equations, time update and measurement update, for the Kalman filter. The time update equations project forward, in time, the current state (x_{k-1}) and error covariance (P_{k-1}) while measurement update equations adjust the projected estimates by an actual measurement at that time. This process is then repeated, using adjusted estimates, to predict new estimates. Figure 3-1 shows the complete picture of the operation of the filter.

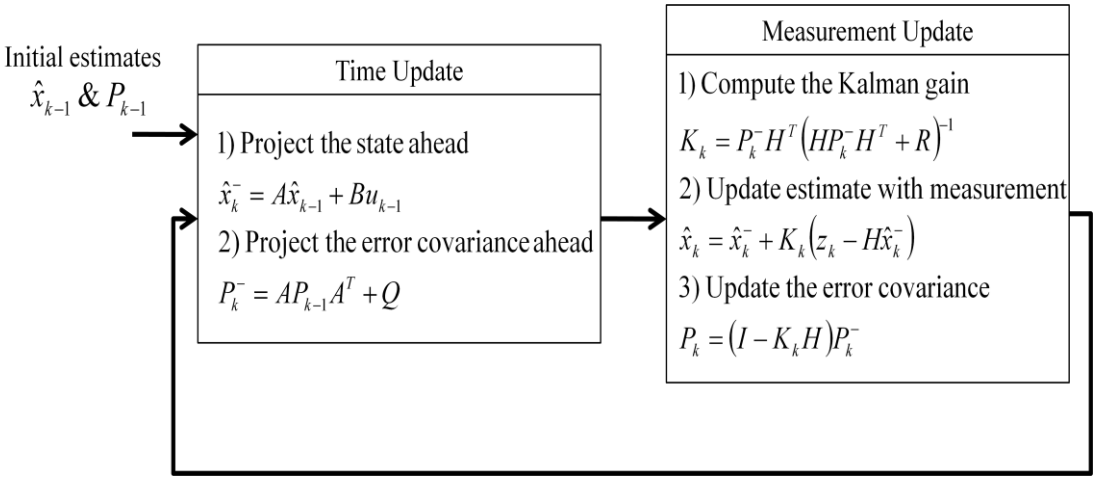

Figure 3-1: Operation of Kalman filter

The Kalman filter as described earlier tries to estimate the state variables of a discrete-time controlled process that is defined by a linear stochastic difference equation. This recursive procedure of Kalman filter is unable to solve/estimate a system with nonlinear behavior and/or nonlinear relationship between measurement and the process. The Kalman filter is then extended to deal with nonlinearity problems.

3.2.1 Extended Kalman Filter (EKF)

In this approach, similar to Taylor series, a system with nonlinear relationship can be linearised using the partial derivation of the process and measurement functions. A process, which is governed by the nonlinear stochastic difference equation, is given by:

$$x_k = f(x_{k-1}, u_{k-1}, w_{k-1}) \quad (3.4)$$

and the measurement ($z \in \Re^m$) by:

$$z_k = h(x_k, v_k) \quad (3.5)$$

The random variables w_k and v_k represent the process and measurement noise. The function "*f*" relates the state at previous time step *k-1* to the state at current time *k* while function *h* relates the state x_k to the measurement z_k.

In reality where individual values of noise (w_k and v_k) are unknown at each time step, the state and measurement vectors can be approximated by:

$$\tilde{x}_k = f(\hat{x}_{k-1}, u_{k-1}, 0) \quad (3.6)$$

$$\tilde{z}_k = h(\tilde{x}_k, 0) \quad (3.7)$$

As with Kalman filter procedure, there are two groups of equations of time update and measurement update. Similarly, the time update equations project the state and covariance estimates from the previous time step and the measurement update equations correct these estimates with the actual measurement z_k. Figure 3-2 presents the complete picture of the operation of the extended Kalman filter.

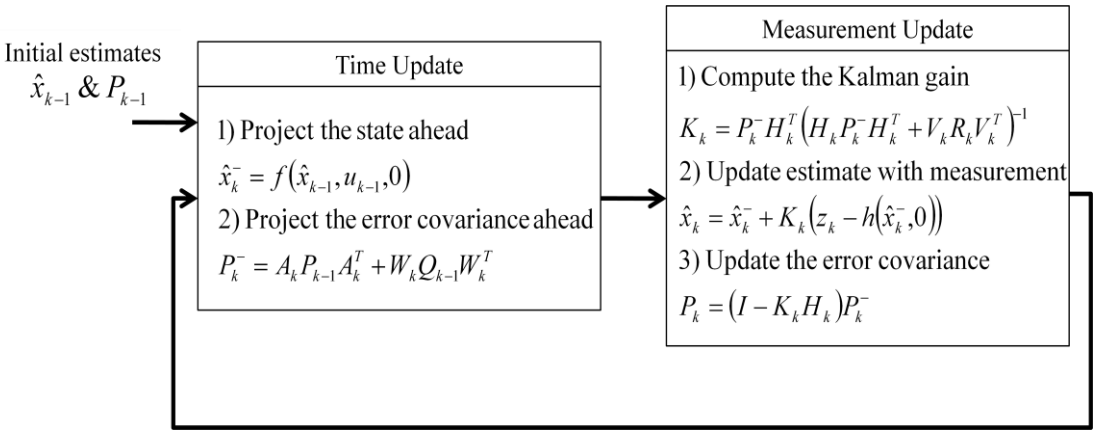

Figure 3-2: Operation of extended Kalman filter

A and *W* are the Jacobian matrices of partial derivatives of *f* with respect to *x* and *w* and *H* and *V* are the Jacobian matrices of partial derivatives of *h* with respect to *x* and *v*

respectively. An important point in EKF is the Jacobian H_k, in the equation for the calculation of the Kalman gain, magnifies the relevant components of the measurement information. That means, if there is not one to one mapping between the measurement, z_k, and the state through function h, the Jacobean H_k affects the Kalman gain and magnifies only the portion of the residual $\tilde{z}_k - h(\tilde{x}_k, 0)$ that affects the state. In this case when there is not a one to one mapping between the measurement, z_k, and the state through function h, then the filter will diverge and the process is non-observable.

It is also important to mention that the distributions of the various random variables are no longer normal after undergoing their respective nonlinear transformation. Therefore, the EFK becomes an *ad hoc* estimator and only approximate by the rule of linearization.

3.3 Observers

In other approach when the state variables are not available by direct measurement, the state variables estimates can be reconstructed by an observer. Luenberger, D. G. (1966) developed a methodology by which observers for multivariable linear systems can be built using available input and output of original system. The observer, in this methodology, has the inputs and available outputs of the original system as its input and has a state vector, which is linearly related to the desired approximated output (Luenberger, D. G., 1971). The basic configuration of a free (i.e. unforced) system (S_1) and its observer (S_2) is illustrated in the Figure 3-3. The available outputs of the system are used to drive another system (observer) whose state will track a linear transformation of the state of the original system.

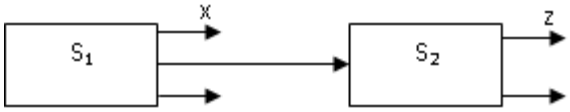

Figure 3-3: A simple observer

Considering a free system, $\dot{x}(t) = Ax(t)$, that its outputs drives other system (observer), which is governed by $\dot{z}(t) = Bz(t) + Cx(t)$ and suppose there is a transformation T that satisfies the following relationship:

$$TA - BT = C \tag{3.8}$$

then the output of observer can be given by:

$$z(t) = Tx(t) + e^{Bt}[z(0) - x(0)] \tag{3.9}$$

Now this approach can be extended to forced system by including the input in both original system and observer.

$$\dot{x}(t) = \boldsymbol{Ax}(t) + \boldsymbol{Du}(t) \tag{3.10}$$

$$\dot{z}(t) = \boldsymbol{Bz}(t) + \boldsymbol{Cx}(t) + \boldsymbol{TDu}(t) \tag{3.11}$$

The construction of an observer depends on the solution of the matrix equation (3.8). The solution of *T* must have the rank great enough to guarantee to recover for immeasurable state variables. Luenberger, D. G., (1964 and 1971) has developed the approach for the construction of an observer for an observable single output system and the same can also be applied to multiple–output systems. In the light of multiple-output systems, if a system consists of *m* components subsystems that each one has one observable output and subsystems are coupled together through their output, then an observer can be constructed for each of the single-output subsystems since the input to the subsystem is available for measurement. By this approach Luenberger (1971) showed how the design of an observer with *m* outputs can be reduced to the design of *m* separate observers for single-output subsystems. The application of observer is further investigated in control design where observer estimates the system state vector.

3.4 Inferential Measurement

Both Kalman filter and Luenberger observer techniques are linear in nature and require model representing system's behavior and immediate output measurement in order to estimate the state variables. However, in the case of ballast water treatment systems, neither physical measuring device to provide immediate measurement exists nor any mathematical model to define the inactivation process of microorganism is available. Hence neither of the above techniques can be viable option to provide observability for ballast water treatment systems. The other way forward to solve observability problem for the ballast water treatment systems is to estimate the quality output variables, using inferential measurement technique, by the help other output variables and a model relating these two variables together. Inferential measurement (also known as soft sensing) is a methodology whereby a difficult to measure process parameter can be

inferred from other easy to measure parameters such as temperature, pressure or flow (Guilandoust, M. T. et al, 1988; Du, Yang-Guang et al., 1997; Tham, M. T., 2000; Bolf, N. et al., 2008). The behaviour of any process/system is indicated by the states of output variables, which in turn depends on the operating conditions of the process and the adjustments applied to it. These indicative output variables, so called primary output, are often difficult to measure online for some processes (Tham, M. T., 2000). To overcome this problem, the primary output variable can be inferred by using an appropriate mathematical model of the process whose input is secondary output variable. The inferential measurement system is feasible when the states of secondary variables reflect the states of primary variables. In this concept, the objective is to model the relationship between primary variables (output of the model) and the secondary variables and input variables. Figure 3-4 presents the generic structure of inferential measurement for a non-observable system.

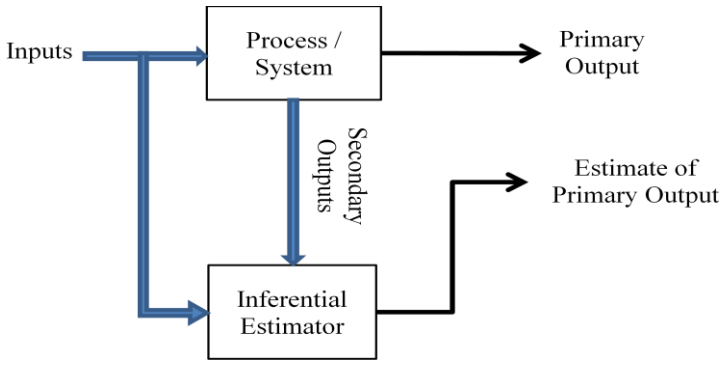

Figure 3-4: Concept of inferential measurement

The inferential estimator can provide the estimates of difficult to measure primary output at the frequency that inputs and secondary variables are measured. If the estimates of the primary output are sufficiently accurate, then the inferred states of primary outputs can be used in optimisation and controlling the process. The essential part of inferential measurement is the development of mathematical model that relates primary output variables to easily measured secondary output variables and input variables. Therefore to construct such inferential estimator any suitable modelling paradigm may be employed, including the modelling technique that uses first principles. Accuracy is an important factor in selection of modelling technique. Due to the nonlinearity of majority of engineering systems and lack of detailed knowledge about the physical behaviour of some systems, such as ballast water treatment systems, data-driven modelling techniques can be used to develop inferential estimator. However, this

does not exclude using knowledge-based modelling technique where possible and appropriate. In the following section two data-driven modelling approaches will be discussed.

3.4.1 Statistical Approach

In this approach statistical technique is used to describe the relationship between data of interest. The models are then presented in terms of parameters that define the functional relationship between independent (input) and dependent (output) variables.

3.4.1.1 Linear Regression Model

In the most general form, linear regression model relates one or more independent or predictor variables (x_1, x_2, …, x_p) to a dependent or response variable y. The simplest way to define the relationship between two variables of x (predictor) and y (response) through linear function is by:

$$y' = \beta_0 + \beta_1 x \tag{3.12}$$

where y' is an estimate of y and parameters β_0 and β_1 are the intercept and the slope of the line respectively.

The equation (3.12), which relates response variable to predictor variable, is called the prediction equation. The objective is to estimate the parameters, β, that makes the prediction equation the best fit for the dataset. Least squares approach that minimises the sum of squared residuals can be used to estimate the parameters. Sum of squared residuals is (Ponce, 1989):

$$\sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (y_i - y_i')^2 = \sum_{i=1}^{n} \left(y_i - (\beta_0 + \beta_1 x_i)\right)^2 \tag{3.13}$$

The minimum can be found by setting the gradient to zero:

$$\frac{\delta}{\delta \beta_o} \left\{ \sum_{i=1}^{n} \left(y_i - (\beta_0 + \beta_1 x_i)\right)^2 \right\} = 0 \tag{3.14}$$

and

$$\frac{\delta}{\delta\beta_1}\left\{\sum_{i=1}^{n}\left(y_i-(\beta_0+\beta_1 x_i)\right)^2\right\}=0 \tag{3.15}$$

Solving equations (3.14) and (3.15) will lead to normal equations and simultaneous solving of equations (3.16) and (3.17) will give parameters of prediction equation (3.12).

$$\sum_{i=1}^{n} y_i - n\beta_0 - \beta_1\sum_{i=1}^{n} x_i = 0 \tag{3.16}$$

$$\sum_{i=1}^{n} x_i y_i - \beta_0\sum_{i=1}^{n} x_i - \beta_1\sum_{i=1}^{n}(x_i)^2 = 0 \tag{3.17}$$

$$\beta_1 = \frac{\sum_{i=1}^{n} x_i y_i - \frac{\sum_{i=1}^{n} y_i \sum_{i=1}^{n} x_i}{n}}{\sum_{i=1}^{n}(x_i)^2 - \frac{\sum_{i=1}^{n}(x_i)^2}{n}} \tag{3.18}$$

$$\beta_0 = \frac{\sum_{i=1}^{n} y_i - \beta_1 \sum_{i=1}^{n} x_i}{n} \tag{3.19}$$

Once the parameters for prediction equation are found, the next step is to evaluate the linear correlation, which describes the quality of the equation. The correlation is calculated by:

$$r_{x,y} = \frac{S_{X,Y}}{\sqrt{S_X^2 S_Y^2}} \tag{3.20}$$

where:

$S_{X,Y}$ is the covariance of X with Y

S_X and S_Y are the variances of X and Y respectively.

Simple linear regression can be extended from one response variable and one predictor to the Multiple Linear Regression (MLR) where a response variable (y) has a linear relationship with several independent predictors (x_1, x_2, …, x_q). In general form, regression models relates y to a function of X and β:

$$y \approx f(X,\beta) \tag{3.21}$$

That means the function model (3.21) depends not only to the independent variables *x*'s, but to parameters β's. It is desirable to find the vector β of parameters so that the prediction equation has the minimum sum of squared residuals. Considering *n* parameters present in the prediction equation, there will thus be *n* gradient equations to solve. The obtained regression model is called linear when there is a linear combination of parameters and becomes non-linear when the derivatives are the functions of both the independent variables and the parameters. For a linear regression, it is then assumed that the mean of response variable *y* can be expressed as (Rencher, 1998):

$$E(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_q x_q \tag{3.22}$$

To estimate the vector β, results of *n* independent observations on *y* and associated *x*'s should be used. The prediction model for i^{th} observation is expressed as:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_q x_{iq} + \varepsilon_i \quad i = 1, 2, \cdots, n \tag{3.23}$$

The general model for *n* observation in the form of matrix will be:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1q} \\ 1 & x_{21} & x_{22} & \cdots & x_{2q} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nq} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_q \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

or

$$\boldsymbol{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{3.24}$$

In MLR, following assumptions should ideally be true before good estimators of the β's could be obtained:

- The error is random variable with a mean of zero; i.e. $E(\varepsilon) = 0$,
- The errors are uncorrelated, meaning that the variance-covariance matrix of errors is diagonal and non zero elements are the variance of error; $\text{cov}(\varepsilon) = \sigma^2\mathbf{I}$,
- The predictors are linearly independent.

Considering all the above assumptions, the least squares approach can be adopted to estimate the β's and as there are *n* observations, then it should be attempted to seek for $\hat{\beta}$'s that minimise:

$$\sum_{i=1}^{n} \hat{\varepsilon}_i^2 = \sum_{i=1}^{n} \left(y_i - \left(\hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \cdots + \hat{\beta}_q x_{iq} \right) \right)^2 \quad (3.25)$$

Equation (5.13) can be expressed as;

$$\boldsymbol{\varepsilon}' \hat{\boldsymbol{\varepsilon}} = \sum_{i=1}^{n} \left(y_i - \mathbf{x}_i' \widehat{\boldsymbol{\beta}} \right)^2 \quad (3.26)$$

where $\mathbf{x}_i'$ is the i^{th} row of **X.**

The value of $\widehat{\boldsymbol{\beta}}$ can be given by (Rencher, 1998):

$$\widehat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathrm{y} \quad (3.27)$$

It is worthwhile to mention that multicollinearity is an important concern when using MLR to model a dataset. Multicollinearity is a statistical phenomenon, when there is strong correlation between two or more predictor variables. In the case of highly correlated predictor variables, it may not be possible to compute the matrix inversion as required to obtain the regression parameters (Equation 3.27), or even if it is computable, the results of inversion will not be accurate. This may lead to the inaccurate prediction by the obtained MLR model. In the extreme case, when there is perfect linearity between two variables, then the matrix $\mathbf{X}'\mathbf{X}$ is not invertible and hence estimation of regression parameters is not possible. In such cases, some other methods have to be adopted, which can handle multicollinearity.

3.4.1.2 Principal Component Regression (PCR)

The vector of regression parameters, $\boldsymbol{\beta}$, estimated by MLR may be inaccurate when there are multicollinearities in the matrix of predictor variables. This may lead to inaccuracy in prediction of response variable for future reference. Principal Components Regression (PCR) is one of the modelling methods, which can handle multicollinearity. This method involves selecting a subspace from the column space of **X** (predictors) in order to project the response variables. In PCR, principal components (PC) of independent variables (predictors) are used to estimate the value of a response variable. The reasons for regressing the response variable on the PCs rather than directly on the

predictor variables are to decompose the highly correlated variables (predictor) to uncorrelated ones and to reduce the dimensionality of the predictor variables and taking only the subset of PCs for predictions. Therefore PCR is performed in two steps; the first step is to decompose **X** matrix to the uncorrelated PCs and then to use all or subset of them to fit into regression analysis (e.g. MLR) to estimate regression parameters. The transformation of data to the new coordinate system is performed in such a way that the highest variance by any projection of data lies on the first coordinate (first principal component). That means the first PC accounts for as much of variability in data as possible. Successively, the second PC has the next highest variance and so on. In this analysis, those PCs with highest variances (reduction of dimension) are used for the further regression analysis, but of course at the expense of some bias in new regression parameters.

In this method all the observations of each predictor variables are mean-centered so that mean of each column becomes zero. Then the covariance matrix of new data is calculated from which PCs can be obtained. The covariance matrix is a square matrix for which eigenvectors and corresponding eigenvalues can be found and then it can be said (Rencher, 1998):

$$\mathbf{X}_c^{'}\mathbf{X}_c a_q = \lambda_q a_q \qquad (3.28)$$

where λ_i's are the eigenvalues of the covariance matrix $\mathbf{X}_c^{'}\mathbf{X}_c$ and the a_i's are the unit-norm eigenvectors of $\mathbf{X}_c^{'}\mathbf{X}_c$. The vector a_i can be used to express the **X**'s in terms of PCs, Z's, in the following form:

$$\begin{aligned} z_{ij} &= a_{j1}(x_{i1} - \bar{x}_1) + a_{j2}(x_{i2} - \bar{x}_2) + \cdots + a_{jq}\left(x_{iq} - \bar{x}_q\right) \\ &= \boldsymbol{a}_j^{'}(\mathbf{x}_i - \bar{\mathbf{x}}), \qquad i = 1, 2, \cdots, n, \quad j = 1, 2, \cdots, q. \end{aligned} \qquad (3.29)$$

where the z_{ij} is the j^{th} principal component of the i^{th} observation vector $\mathbf{x}_i$.
Then the i^{th} row of $\mathbf{X}_c$ can be transformed to a vector of principal components by:

$$\mathbf{z}_i^{'} = (\mathbf{x}_i - \bar{\mathbf{x}})^{'}\mathbf{A} \qquad (3.30)$$

And in general form:

$$\mathbf{Z} = \mathbf{X_c A} \tag{3.31}$$

These principal components, z_i's, are orthogonal to each other and hence become independent new variables. Now the response variable, *y*, can be regressed on the all PCs as shown below:

$$\mathbf{y} = \mathbf{Z\delta} + \boldsymbol{\varepsilon} \tag{3.32}$$

Considering only *m* first principal components, which account for maximum variability, then Equation (3.32) becomes:

$$\mathbf{y} = \mathbf{Z}_m\boldsymbol{\delta}_m + \boldsymbol{\varepsilon} \tag{3.33}$$

Then parameters $\boldsymbol{\delta}_m$ can be estimated by:

$$\boldsymbol{\delta}_m = (\mathbf{Z}_m^{'}\mathbf{Z}_m)^{-1}\mathbf{Z}_m^{'}\mathbf{y} \tag{3.34}$$

From $\boldsymbol{\delta}_m$, the regression parameters βs can be estimated as:

$$\widehat{\boldsymbol{\beta}}_{PCR} = \mathbf{A}_m\widehat{\boldsymbol{\delta}}_m \tag{3.35}$$

where $\boldsymbol{A}_m$ is a matrix consisting of the first *m* unit-norm eigenvectors.

3.4.1.3 Partial Least Squares (PLS)

Similar to PCR, Partial Least Squares (PLS) is a method to construct the prediction model when MLR cannot handle the data due to multicollinearity or when the number of predictive variables is higher than the number of observations. The similarity between PCR and PLS methods is the attempts to regress response variable on some other factors. However, unlike the PCR that uses the predictor variables, **X**'s, to find new factors, in PLSR method both predictors and response variables, **X**'s & **Y**'s, are used to construct new factors. These factors are actually playing the role of predictor variables. The main idea in PLS is to extract those underlying factors from many factors (predictor variables), which contain most of the information. These underlying factors or latent variables are useful for prediction the response variable as well as reducing the dimension of the regression problem (Garthwaite, 1994).

To predict the PLS estimators of β, matrix **X** is decomposed in the following way:

$$\mathbf{X} = \sum_{i=1}^{p} \mathrm{t}_i \mathrm{p}_i^{'} = \mathbf{T}\mathbf{P}^{'} \tag{3.36}$$

In the equation (3.36), **T** is a linear combination of **X** (**T** = **X**r_i), which is also known as matrix of latent components and the $p \times 1$ vectors p_i are loadings. Similar to principal components in PCR, z_i, latent components, t_i, are orthogonal and is computed by:

$$\mathbf{t_i} = \mathbf{E_{i-1}}\boldsymbol{w_i}, \quad \mathbf{E_i} = \sum_{j=1}^{i} \mathrm{t}_j \mathrm{p}_j^{'}, \quad \mathbf{E}_0 = \mathbf{X}, \tag{3.37}$$

where $\mathbf{w}_i$ and $\mathbf{r}_i$, $i = 1, 2, \ldots, m$, are weight vectors and span the same space (Phatak and Jong, 1997). In either of univariate or multivariate PLS, the first step to calculate t_i is to derive either $\mathbf{w}_i$ or $\mathbf{r}_i$ and then $\mathbf{p}_i$'s are calculated by regressing **X** onto $\mathbf{t}_i$. When only m factors are going to be considered then:

$$\mathbf{T}_m = \mathbf{X}\mathbf{R}_m \tag{3.38}$$

$$\mathbf{P}_m = \mathbf{X}'\mathbf{T}_m(\mathbf{T}_m'\mathbf{T}_m)^{-1} \tag{3.39}$$

$$\mathbf{R}_m = \mathbf{W}_m(\mathbf{P}_m'\mathbf{W}_m)^{-1} \tag{3.40}$$

When the first m dimensions have been extracted, then the vector of fitted values from PLS can be represented by linear combination of $\mathbf{T}_m$ as shown below:

$$\boldsymbol{y}_{PLS}^{m} = \mathbf{T}_m(\mathbf{T}_m'\mathbf{T}_m)^{-1}\mathbf{T}_m'Y \tag{3.41}$$

Substituting $\mathbf{T}_m$ for its equivalent in (3.38) and $\widehat{\boldsymbol{\beta}}_{OLS}$ for y would turn equation (3.41) into (Phatak and Jong, 1997):

$$\boldsymbol{y}_{PLS}^{m} = \mathbf{X}\mathbf{R}_m(\mathbf{R}_m'\mathbf{X}'\mathbf{X}\mathbf{R}_m)^{-1}\mathbf{R}_m'\mathbf{X}'\mathbf{X}\beta_{OLS} \tag{3.42}$$

Then:

$$\beta_{PLS}^{m} = \mathbf{R}_m(\mathbf{R}_m'\mathbf{X}'\mathbf{X}\mathbf{R}_m)^{-1}\mathbf{R}_m'\mathbf{X}'\mathbf{X}\beta_{OLS} \tag{3.43}$$

3.4.1.4 Nonlinear Regression

Basically nonlinear regression is similar to linear regression in a way of relating response variable to a vector of predictor variables. In statistics, this form of regression analysis models observational data by a nonlinear function, which is a combination of the model parameters and depends on one or more independent variables. A nonlinear regression has the following form:

$$Y_i = f(\mathbf{x}_i, \boldsymbol{\theta}) + \varepsilon_i, \quad i = 1, 2, \cdots, n \tag{3.44}$$

where, the Y_i are responses, f is the function of the vector of predictor variables $\mathbf{x}_i$ and the parameter vector $\boldsymbol{\theta}$, and ε_i are random errors (Smyth, 2002).

Some of nonlinear functions are exponential functions, logarithmic functions, trigonometric functions, power functions, Gaussian function, and Lorentzian curves. One of the most common nonlinear models is exponential growth of exponential decay model, which are expressed by:

$$y = f(x, \theta) = \theta_1 e^{\theta_2 x} \quad \text{OR} \quad f(x, \theta) = \theta_1 e^{-\theta_2 x} \tag{3.45}$$

The other common form of model, which can be used to approximate variety of functional shapes, is the rational function. This function is the quotient of two polynomial functions and expressed by (Smyth, 2002):

$$f(x, \theta) = \frac{\sum_{j=1}^{k} \theta_j x^{j-1}}{1 + \sum_{j=1}^{m} \theta_{k+j} x^j} \tag{3.46}$$

Functions, such as the exponential or logarithmic functions can be transformed to the linear functions and dealt with accordingly. For example, an exponential growth nonlinear model (Equation 3.45) can become linear Equation (3.47) by taking the natural logarithm of both sides and then the unknown parameters can be estimated by a linear regression of ln(y) on x.

$$\ln y = \ln \theta_1 + \theta_2 x \tag{3.47}$$

Transformability of linear model is only possible for the nonlinear models such as exponential and logarithmic. In general, unlike the linear regression, there is no closed-

form expression for the regression parameters. The usual method to determine the regression parameters for the best fit curve is the optimisation algorithm. In practice, the model is approximated to linear one and estimated values of parameters are initially used and refined by an optimisation algorithm to find the global minimum of a sum of squares. Now if the nonlinear function *f* is continuously differentiable in θ, then it can be approximated locally by a linear function as:

$$f(\mathbf{x}_i, \theta) = f^0 + \sum_j J_{ij}\theta_j \qquad (3.48)$$

where $\mathbf{J}_{ij}$ is the matrix of gradients:

$$\mathbf{J}_{ij} = \frac{\delta f(\mathbf{x}_i, \theta)}{\delta \theta_j} \qquad (3.49)$$

The nonlinear regression can be computed similar to linear regression, but using **J** rather than **X** and hence estimator can be given by:

$$\hat{\theta} \approx (\mathbf{J}'\mathbf{J})^{-1}\mathbf{J}'\mathbf{y} \qquad (3.50)$$

3.4.1.5 Multivariate Multiple Regression (MMR)

In the multivariate multiple regression, there are multivariate dependent variables (response variables) and multiple independent variables (predictor variables), meaning that *p* response variables ($y_1, y_2, \ldots, y_p$) will be predicted by *q* predictor variables ($x_1, x_2, \ldots, x_q$). The matrix form of *n* observations is (Rencher, 1998):

$$\mathbf{Y} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1p} \\ y_{21} & y_{22} & \cdots & y_{2p} \\ \vdots & \vdots & & \vdots \\ y_{n1} & y_{n2} & \cdots & y_{np} \end{bmatrix} = \begin{bmatrix} \boldsymbol{y}_1' \\ \boldsymbol{y}_2' \\ \vdots \\ \boldsymbol{y}_n' \end{bmatrix} \qquad (3.51)$$

Each column of **Y** consists of the *n* observations of one of *p* response variables and hence corresponds to the **y** vector of that particular variable as in the univariate multiple regression model (3.24). **Y** can be expressed in column and row vectors forms:

$$\mathbf{Y} = \begin{bmatrix} \boldsymbol{y}_1' \\ \boldsymbol{y}_2' \\ \vdots \\ \boldsymbol{y}_n' \end{bmatrix} = [\boldsymbol{y}_{(1)} \quad \boldsymbol{y}_{(2)} \quad \cdots \quad \boldsymbol{y}_{(p)}] \qquad (3.52)$$

Each column of *y*'s will depends on the *x*'s and is different from the other columns of *y*'s. Based on the regression model expressed in (3.24), each $y_{(j)}$ can be written as:

$$\boldsymbol{y}_{(1)} = \mathbf{X}\boldsymbol{\beta}_{(1)} + \boldsymbol{\varepsilon}_{(1)} \quad \boldsymbol{y}_{(2)} = \mathbf{X}\boldsymbol{\beta}_{(2)} + \boldsymbol{\varepsilon}_{(2)} \quad \cdots \quad \boldsymbol{y}_{(p)} = \mathbf{X}\boldsymbol{\beta}_{(p)} + \boldsymbol{\varepsilon}_{(p)} \qquad (3.53)$$

These columns can now be put side by side to develop the combined model for **Y**.

$$\mathbf{Y} = \left(\boldsymbol{y}_{(1)}, \cdots, \boldsymbol{y}_{(p)}\right) = \mathbf{X}\left(\boldsymbol{\beta}_{(1)}, \cdots, \boldsymbol{\beta}_{(p)}\right) + \left(\boldsymbol{\varepsilon}_{(1)}, \cdots, \boldsymbol{\varepsilon}_{(p)}\right) \qquad (3.54)$$

This model can be written as:

$$\mathbf{Y} = \mathbf{XB} + \mathbf{E} \qquad (3.55)$$

Considering the following assumptions, $\widehat{\mathbf{B}}$ can be estimated as shown in (3.56):

1. $E(\mathbf{Y}) = \mathbf{XB}$ or $E(\mathbf{E}) = 0$,
2. $\text{Cov}(\boldsymbol{y}_i) = \boldsymbol{\Sigma}$ or $\text{cov}(\boldsymbol{\varepsilon}_i) = \boldsymbol{\Sigma}$ for all $i = 1, 2, \ldots, n$,
3. $\text{Cov}(\boldsymbol{y}_i, \boldsymbol{y}_j) = \mathbf{0}$ or $\text{cov}(\boldsymbol{\varepsilon}_i, \boldsymbol{\varepsilon}_j) = \mathbf{0}$ for all $i \neq j$.

$$\widehat{\mathbf{B}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y} \qquad (3.56)$$

3.4.1.6 Canonical Correlation Analysis (CCA)

Canonical correlation analysis (CCA) is a multivariate statistical method, which correlates two sets of multidimensional variables. It identifies components of one set of variables (predictors) that have the highest linear correlation with components of other set of variables (responses). For a given pair of multivariates, $X \in \Re^q$ and $Y \in \Re^p$, CCA (Figure 3-5) involves the derivation of linear combination of variables from each of the two sets of variables (called canonical variables) such that correlation between the two sets is maximized (Akaho, 2001).

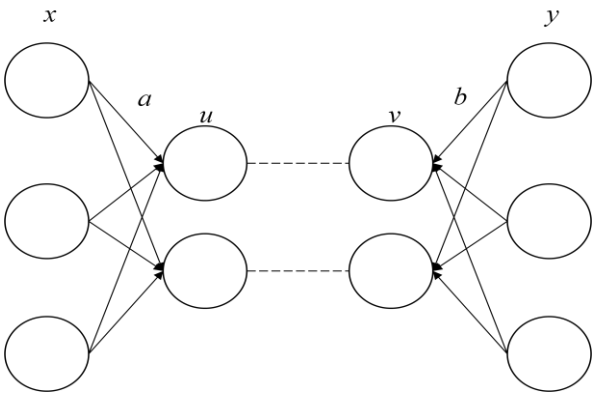

Figure 3-5: Concept of Canonical Correlation Analysis (Akaho, 2001)

With the assumption that the average of **x** and **y** are zero, two new coordinates for both data sets can be defined by choosing direction vectors, *a* & *b*, and projecting **x** and **y** onto them respectively.

$$u = a'X \quad \text{and} \quad v = b'Y \tag{3.57}$$

The variables *u* and *v* are called the canonical variates and the correlation between them is given by:

$$\rho = \frac{Cov(u,v)}{\sqrt{Var(u)Var(v)}} \tag{3.58}$$

where ρ is the correlation between two variables. Replacing covariance (*u*, *v*), variance (*u*) and variance (*u*) with their equivalent would render equation (3.58) to:

$$\rho(a,b) = \frac{a'\Sigma_{XY}b}{\sqrt{(a'\Sigma_{XX}a)(b'\Sigma_{YY}b)}} \tag{3.59}$$

The main target now is to find the direction vectors, *a* & *b*, which maximises the above correlation (3.58) subject to the following constraints (Akaho, 2001):

$$Var(u) = a'\Sigma_{XX}a = 1 \tag{3.60}$$

$$Var(v) = b'\Sigma_{YY}b = 1 \tag{3.61}$$

To solve the maximisation problem, the equation can be written in Lagrange form and further derivation of it with respect to *a* and *b* would eventually lead to:

$$\left(\Sigma_{XX}^{-1}\Sigma_{XY}\Sigma_{YY}^{-1}\Sigma_{YX} - \rho^2\mathbf{I}\right)a = 0 \qquad (3.62)$$

and similarly:

$$\left(\Sigma_{YY}^{-1}\Sigma_{YX}\Sigma_{XX}^{-1}\Sigma_{XY} - \rho^2\mathbf{I}\right)b = 0 \qquad (3.63)$$

where *a* and *b* are eigenvectors and ρ^2 are the eigenvalues of $\Sigma_{YY}^{-1}\Sigma_{YX}\Sigma_{XX}^{-1}\Sigma_{XY}$.

3.4.2 Artificial Neural Networks Approach

Artificial neural networks, in general, is information processing system that mimics the way human brain behaves by emulating the operations and connectivity of biological neurons (Solomatine, D. P., 2002). That means a computing architecture consisting of large number of parallel interconnections of simple "neural" processors working in unison to solve specific problems (Lau, 1992).

An artificial neural networks consists of number of simple processing units (Figure 3-6), which communicate with each other by sending signals through a large number of weighted connections. Each processing units receive input from neighbours or external sources, perform computing process and generate output, which is then propagated to other units.

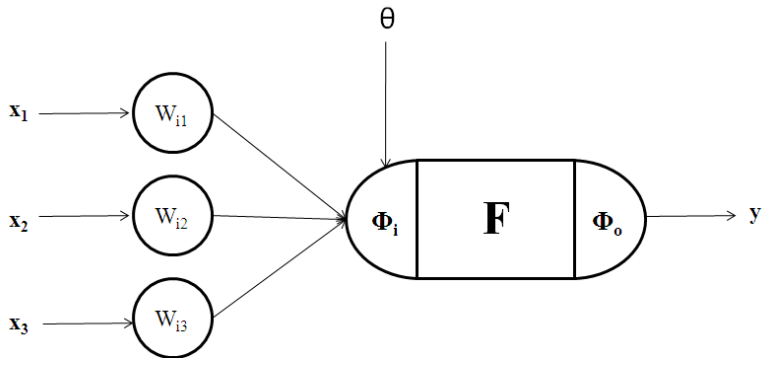

Figure 3-6: A simple processing unit

From the Figure 3-6 it can be seen that the vector [$x_1(t)$, $x_2(t)$, …] is the input vector, which carries information either from outside or from previous processing unit. The weighting or strength vector [w_{i1}, $w_{i2,}$ …] has exhibiting or inhibiting contribution depending on their positive or negative sign respectively. Each input vector parameter will then become inhibited or exhibited by corresponding member of weighting vector.

All the incoming values to the unit will then be summed up and a *bias* or *offset* term, θ, will simply be added to the result (Equation 3.64), which is said to be *input function*.

$$\Phi_i = \sum_{j=1}^{n} x_j \, w_{ij} + \theta \qquad (3.64)$$

Total input to the processing unit is then processed by the *activation function* (F) to produce a new value. Some examples are identity function, threshold function, sigmoid function and tan hyperbolic function.

The data after activation function is fed into the output function, Φ, which in most cases is considered to be as identity function. Taking all into account, the output "y" may be given as:

$$y = F\left(\sum_{j=1}^{n} x_j \, w_{ij} + \theta\right) \qquad (3.65)$$

In general artificial neural networks are characterised by three types of units: *input*, *hidden* and *output*. In this architecture, input units receive data from external source and feed the data into hidden layer, which is not visible to the outside. The output from this layer is passed to the final layer (output layer) from which the processed signal will be sent out. The processing units are connected to each other and each provides contributions to the next one. The resulting model is called Multilayer Perceptron.

The architecture of ANN depends on the pattern of connections between the units and how data propagates in the networks. There are two main ANN architectures known as feed-forward networks and recurrent networks. Figures 3-7 and 3-8 illustrate feed-forward and recurrent networks respectively.

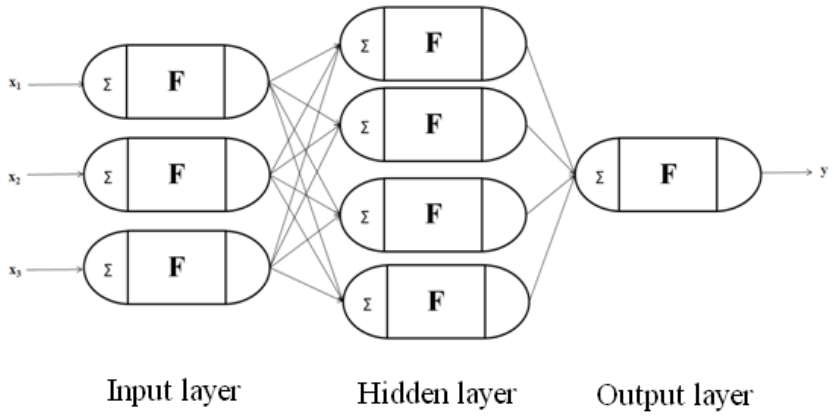

Figure 3-7: Feed-forward networks

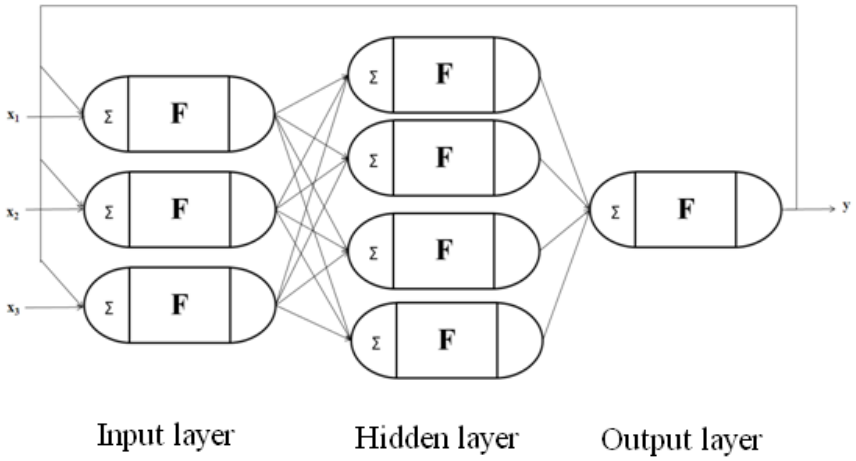

Figure 3-8: Recurrent networks

In the feed-forward networks data flows strictly in one direction, from input layer to the output layer with no feedback connections. That means, in this architecture the processing units do not receive signal from their own output or from the units in front of them. Contrary to the feed-forward networks, recurrent networks do contain feedback connections in addition to the signals from preceding units.

Similar to human, ANN needs a learning rule to produce the desired set of outputs when a set of inputs are introduced to the networks. The strengths of each connection have to be modified in order to achieve the desired outputs. One way is to train the neural networks by providing a learning pattern, which enables the ANN to change the weights of each connection according to the learning rule. Since beginning various learning rules have been introduced. The most commonly algorithm used as learning rule to adjust the weights for multilayer networks is Backpropagation. In this algorithm the learning strategy is to modify two sets of weights, from hidden layer to output layer and from input layer to hidden layer. The weight adjustment for a connection is done by the

following:

$$\Delta_p w_{ij} = \gamma \delta_j^p y_i^p \tag{3.66}$$

Training of feed-forward networks with backpropagation learning rules accomplishes in two stages. In the first stage the error signal (δ) for an output unit, which adjust the weights on the connections between hidden and output layers, is given by:

$$\delta_o^p = \left(d_o^p - y_o^p\right) F'\left(s_o^p\right) \tag{3.67}$$

where d_o is the desired output and $F(s_o)$ is the activation function of output unit.

In the second stage, the desired output of hidden layer is not known, so the difference between actual and desired outputs of each unit in hidden layer cannot be calculated. Backpropagation makes the use of weights and error in the first stage to modify the weights on the connections between input and hidden layers. The error signal is calculated by the following equation:

$$\delta_h^p = F'\left(s_h^p\right) \sum_{o=1}^{N_o} \delta_o^p \, w_{ho} \tag{3.68}$$

Execution of training the networks with backpropagation algorithm starts by construction of networks with the desired number of units in both hidden and output layers followed by selecting the appropriate activation function. Initial weights are chosen randomly and the networks, based on its structure, process the input data and compute the output error using data provided for training. The learning algorithm (backpropagation) updates the weights and the network iterates the process repeatedly until acceptable output is achieved. The resulting error is influenced by:

- Number of iterations.
- The number of learning samples.
- The number of hidden units.

Learning is not guaranteed if the numbers of iteration or learning samples are too few. Typically there are termination conditions that can be used to stop training procedure. For instance one can choose to stop training when error decreases below a certain value.

The choice of termination is important as a few iterations may be insufficient to reduce the error below certain value (under-training) and conversely too high number of iterations may lead to over-training of the networks. Over-training may also happen if there are too many hidden units. In the case of over-training, the networks will lose its ability of generalising or interpolation of data. In other words the over-trained networks will have small error on the training data but not necessarily on the test data. With increasing the number of learning samples both error rates (learning set and testing set) will converge to the same value. This error depends on the number of hidden units and the activation function. If the learning error does not converge to the test error, it indicates that the learning procedure has not found a global minimum (Kros and Van Der Smagt, 1996).

ANNs have been extensively and successfully used in various subjects. In the following some examples of using ANN modelling technique to provide online estimation have been presented.

Du Young-Guang et al (1997) developed neural net-based soft sensor for the estimation of dynamic particle size distribution in grinding circuit product. They also developed simplified neural networks based soft sensor by making the use of principal component analysis for online adaptation.

Assis et al. (2000) developed soft sensors for online bioreactor state estimation using ANN.

Bolf et al. (2007) used neural networks to develop intelligent software sensors for monitoring of a solid waste composting process. They also stated that the models have potential for inferential control of composting process in batch reactor.

Bolf et al. (2008) developed soft sensors, using ANN, for the estimation of quality of kerosene of crude distillation unit. Two soft sensors were able to estimate kerosene distillation end point and freezing point from temperature and flow measurements.
Pazouki et al. (2008a) modelled, using ANN, the operation of electrolysing generator to produce chlorine for ballast water treatment. The model was then used to simulate the biological effectiveness of ballast water treatment system using chlorination (Pazouki et al., 2008b).

3.5 Observation for Ballast Water Treatment Systems

In the ballast water treatment systems, mechanical, physical or chemical or combination of technologies are used to inactivate living microorganisms so that the quality of discharged ballast water complies with the standard of IMO Convention. Ballast water treatment system was introduced as non-observable system in the previous chapter and the quality of discharge cannot be easily monitored. To provide observability for non-observable system, three techniques of Kalman filter (Kalman and Bucy, 1961), Luenberger observer (Luenberger, D. G., 1964) and inferential measurement (Guilandoust, M. T. et al, 1988; Du, Yang-Guang et al., 1997; Tham, M. T., 2000; Bolf, N. et al., 2008) were introduced in this chapter. The first two techniques are actually linear in nature, but have been extended to deal with nonlinearity to some extent. However, the applications of both techniques (Kalman filter and Luenberger observer) were mostly restricted to universities laboratories and few industrial studies. The possible reasons are nonlinearity of some of industrial systems/processes and multitude unmeasured disturbances, which may result in unsatisfactory estimation of system/process variables. (Du, Yang-Guang et al., 1997 and references therein). These two techniques also require measurements of primary output variables at some point to correct the estimations. However, for some systems such as ballast water treatment systems, it is difficult, if not impossible, to measure the primary output. Measurement difficulty for ballast water treatment system is due to lack of appropriate online instrumentation. That means measurement of primary output (i.e. number, types, sizes and live/dead status of microorganisms exiting treatment systems) depends on laboratory assays with long analysis delays.

Due to the inability to measure the primary output variables, lack of biological model to relate inactivation rate of microorganisms to the performance of treating technology and possibility of nonlinearity in inactivation process of microorganisms when subjected to the treatment, Kalman filter and Luenberger Observer techniques were not considered as suitable methodology to provide estimator for the ballast water treatment systems. The inferential measurement concept, in this case, can be adopted to suit ballast water treatment systems and provide observability for such systems.

To implement inferential measurement, the secondary outputs of the ballast water treatment systems should be measurable by reliable instrumentation and importantly

reflect the primary variables. The inferential estimator in this case will be the mathematical model relating measurable secondary output such as temperature or flow to the number of live microorganisms leaving treatment system. For instance, temperature and exposure time are secondary variables that can be related to the mortality of microorganisms in the heat treatment system. It is worthwhile to mention that for a hybrid ballast water treatment system, which is consisted of two or more individual systems; there should be an inferential estimator for each system whose output becomes the input to the subsequent system. The estimate of the primary output of each estimator reflects the performance of the individual system and the performance of the whole system is estimated by the output from final inferential estimator. In this approach monitoring at each stage can be provided for a non-observable hybrid system. The knowledge obtained from inferential observation can be further used to optimise and control the system. Figure 3-9 shows the general concept of inferential observation for hybrid ballast water system.

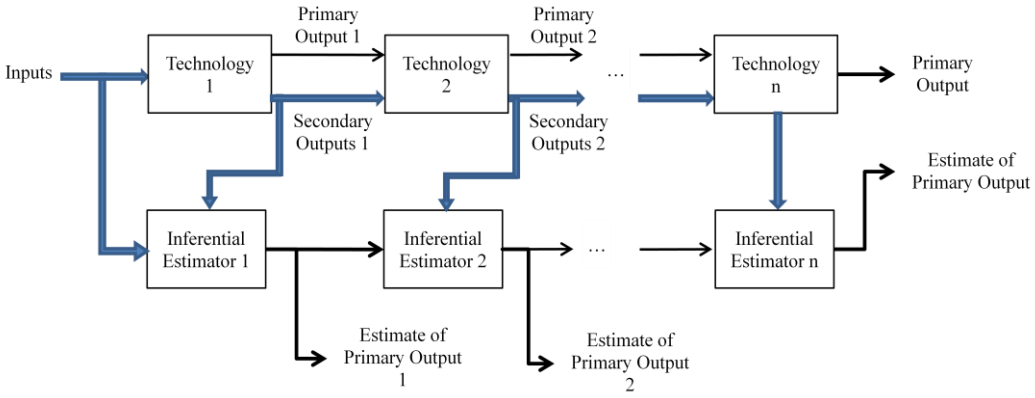

Figure 3-9: Concept of inferential observation for hybrid ballast water treatment system

In some cases the intended secondary outputs cannot be reliably measured, but can be calculated through valid mathematical model representing the system. This model estimates the secondary output by relating the input variables to the intended secondary variables. For instance, in a UV treatment system, UV dose delivery (secondary output) can be calculated using the measurements of input variables and with the help of mathematical model of UV reactor. In such cases, ballast water system can be conceptually divided into two technological and biological systems that the outputs of the first model are actually the secondary outputs of the system. That means the inferential estimator consists of two mathematical models as shown in Figure 3-10.

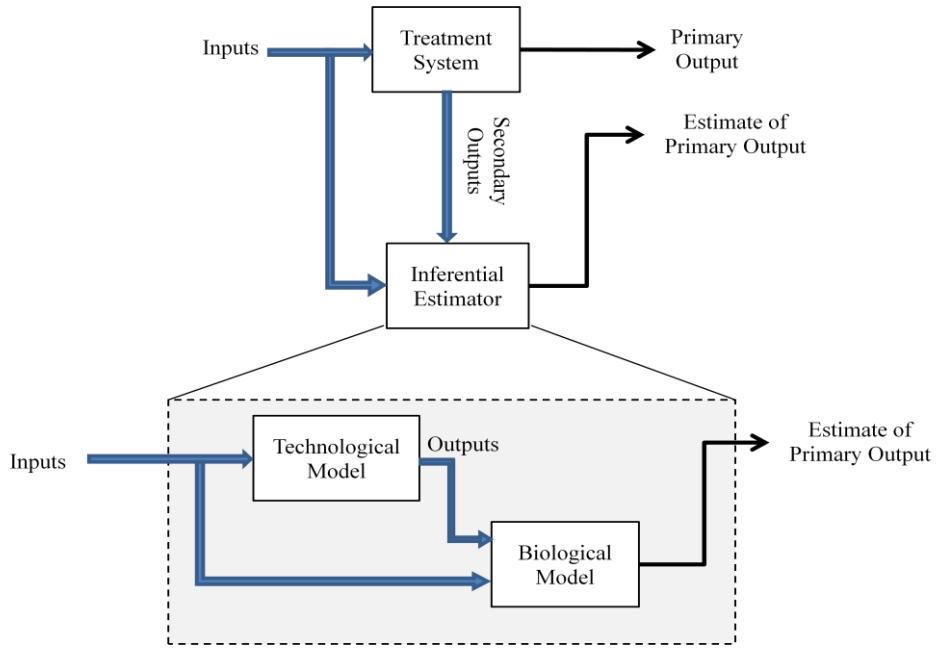

Figure 3-10: Structure of inferential measurement for ballast water systems consisting one technology

3.6 Case Study

To validate the developed methodology for the inferential measurement of ballast water treatment system, a case study was conducted. In this study series of experiment were conducted on small scale UV reactor (suitable for low flow rate up to $15m^3h^{-1}$) to generate required data for the development of inferential estimator.

UV reactor (Figure 3-11) used in the experiment had one Medium MP-HI lamp with the power output of 7.3 kW. The configuration of UV reactor was perpendicular inlet and outlet with the UV lamp located at the centre of the reactor parallel to the flow. The UV reactor was equipped with automatic cleaning system, which was activated by the control panel. The calculation of average UV dose delivery under varying operational conditions was done by the empirical formula supplied by the manufacturer.

The UV reactor (Figure 3-11) had the following physical specifications:

- Length of the reactor 0.7 m
- UV reactor internal diameter 0.1082 m
- External diameter of Lamp sleeve 0.049 m
- Size of inlet and outlet flange 4 inch

UV lamp specifications:

- Lamp power 7.3 kW

- UVC efficiency 15.7%
- Quartz efficiency 90%

Figure 3-11: UV reactor used in case study

The experiment setup was equipped with flow sensor to measure the seawater flow passing through the treatment system. The output signal of the used flow sensor was a sinusoidal frequency, which was firstly read by Data Acquisition card (NI USB-6210) and then converted into m^3h^{-1} by a developed computer program.

3.6.1 Experiment Procedure

In total two series of tests were conducted at different flow rates, turbidity and test arrangements. General procedure for conducting any test was to prime the whole setup by supplying sand-filtered seawater from storage tank prior to the commencement of the test. Apart from priming the system, this preliminary test procedure was required to let the seawater pass through UV reactor while UV lamp reach to its maximum power output. When UV reactor was ready (maximum power output) for the treatment operation, then seawater supply was changed over to the test tank and flow rate was adjusted to the nominated flow for the particular test and continuous sampling strategy were practiced throughout the test. Samples from allocated locations (before and after treating technology) were taken simultaneously in triplicate. Collected samples were assessed for enumeration and effectiveness of the tested technology.

3.6.1.1 UV Test Series 1

In total eight tests were performed at the Dove Marine Laboratory in March, April and June 2008. The flow rate of water through the UV system was altered and six flows were tested; 2.5, 3.0, 3.9, 5.5, 9.5 and 12.5m^3hr^{-1}. A 1 tonne storage 'control' tank was filled with sand-filtered and pumped seawater from Cullercoats Bay. The test organism

Tetraselmis suecica, a single celled green alga, was added to the tank. Turbidity of seawater for the tests performed in June 2008 was increased by adding Koaline into the test tank in order to assess performance of UV reactor under different turbidity test conditions. The water was then passed through UV reactor and continuous sampling strategy was practiced throughout the duration of tests. Three replicate 1L 'control' (before treatment) and three replicate 10L 'treated' (after treatment) samples were collected for each test.

3.6.1.2 UV Test Series 2

In this series, two UV exposures with inclusion of five days retention of treated water in a holding tank between two exposures were performed in June 2008. The schematic arrangement of the performed test including sampling locations is shown in the Figure 3-12. A 1 tonne storage 'control' tank was filled with sand-filtered seawater from Cullercoats Bay. On Day 0 of testing the standard test organisms *T.suecica* and *Artemia salina*, a brine shrimp, were added to the tank. These two standard organisms were selected in accordance with size category defined in the guidelines of the Convention. In order to modify the turbidity of seawater, Koaline was also added to the tank. The seawater was pumped from the tank using a centrifugal pump through the UV system (1^{st} exposure) to the holding tank at the flow rate of approximately $10m^3h^{-1}$. Similarly continuous sampling performed and samples were collected in triplicate before and after the UV reactor. Once all the water was pumped into a holding, then it remained, in the dark, for five days.

On Days 1, 3 and 5 three replicate 10L samples were taken from the 'treated' tank to monitor possible changes in mortality of the microorganisms in the holding tank. On Day 5 the remaining water was pumped back through the UV system (2^{nd} exposure). Three replicate 'Before UV' samples and three replicate 'After UV' samples, via continuous sampling strategy, were collected. Sizes of samples taken for this test were as follows:

Sample size before filter: 3 × 1 litre for *T.Suecica*
3 × 20 litre for *A. salina*

Sample size after filter: 3 ×10 litre for *T.Suecica*
3 ×100 litre for *A. salina*

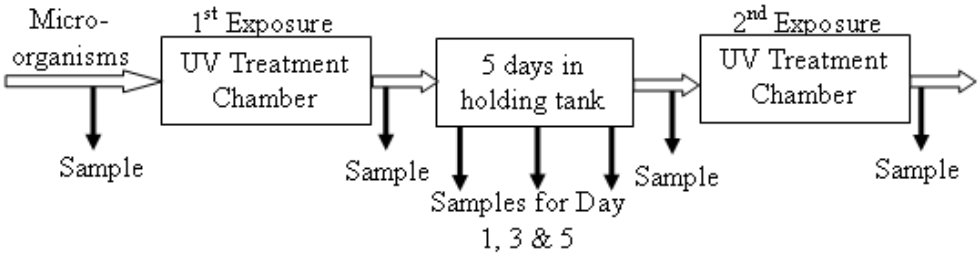

Figure 3-12: Diagrammatic setup of UV test with holding tank experiment

3.6.2 Biological Results

All operational parameters were measured online during the treatment process for each individual test. In this thesis, the delivered UV dose was determined using a calculated dose approach (discussed in next chapter) for which the UV reactor was validated.

3.6.2.1 UV Test Series 1

In the first 6 tests numbers of test microorganisms, *T.Suecica*, in the influent water were too low to draw biological conclusion on the effectiveness of UV irradiation. However, the biological results of the first 6 tests clearly show that the higher flow rate ($12.5 m^3 h^{-1}$) has the least inactivation rate among the other. The low mortality rate can be attributed to the lower transit time in the UV reactor and hence less UV irradiation exposure for the test microorganism (*T.suecica*). For the last two tests, number of *T. suecica* in the influent water was increased and log reduction of 2.3 and 1.4 were noted for the UV dose of 1826 and $851 mJcm^{-2}$ respectively. The experimental conditions and test results of each test in the UV tests are shown in Table 3-1 and Figures 3-13 and 3-14.

Table 3-1: The biological results of UV test with their respected UVT %and UV dose

Test Cycle	Flow rate (m^3h^{-1})	UVT	UV Dose ($mJcm^{-2}$)	Sample code	No. of *T. suecica* calculated in 1 ml (*n*±StDev)
1	3	93.1	2181	Control	24.7±6.1
				Treated	2.5±1.2
2	3	95.0	2280	Control	17.1±4.8
				Treated	1.9±1
3	3	95.5	2322	Control	12.7±4.7
				Treated	1.5±0.9
4	12.5	95.7	560.8	Control	11.6±3.1
				Treated	7.2±3.2
5	9.5	95.3	733	Control	11.1±1.5
				Treated	6.0±1.6
6	4	95.3	1731	Control	20.9±5.5
				Treated	1.7±0.9
7	2.5	82.8	1826	Control	243.5±163.9
				Treated	1.2±0.2
8	5.5	83.5	851	Control	775.8±381.7
				Treated	28.2±1

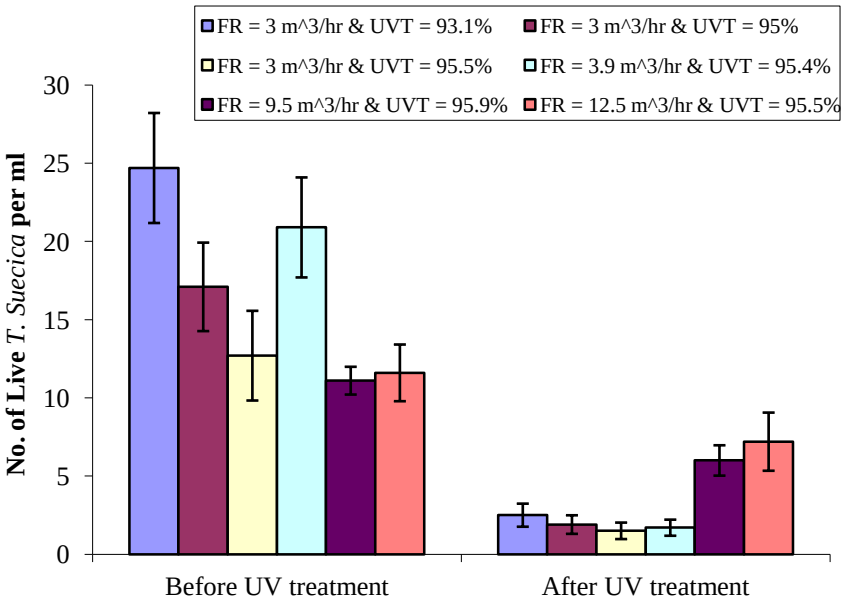

Figure 3-13: The total number of live *T. suecica* in 1ml before and after UV exposure at different flow rate. All data are the average of three replicates ± standard error

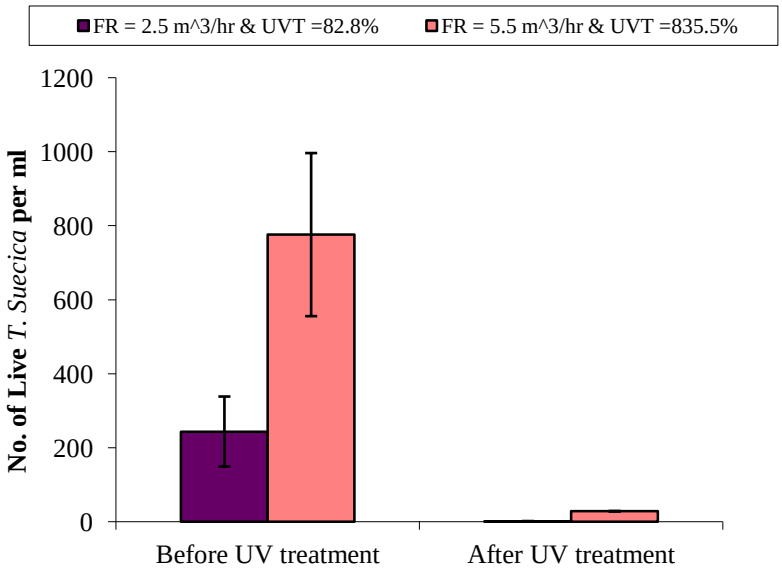

Figure 3-14: The total number of live *T. suecica* in 1ml before and after UV exposure. UVT of test water is modified by kaolin. All data are the average of three replicates ± standard error

3.6.2.2 UV Test Series 2

The 1st UV exposure was conducted at 10.2m^3hr^{-1} with modified UVT approximately to 70% by adding kaolin. The UV dose for this exposure was 276$mJcm^{-2}$. The flow rate for the 2nd UV exposure was 9.5m^3h^{-1} and UVT was approximately 91% giving the calculated UV dose of 642$mJcm^{-2}$. The number of live organisms present was significantly different between samples for both target microorganisms (*A. salina* and *T. suecica*). Table 3-2 presents the number of live target microorganisms at each sampling points as well as test conditions, Figures 3-15 and 3-16 also show the number of live *T. suecica* and *A. salina* at each sampling point respectively. No surviving *A. salina* individuals were found after the 2nd exposure of UV treatment on the fifth day while 90.8±2.2 live *T. suecica* cells per ml were present after UV treatment on the fifth day. The possible reason could be attributed to the high number of larger microorganisms (*A. salina*), which could shade *T.Suecica* from the UV irradiation. This reflects the importance of micro-filter to be included as part of treatment system in order to remove larger microorganisms and improve the water quality for UV treatment.

Table 3-2: The biological results of UV test with their respected UVT %and UV dose

Test Cycle	Flow rate (m^3h^{-1})	UVT (%)	UV Dose ($mJcm^{-2}$)	Sample code	No. of *A. salina* calculated in 1 m^3 (*n*±StDev)	No. of *T. suecica* calculated in 1 ml (*n*±StDev)
UV Test Run 1	10.2	70.3	276	Control	114300±67303	292.4±113
				Treated	2000±2066	222.7±120
Holding tank Day 1	------	------	------	Control	54467±16906	153.7±13
	------	------	------	Treated	700±500	208.9±45
Holding tank Day 3	------	------	------	Control	27013±53809	173.2±14.7
	------	------	------	Treated	1100±100	129.2±10.7
Holding tank Day 5	------	------	------	Control	70167±20378	256.5±19.8
	------	------	------	Treated	700±100	148.5±36.1
UV Test Run 2	9.5	91.3	642	Control	967±378	135.7±29.6
				Treated	0±0	90.8±2.2

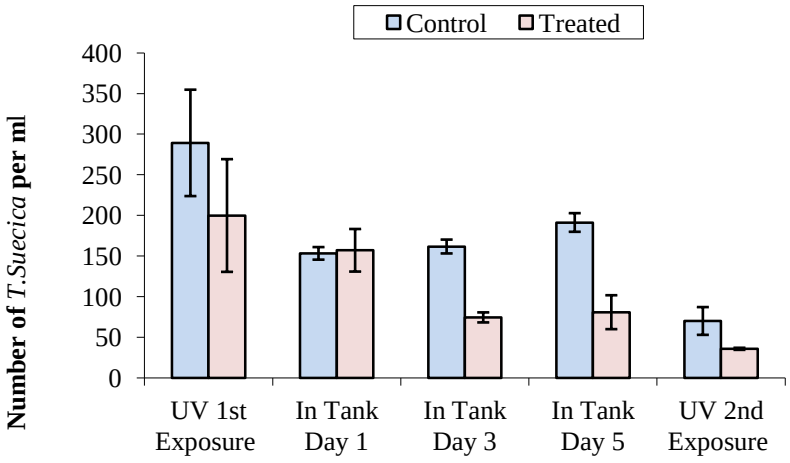

Figure 3-15: The total number of live *T. suecica* in 1ml. All data are the average of three replicates ± standard error

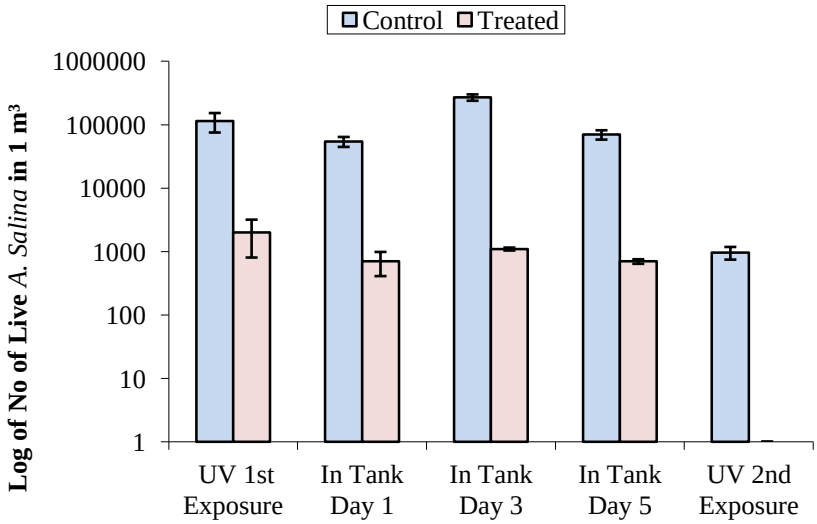

Figure 3-16: The total number of live *A. salina* in 1m^3. All data are the average of three replicates ± standard error

3.6.3 Inferential Estimator for Small Scale UV System

Each technology has unique characteristics that inactivate microorganisms. According to the literatures, for UV treatment system UV dose delivered in the reactor has direct effect on the inactivation of microorganisms. Hence UV dose delivery can be considered as the secondary output variable that should be related to the inactivation of microorganisms. One accurate way to determine the delivered dose on target microorganisms is the collimated beam study where a petri dish containing target microorganism is stirred and a collimated UV light beam is applied on to microorganisms. Collimating beam study and associated UV dose calculation is an example of completely mixed batch system. In ballast water treatment system, however, a continuous flow UV reactor should be used. Dose delivery in such system is considerably more complex than in a completely mixed batch reactor. In continuous flow through system, it is important to calculate the distribution of UV intensity ($mWcm^{-2}$) throughout the reactor so that in case of identification of darker space, then effective baffles can be placed to provide ideal plug flow. In such situation where there is a good radial mixing, the delivered UV dose ($mJcm^{-2}$) may be calculated by multiplication of the average UV intensity and the retention time in seconds. There are two different approaches to monitor UV dose delivery for the continuous flow UV reactors:

1. The UV intensity setpoint approach
2. The calculated dose approach

In the first approach, UV intensity will be measured by UV sensors without monitoring UVT during operation. The position of UV sensors is very important and should be as close as possible to ideal location. However, in the second approach, a dose monitoring equation is used to estimate the UV dose according to the measured parameters, such as flow rate, UV intensity and UVT, during reactor operations. UV intensity setpoint approach is simpler and does not consider UVT of flowing water. Hence it is more suited for small system where there is no change in UVT. In contrast, calculated UV dose approach is more advantageous over UV intensity setpoint due to possibility of comparing the calculated dose with the required dose for target microorganisms (USEPA, 2006). UV dose calculation approach can be adopted to develop a soft sensor by which UV dose delivery is monitored using measurement of operational parameters including UVT. EPA also recommends using an empirical monitoring equation

developed during validation testing. Validation tests are conducted over a wide range of flow rates, UVT values and lamp power combinations and then the empirical equation will be generated based on those tests (USEPA, 2006).

Either software-based model or empirical formula can be used for the calculation of UV dose in continuous flow reactor. The estimator for UV reactor should then consist of a mathematical model that calculates UV dose delivery and a biological model. Figure 3-17 illustrates the structure for the development of inferential estimator for UV treatment system.

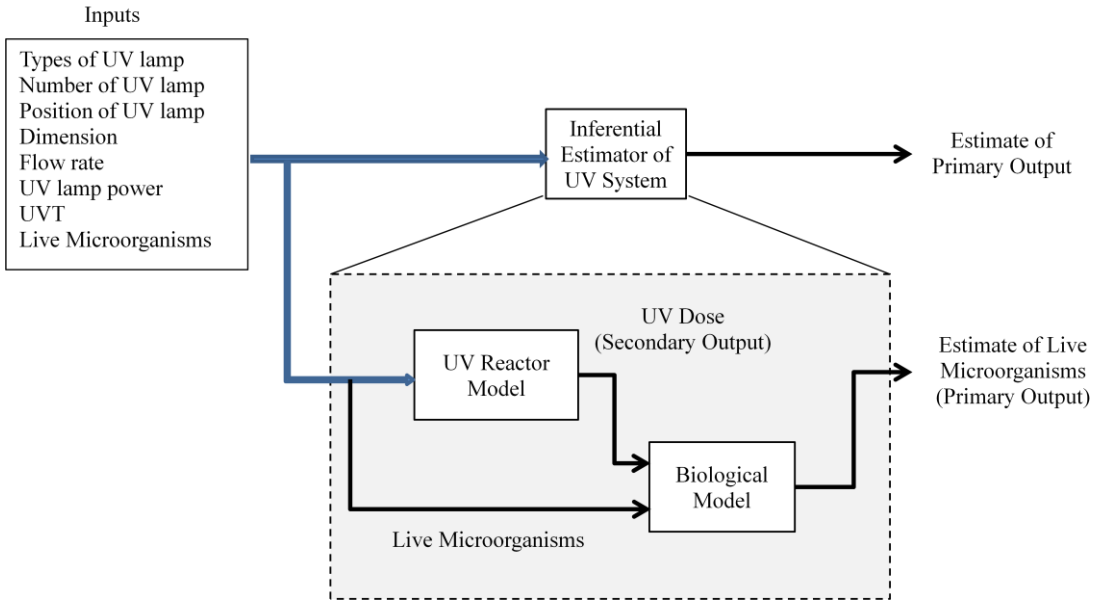

Figure 3-17: Inferential measurement for UV system

In this system, the first model calculates the UV dose, which is then fed into the biological model to estimate the primary output. Calculation of UV dose depends on the design and operational parameters of the UV reactor as well as seawater related parameters such as UVT and flow rate. Both models should be first developed before combining together to form inferential estimator.

3.6.3.1 UV Reactor Model

For the calculation of average delivered UV dose of the UV reactor used in this case study, an empirical formula which has been developed during validation process is used. Empirical formula supplied by UV manufacturer for the calculation of average UV dose for this UV reactor is given by:

$$UV\ Dose\ (\mathrm{mJcm^{-2}}) = I(mWcm^{-2}) \times Contact\ time \qquad (3.69)$$

where

$$I(mW\,cm^{-2}) = \frac{P(W) \times UVC\% \times Quartz\ \eta \times UVT^{Path\ Length}}{\pi \times D\ (m) \times L\ (m)} \quad (3.70)$$

$$Contact\ time = \frac{A\ (m^2) \times L\ (m)}{Q\ (m^3/s)} \quad (3.71)$$

P = UV lamp Power (W)

UVT = UV Transmittance

D = Diameter of reactor (m)

L = Length of reactor (m)

A = Effective area of reactor (m^2)

Q = Flow rate (m^3h^{-1})

Note: Effective area is the cross section area of UV reactor minus the area of UV lamp liner.

3.6.3.2 Biological Model of Small Scale UV Reactor

The biological results from the various experiments were used to develop biological model of the inferential estimator for the UV treatment system. Datasets were arranged in such a way that UV dose ($mJcm^{-2}$) exposure and number of *T. suecica* per ml entering the UV reactor considered as input variables and the number of *T. suecica* per ml leaving the UV reactor as output of the model. Figure 3-18 represents biological model with associated input and output. The functional relationship that defines the number of live *T. suecica* per ml leaving the reactor is given by:

(*No. of live organisms leaving*) = *f* (*UV Dose, No. of live organisms entering*)

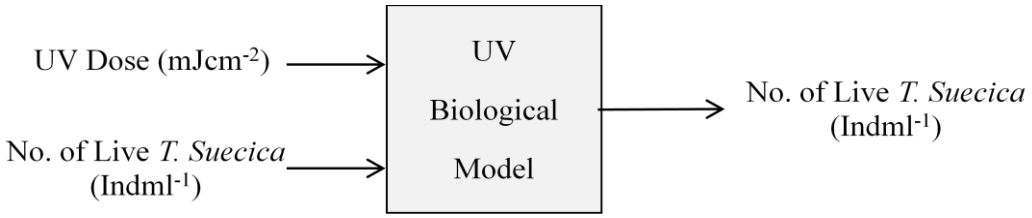

Figure 3-18: Biological model for UV reactor used in the case study

Three different modelling techniques, MLR, MNLR and ANN, were used to generalise this relationship. The results from all three models were compared and presented later in the chapter.

I. Multiple Linear Regression Model

MLR method is used to model the relationship of number of live *T. suecica* per ml before treatment and applied UV dose to the number of live *T. suecica* after treatment. The data prepared for this modelling technique consisted of two independent variables (predictors) and one dependent variable (response). One of the limitations of MLR is multicollinearity in the independent variables when there are two or more independent variables. Correlation of two independent variables calculated, using statistical software (SPSS), and found to be minus 0.3. This shows that two independent variables are not highly correlated and as there are only two independent variables, then statistical analysis such as PCA or PLS is not needed to reduce the dimension and /or transform them to uncorrelated variables.

The prediction equation of MLR for the arranged data is defined as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \qquad (3.72)$$

where:

y = No. of live *T. suecica* exiting the treatment chamber,

x_1 = No. of live *T. suecica* entering the treatment chamber,

x_2 = Applied UV dose.

Regression analysis was used to determine the parameters of the Equation (3.72), using the obtained data from biological experiments. The prediction equation, after determination of β's, becomes:

$$y = 50.74 + 0.024x_1 - 25.2x_2 \qquad (3.73)$$

II. Multiple Nonlinear Regression Model (MNLR)

Power nonlinear function was considered to develop the prediction equation for the experimental data. This nonlinear function, as explained earlier in this chapter, can be transformed into linear function in order to determine the equation parameters. The prediction equation and its linearised form are given by:

$$y = 10^{\beta_0} \times x_1^{\beta_1} \times x_2^{\beta_2} \qquad (3.74)$$

$$\log y = \beta_0 + \beta_1 \log x_1 + \beta_2 \log x_2 \qquad (3.75)$$

To solve Equation (3.75), all the experimental data should be modified by taking the logarithm of each value and then apply the MLR technique for Equation (3.75) to find the prediction equation parameters.

The mathematical model for the prediction of live *T. suecica*, based on the nonlinear function becomes:

$$y = 10^{0.3303} \times x_1^{0.2804} \times x_2^{-1.654} \qquad (3.76)$$

III. ANN Model

To develop ANN model feed-forward networks containing three layers (input, hidden and output) with backpropagation technique as learning rule was used. Five neurons were chosen for the hidden layer and training of ANN began with 1000, 5000, 10000 and 15000 iterations. After successful training, linear correlation coefficients of 0.9723, 0.9743, 0.9768 and 0.9996 were obtained respectively. The weights from last training (5 neurons and 15000 iterations), which showed the least error, were used to develop biological model.

IV. Comparison of MLR, MNLR and ANN Models

All dataset obtained from biological experiments were used to evaluate and compare the predictability of MLR, MNLR and ANN models. The absolute error of each prediction by three models were calculated for comparison and presented in the Table 3-3 and Figure 3-19.

Table 3-3: Results of prediction models and their absolute errors

No. of Live T. suecica before treatment	UV dose ($mJcm^{-2}$)	No. of Live T. suecica after treatment	MLR Prediction	MNLR Prediction	ANN Prediction	Absolute Error (MLR)	Absolute Error (MNLR)	Absolute Error (ANN)
28.8	2000	4	1.03	1.74	1.76	2.97	2.26	2.24
27.7	2216	2	-4.44	1.46	1.83	6.44	0.54	0.17
17.7	2244	1.62	-5.38	1.26	1.84	7.00	0.36	0.22
14.7	2265	1.12	-5.99	1.18	1.85	7.11	0.06	0.73
13.8	2287	1.56	-6.56	1.14	1.85	8.12	0.42	0.29
22.7	2301	3.08	-6.70	1.29	1.86	9.78	1.79	1.22
7.3	2301	1.02	-7.07	0.94	1.86	8.09	0.08	0.84
13.6	2308	2.58	-7.10	1.11	1.86	9.68	1.47	0.72
17.1	2359	0.98	-8.30	1.15	1.88	9.28	0.17	0.90
15.1	563	6	36.91	11.84	5.02	30.91	5.84	0.98
10.5	564	4.74	36.78	10.66	4.66	32.04	5.92	0.08
12.1	733	7.88	32.56	7.19	4.57	24.68	0.69	3.31
11.8	733	4.64	32.55	7.14	4.55	27.91	2.50	0.09
9.3	743	5.48	32.24	6.53	4.35	26.76	1.05	1.13
16.8	1781	2.74	6.26	1.82	1.66	3.52	0.92	1.08
27.2	1753	1.48	7.22	2.13	1.71	5.74	0.65	0.23
18.7	1786	1.02	6.18	1.86	1.67	5.16	0.84	0.65
247.7	2028	1.46	5.58	3.12	1.83	4.12	1.66	0.37
472.8	2072	1.02	9.87	3.60	1.74	8.85	2.58	0.72
247.9	2065	1.1	4.65	3.02	1.83	3.55	1.92	0.73
634	874	28.65	43.93	16.32	26.62	15.28	12.33	2.03
485	880	27.05	40.20	14.97	28.89	13.15	12.08	1.84
1208.25	874	28.95	57.71	19.55	29.40	28.76	9.40	0.45
253.187	276	106.83	49.86	84.89	107.42	56.97	21.94	0.59
416.22	279	157.03	53.70	95.86	154.41	103.33	61.17	2.62

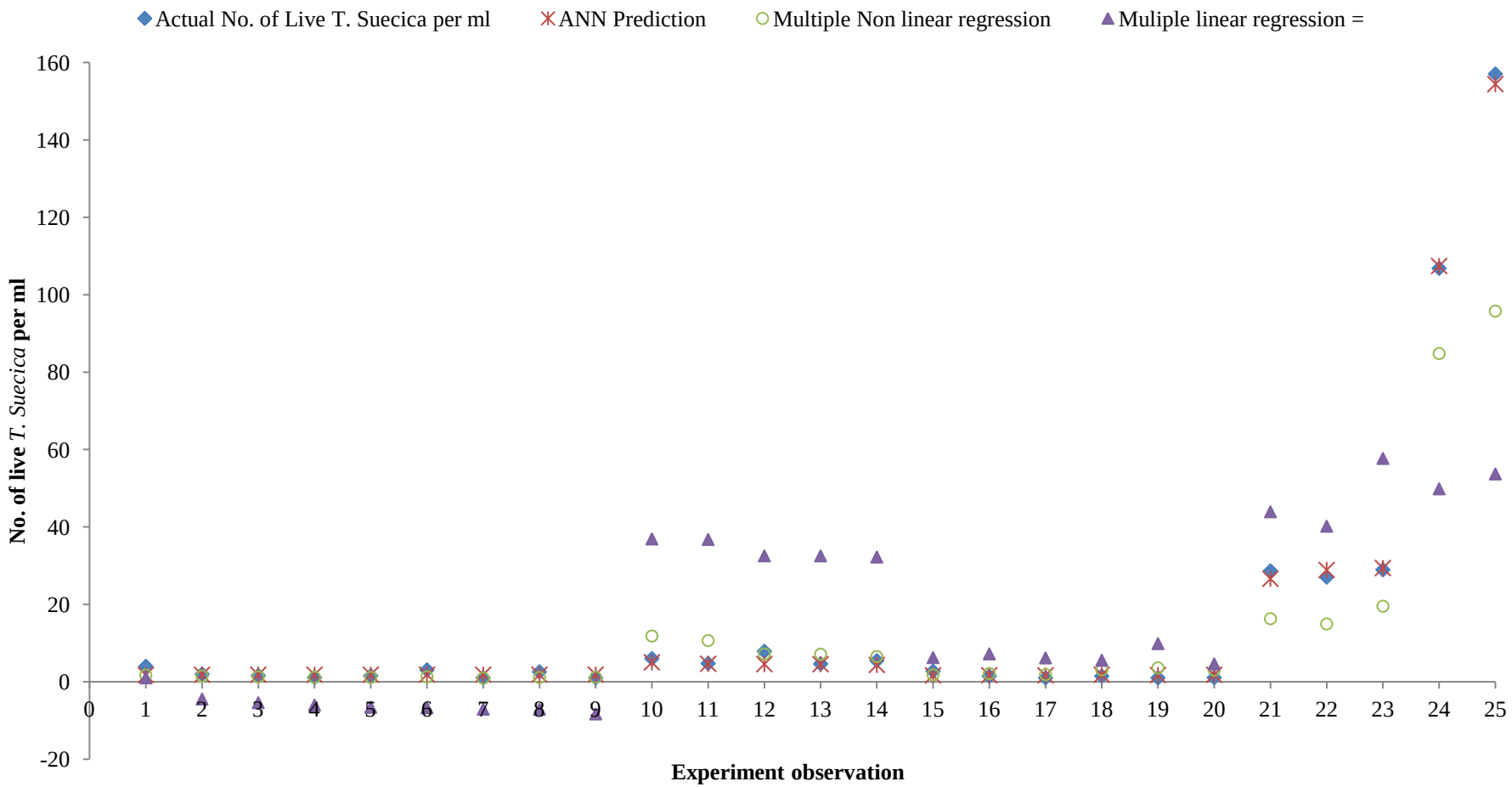

Figure 3-19: Comparison of actual results from experiment with predicted results from models

The predicted results of all three models, when compared to actual observed results from biological experiments, reveals that ANN model predicts more accurately than the other two modelling techniques. The Maximum Absolute Error (MAE) of prediction results by ANN is 3.31 only, whereas MAE values for MLR and MNLR are 103.33 and 61.17 respectively. Additionally, predicted results from these models were statistically analysed and the accuracy of each model was then examined by comparing the calculated Root Mean Squared Error (RMSE) and Linear Correlation Coefficient (LCC) of each individual model. The RMSE value is a measure of the differences (residuals) of prediction values by the model and that of actually observed. The LCC also shows the strength of the linear relationship between two variables. The performances of the three modelling techniques are presented in the Table 3-4.

Table 3-4: Statistical analysis and comparison of three prediction models

	MSE	RMSE	NMSE	Mean Absolute Error	LCC
MLR	799.8	28.26	0.01427	18.37	0.6154
MNLR	188.5	13.73	0.04218	5.95	0.985
ANN	1.604	1.266	0.000753	0.97	0.9994

The RMSE values of three prediction models for the number of live *T.suecica* per ml shows that ANN prediction is more accurate than the other two. The accuracy of ANN modelling for the prediction of biological performance of UV treatment on *T.suecica* is also confirmed by LCC (Table 3-4).

The ANN model can now be combined with UV reactor model to form inferential estimator to predict the performance of small scale UV reactor on the inactivation of *T. suecica*.

3.6.3.3 Simulation model of Inferential Estimator

Both UV dose calculation model and ANN model were programmed in a graphical modelling environment, LabVIEW®, to develop the simulation model of inferential estimator. Various inputs, regarding design, operation and testing conditions, can be introduced into this user-interface simulation model (Figure 3-20) and after running the program; it predicts the biological performance of UV treatment system on *T. suecica*.

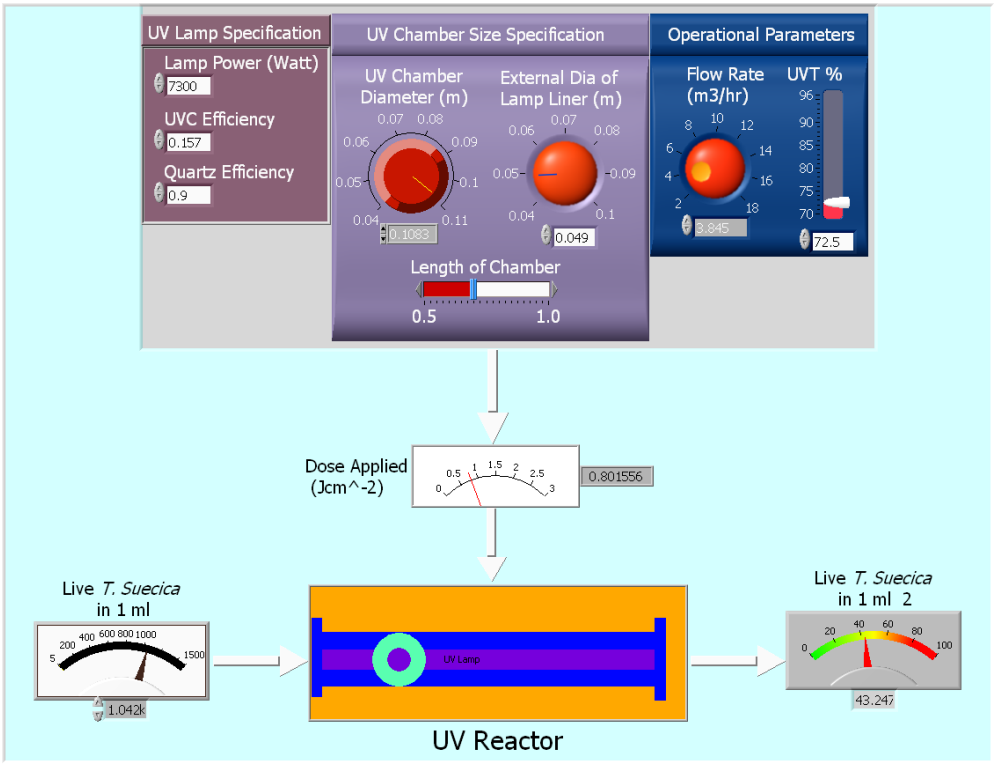

Figure 3-20: Inferential estimator of small scale UV reactor on *T.Suecica*

This simulation model can also be used to establish the performance map of UV treatment system. The performance map (Figure 3-21) shows the relationship of two independent variables (UV dose delivery and No. of live *T. suecica* per ml before treatment) to the no. of live *T. suecica* per ml leaving the system (dependent variable).

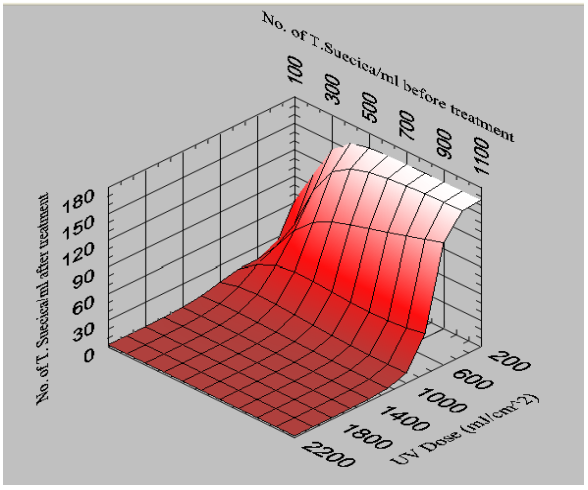

Figure 3-21: Performance map of UV treatment on *T. suecica*

In the left corner of the graph shows a downward trend for the number of microorganisms leaving UV reactor for the same average UV dose. This may be due to the fewer number of microorganisms entering the UV reactor and therefore chance of

UV exposure for those free floating microorganisms at the further distance from UV lamp is increased. From the graph, it can also be concluded that average UV dose of more than 1200 mJcm^{-2} is required to inactivate high number of *T. suecica* (1000 cell ml^{-1}) in one exposure and satisfy IMO discharge standard for this type of microorganisms.

3.6.4 Inferential Measurement for Experiment Setup

The inferential estimator is the main building block of the inferential measurement of a system. The final series of test carried out on this case study consisted of two UV treatment (day0 and day5) and five days retention in the holding tank. The experiment setup was inspired from the IMO guidelines for land-based test and shipboard ballasting and de-ballasting operations. To develop inferential measurement for this experiment setup, each treatment section of experiment should be considered separately. Figure 3-22 illustrates the inferential measurement for this experiment.

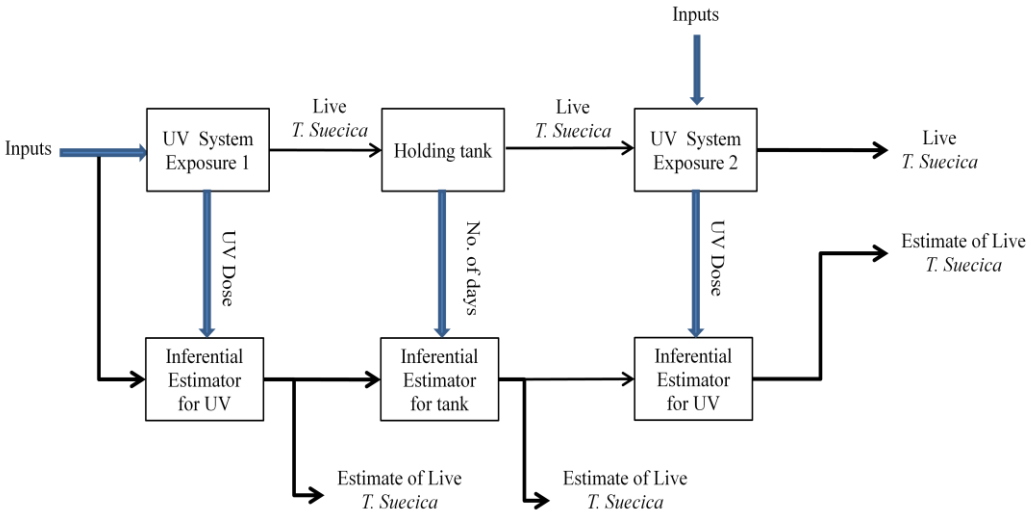

Figure 3-22: Inferential measurement for experiment setup in the case study

The inferential measurement model (Figure 3-22) shows the possibility of monitoring of performance at each section of treatment setup. The output of each estimator predicts the number of live *T. suecica* (indml^{-1}), which is the primary output of the setup. The results obtained from experiment were used to develop model for the holding tank in order to complete the model presented in the Figure 3-22. Number of days in retention, due to the controlled environment in the tank except for darkness, was considered as contributory element in mortality of *T. suecica*. A regression formula for mortality rate of microorganisms in the holding tank was then derived to develop inferential estimator for the holding tank. The inferential measurement model for the experiment setup in this

case study was developed by programming each inferential estimator into LabVIEW® to provide a user friendly interface (Figure 3-23) that could be used for various operational and testing Scenarios. The simulation model has the capability to monitor the immediate biological results of each section of the treatment setup under varying conditions. It can also provide the knowledge about operating profile of UV system under which the primary output of the setup at the final stage of treatment can be observed.

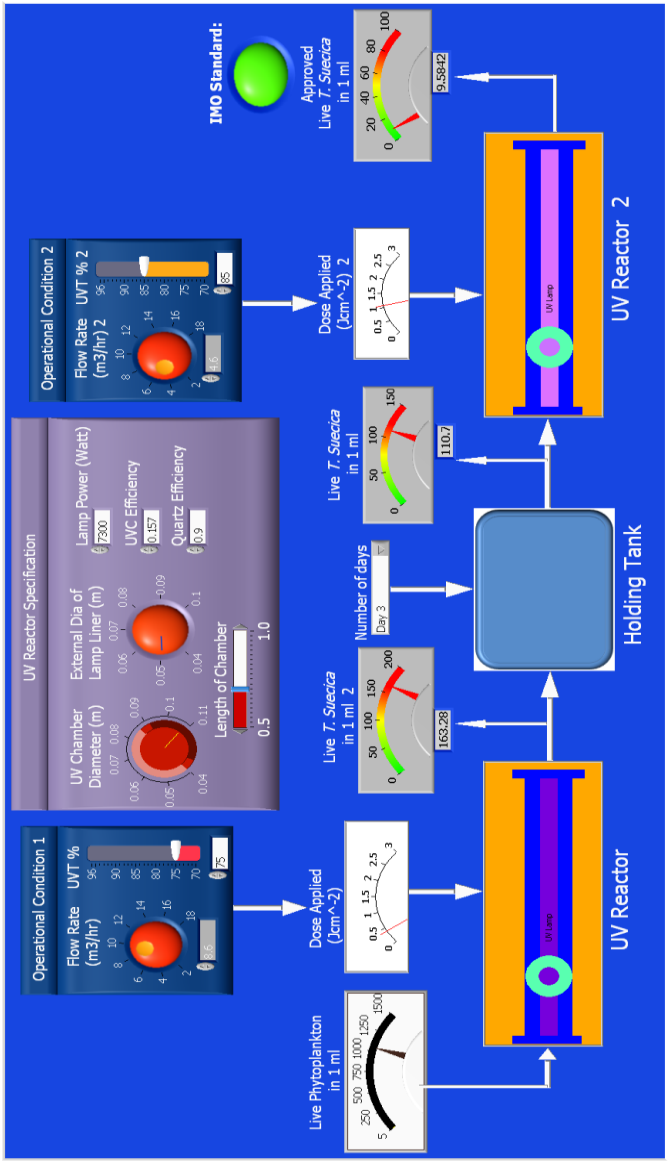

Figure 3-23: Simulation model for the inferential measurement of small scale setup

The simulation model and in particular inferential measurement concept showed that how observability could be provided for the UV treatment system whose primary output measurement depends on laboratory assays with long analysis delays. This methodology can also be extended further to the different treatment technologies and other microorganisms. In the next chapter the same methodology will be applied to develop

inferential measurement for ballast water system consisting of micro-filter and UV reactor.

3.7 Conclusion

Observability provides evidence of the actual behaviour of a system under observation from the knowledge of its state variables. Therefore to observe the actual behaviour of a system, reliable measurement devices are required to measure the data proportional to certain variables of interest. Different techniques were introduced to reconstruct the unmeasured variables in some cases where state variables cannot be obtained through physical measurement.

Two well-known techniques of kalman filter and Luenberger observers for the reconstruction of unmeasured state variables were reviewed in the chapter. Both of these methods found to be linear in nature and to some point can be extended to deal with nonlinearity. In both techniques, the output variables of the system together with the disturbance noises should be available to estimate the state variables. Due to the nonlinearity and time varying nature of some systems and multitude unmeasured disturbances, however, the applications of these techniques were mostly restricted to universities laboratories and few industrial studies. It is also noteworthy to mention that in ballast water treatment system due to:

- Lack of reliable online sensor to measure the output of treatment system i.e. number, types, sizes and live/dead status of microorganisms exiting treatment systems, and
- Lack of biological model to represent the nonlinear and time varying nature of inactivation process of microorganisms,

Kalman filter and Luenberger observer are suitable technique to solve non-observability problem of ballast water treatment systems.

Inferential measurement methodology was introduced for the systems where the primary variables that define the quality of the system cannot be measured. The primary variables in this methodology can be inferred from other measurable variables provided the relationship exists between secondary and primary variables.

A methodology was developed, using inferential measurement system, to provide observability for the ballast water treatment system in which the measurement of

primary output variables (number of live microorganisms per specified unit volume) requires laboratory assays with long delays analysis.

The ballast water treatment system, in this methodology, is conceptually divided into technological and biological systems for which mathematical models should be developed. The output of technological model is the secondary output of the system that together with inputs to the system relates to the primary output of the system.

Case study was conducted to validate the concept of inferential measurement for ballast water treatment system. In this study, various tests were conducted on UV system and the results were used to develop biological model for UV system. Numbers of test microorganisms in some of tests were too few to draw any substantial conclusion on the effectiveness of UV irradiation. However, for two tests when the number of microorganisms in the influent water was increased, log reduction of 2.3 and 1.4 were noted for the UV dose of 1826 and 851mJcm^{-2} respectively.

Three different data driven modelling techniques (MLR, MNLR and ANN) were used to develop biological model and thus online estimator for the UV technology used in the case study. The prediction of each model statistically analysed and ANN model proved to be more accurate modelling technique when compared to the other two. The statistical results for the linear correlation coefficient of ANN, MLR and MNLR models were 99.94%, 61.5% and 98.5% respectively. In the other statistical comparison, the RMSE values of ANN, MNLR and MLR models were 1.26, 13.7 and 28.26 respectively. Both of these statistical analysis show that the ANN prediction is more accurate than the other two.

The software-based inferential measurement provided observability for the UV treatment system used in the case study. This concept showed how the performance of each section of treatment can be monitored. The same methodology can be used to develop observability for the ballast water treatment system consisting two or more technologies.

Chapter 4 Inferential Measurement for Ballast Water Treatment System

Summary

The main goal of this chapter is to develop inferential measurement for ballast water treatment setup. The inferential measurement estimates the biological output after each section of treatment and provides monitoring for the treatment system. To generate supporting data for the development of inferential estimators of involved technologies in the treatment setup, various tests at two different locations were conducted.

Chapter 4's objectives may be briefly summarised as:

- *To develop ballast water treatment setups,*
- *To conduct experiments at various test conditions in order to generate a broad range of data,*
- *To analyse the biological results and investigate the efficacy of involved technologies,*
- *To review calculation and monitoring of UV dose delivery and develop a soft sensor for UV dose delivery under varying operational conditions,*
- *To develop inferential estimators for UV reactor used in the treatment setup from offline data,*
- *To develop inferential estimator for micro-filter from offline data,*
- *To develop inferential measurement systems for the biological performance monitoring of ballast water treatment setup.*

4.1 Introduction

Measurements of output variables of a system are used to monitor and ultimately control its performance. Monitoring and thus controlling of the processes, e.g. ballast water treatment system, provides consistent performance and deliver the required quality. However, to achieve this, regular and reliable measurements should be available at the appropriate frequency. In the ballast water treatment system, online measurements of primary output variables (biological effectiveness of microorganisms leaving treatment system) are not possible and reliable measurement depends on off-line laboratory assays with long analysis delays. Case study conducted in the previous chapter showed that online performance monitoring of UV treatment system is possible through inferential estimator (soft sensing). With the software-based estimator, the values of primary variables (number of live microorganisms) could be inferred by the knowledge of UV dose through calculation and some input variables. This methodology

is extended to develop an inferential measurement for the ballast water treatment system consisting of micro-filter and UV reactor. Similar to the case study, series of tests should be conducted on the ballast water treatment system to generate required data for the development of inferential estimator for each technology. In this light, a large experimental setup was developed and series of tests performed at two different locations. In this chapter experimental setup, test procedures, biological results and development of inferential measurement for the treatment setup will be discussed and presented.

4.2 Ballast Water Treatment Setup

The ballast water treatment system, for which software-based inferential estimator (soft sensor) will be developed, consisted of micro-filter and UV irradiation technologies. The targeted capacity of the large scale ballast water treatment system was considered as $100 m^3 h^{-1}$. Deciding factor for the size of pipe to connect the components together was the inlet and outlet flange size of UV reactor and it was reduced to appropriate size to match with the inlet and outlet flanges of micro-filter and seawater pump. By-pass lines were considered for each technology to facilitate priming of the system and provide possibility of conducting the experiment for the individual technology, if required. Figure 4-1 shows the schematic diagram of the treatment system. To provide mobility and for the sake of ease of transportation, it was decided to contain treatment setup in a 20ft container so that experiment can be conducted at different locations. The schematic diagram was then turned into virtual design using AutoCAD software to achieve optimum arrangement inside the container. Figure 4.2 shows the AutoCAD design of the large scale treatment system inside a 20 ft container.

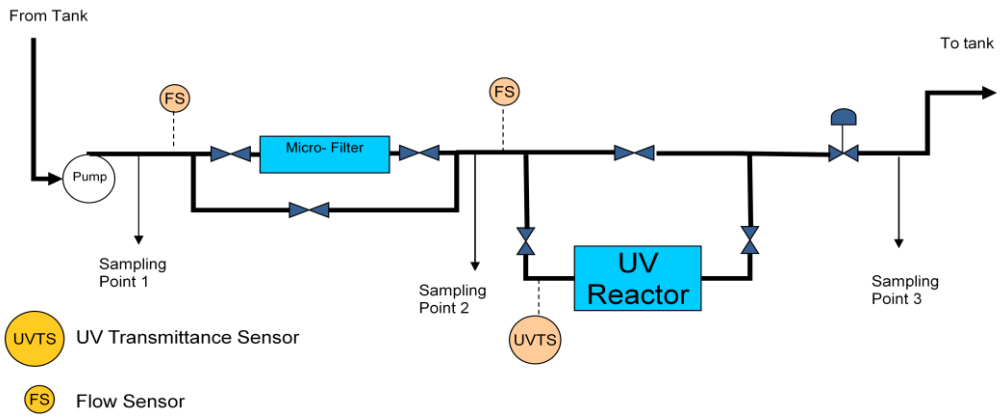

Figure 4-1: Schematic diagram of ballast water treatment system

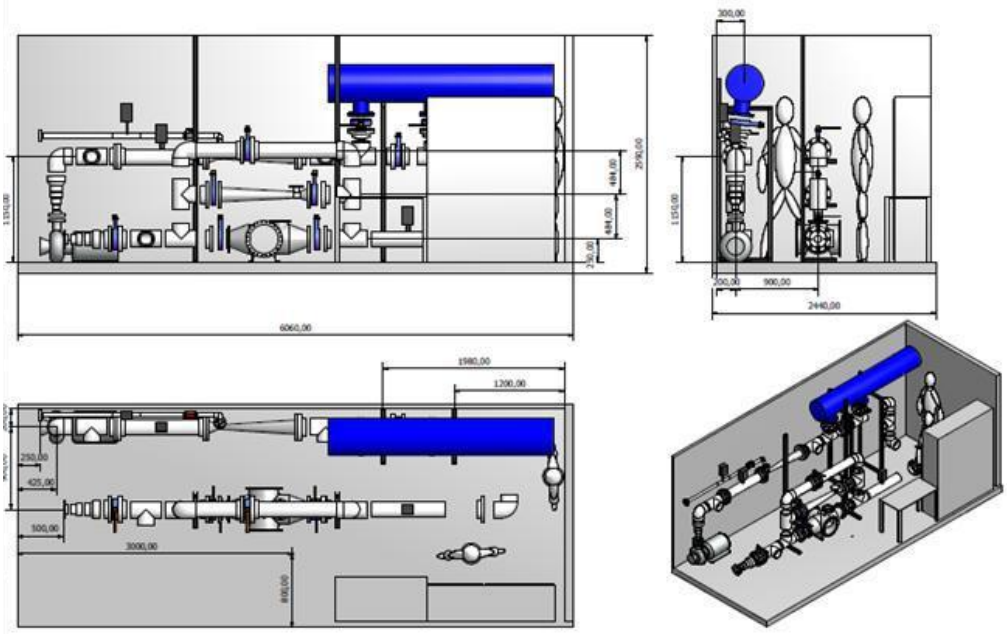

Figure 4-2: 3D design of ballast water treatment system

Sampling facility was arranged for each sampling point, considering following factors:

- Simultaneous triplicate samples at each point
- Provision for adjusting the flow at each sampling point

Size of sampler was calculated based on formulae recommended in IMO guidelines (G2). It is also recommended that the sample port diameter to be 1.5 to 2.0 times the diameter obtained from this equation.

$$D_{sample\ point} = D_{SP} = D_{main\ pipe}\sqrt{Q_{sample\ point} / Q_{main\ pipe}} \qquad (4.1)$$

Each sampler had a sample tube with 90° bend towards the direction of the flow, located in the centre of the main piping system and connected to three outlet branches for simultaneous collection of samples as shown in Figure 4-3.

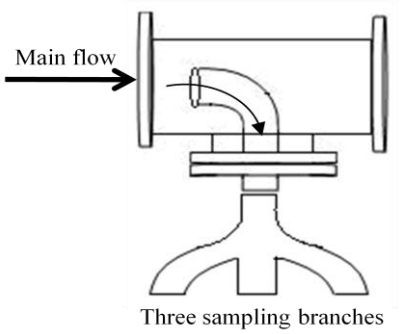

Figure 4-3: Connection for each sampling point

The treatment setup was built and all instrumentations were installed in the appropriate positions. The completed setup with flexible pipe work connection to and from tanks is shown in Figure 4-4.

Figure 4-4: Large scale setup in 20 ft container

Specification of different components used in the treatment system will be discussed in the next subsections.

4.2.1 Components of Treatment Setup

4.2.1.1 Seawater Pump

A single stage 3 phase electrical drive centrifugal pump with bronze impeller and casing was used to supply the seawater at the required flow rate (Maximum 135 m^3h^{-1} at the pressure head of 22.5 m) to the treatment system. The $NPSH_r$ of the pump for targeted flow rate was 4.8 m, which is suitable for the experiment. The inlet and outlet connections of seawater pump are 3 and 2½ inch respectively. The outlet flange was connected to main pipe by using an adaptor.

4.2.1.2 Micro-Filter

The body of micro-filter is constructed of carbon steel with protective coating of durable polyester to protect against corrosion. One end of the filter has removable bolted cover for ease of maintenance and in the other end an electric worm-gear motor is mounted to perform two simultaneous operations during flushing cycle. Two operations are:

- Rotation of the collector assembly to clean internal surface of micro-filter's screen circumferentially, and
- To and fro movement of the collector assembly to clean the internal surface of screen longitudinally.

The combination of these two movements causes the suction nozzles of the collector assembly run through the entire internal surface of screen. Part of the flowing seawater, at the time of flushing, is used to create required suction at the nozzles and draw accumulated particles attached to the screen. These removed particles along with seawater will be discharged out through flushing valve.

This micro-filter, shown in Figure 4-5, has two coarse and fine screens. The coarse screen is located at the inlet section of micro-filter and removes larger particles that would otherwise damage the fine screen. The fine screen consists of a multilayer sintered stainless steel mesh. The pressure differential across the micro-filter will activate the flushing cycle. There are three different modes of flushing such as:

- Automatic mode: Activated when differential pressure reaches the predetermined setting.
- Continuous mode: Continuous flushing irrespective of pressure differential.
- Manual mode: Activation of flushing occurs by operator only.

Figure 4-5: Micro-filter with 40 micron screen

4.2.1.3 UV Reactor

The UV reactor designed for the disinfection of ballast water has the configuration of straight inlet and outlet with smooth gradual changes in cross sectional area as shown in the Figure 4-6. The UV reactor configuration was to utilise the hydraulic benefits gained from this design of UV reactor. The designed UV reactor has 6 inch inlet and

outlet flanges with 8 MP-HI UV lamps located perpendicular to the direction of seawater flow. Each lamp is housed in a transparent liner to receive protection from damage and breakage as could possibly be caused by the flow of seawater with its suspended materials over the lamps. An automatic online cleaning method has been employed for cleaning the liners of 8 UV lamps, which receive signal for operation (cleaning of the UV lamp sleeves) from the sensor installed on the reactor.

Figure 4-6: UV reactor for the large scale setup

The specifications of designed UV reactor and UV lamps are as follows:

UV reactor diameter	31.4 cm
UV lamp liner	4.9 cm
Desired angle	8 degree
Pitch Circle diameter of lamps	22 cm
Arc (disinfection diameter)	33 cm
Power of each lamp	3500 w
UVC efficiency of Lamp	15.7%

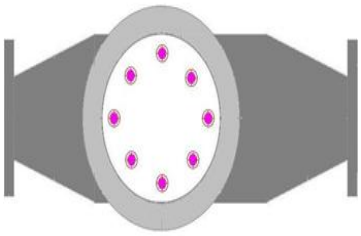

Figure 4-7: UV Reactor showing UV lamps

4.2.1.4 Online Measuring Sensors

Ballast water treatment setup was also equipped with flow and UVT sensors to measure these two parameters online and a data acquisition card to connect sensors to the computer.

I. Flow Sensor

Two self-powered, reliable paddle wheel flow sensors were used to measure the seawater flow passing through the treatment system. The signal from flow sensor installed after micro-filter (before UV reactor) that shows the flow through UV reactor

is used for the accurate calculation of average UV dose. The output signal of these flow sensors were similar to the one used in the case study; hence a transmitter was installed for each flow sensor to convert the sinusoidal frequency into current. Sufficient straight pipe for each of the flow sensors were considered to ensure appropriate flow profile just before flow sensors. The standard output of flow sensors were current ranging from 4 to 20 mA, which were converted into corresponding flow rate of seawater passing through system by transmitter.

II. UVT Analyser

UVT analyser shown in Figure 4-8 uses microprocessor technology for monitoring the percentage transmission of flowing water in UV disinfection systems. The analyser benefits from ultrasonic auto-cleaning system, which continuously cleans the optical chamber and ensures reliable monitoring throughout the treatment process. Flow of seawater passing through UVT analyser is controlled at 100mlmin^{-1} by the provided flow regulator. The analyser receives continuous flow at required flow rate through the assembly with a 30 ml cuvette and then the water is drained out from the sensor.

Figure 4-8: UVT online analyser

. The specifications of UVT analyser are as follows:

Range	0 – 100% Transmission
Resolution	± 0.1% T
Accuracy	± 1.0% T
Wavelength	Ultraviolet 253.7nm
Standard Output	4-20 mA with isolator

The analyser was calibrated with standard solution before commissioning.

III. Data Acquisition Device

Data acquisition (DAQ) card (NI USB 6211) with 16 analogue input and 2 analogue output was wired to both measuring sensors in order to monitor and record the required data. The output current signal from each measuring device was converted to voltage using high precision resistor to make it readable for DAQ card. A LabVIEW® program was developed to convert all of the receiving signals into corresponding and meaningful parameters in a user-friendly format. The analogue output of the DAQ card was connected to the flow control valve via a transformer to adjust the position of the control valve upon receiving signal from program. Figure 4-9 shows the DAQ card and its connections to the flow transmitters and UVT analyser.

Figure 4-9: DAQ card wired up to the sensors

4.2.2 Experiment Procedure

Different testing conditions and combinations were used to generate broad range of data for modelling purpose as well as understanding the capabilities of these technologies for targeted microorganisms. In the next sections testing procedures and conditions of each series for the treatment setup will be described.

4.2.2.1 Test Procedure for Ballast Water Treatment Setup

In total two series of tests were conducted at two different locations. The first series of tests was performed at the Dove Marine Laboratory in May 2009 and the second series was conducted at the Port of Blyth in August 2009. The same testing procedure was adopted for both series. In both series of tests, the effectiveness of the combined treatment technologies (Micro-filter and UV irradiation) on the brine shrimp, *A. salina*, and the single cell green alga, *T. suecica*, was assessed. The test setup in each location

included the treatment system and five days storage of treated and untreated (control) seawater prior to final discharge. Figures 4-10 and 4-11 illustrate the test procedures during the uptake, Day 0, and discharge, Day 5, of seawater respectively.

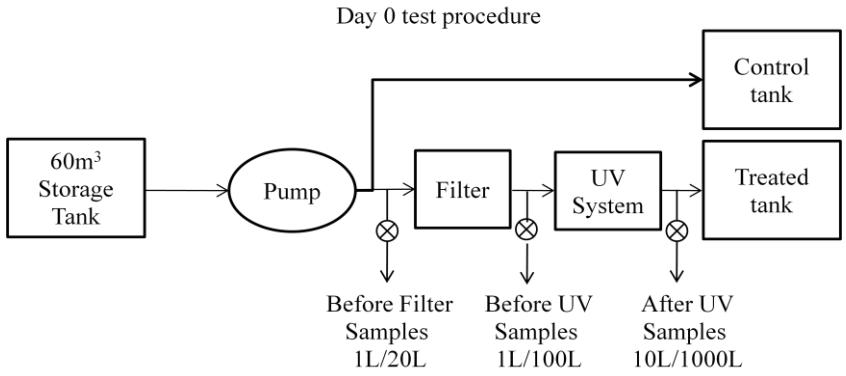

Figure 4-10: Schematic diagram of test procedure in Day 0, showing three sampling points. - ⊗ indicates the sampling valves in the diagram.

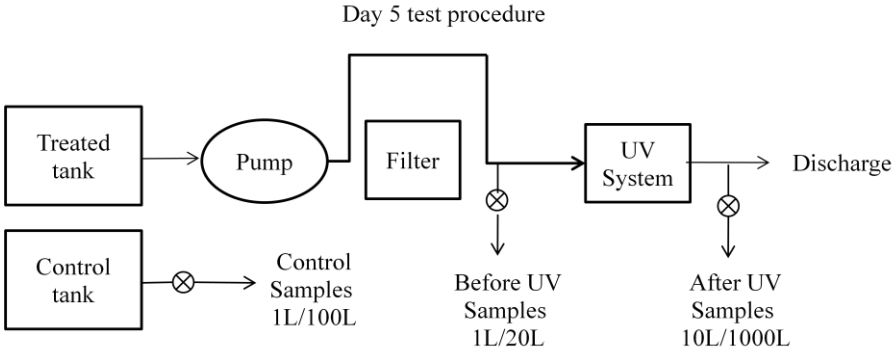

Figure 4-11: Schematic diagram of test procedure in Day 5, showing three sampling points

In the first series of tests, the storage tanks were constructed of concrete and remained uncovered, leaving the contents open to the atmosphere (e.g. sun light, rain, etc.). In contrast, sealed metallic tanks were used for the second series of tests.Table 4-1 summarises the similarities and differences between these two test series.

Table 4-1: Test conditions at both locations

	Parameters	Test at Dove Marine Laboratory	Tests at Port of Blyth
Control & Treated Tanks	Shape	Rectangular	Cylindrical
	Material	Cement	Metallic, coated internally
	Internal condition	Sludge/ mud at the bottom	Clean (some rusty area)
	Enclosed	No (open to atmosphere at top)	Yes
	Capacity (m^3)	60	55
Seawater	Source	North Sea (sand-filtered)	North Sea (Harbour area)
	Salinity ‰	30	30
	Temperature (º C)	15.5 ~ 16.3	13.8 ~ 14.5
	pH	8.0	8.0
Pump and piping arrangement	Adding organisms to the tank	Aquarium pump with flexible plastic hose	Aquarium pump with flexible plastic hose
	For treatment purpose	Centrifugal pump with reinforced flexible hose	Centrifugal pump with reinforced flexible hose
Organism	Zooplankton	*Artemia Salina*	*Artemia Salina*
	Phytoplanton	*Tetraselmis Suecica*	*Tetraselmis Suecica*
Tests conducted	Month	May 2009	August 2009
	Air Temperature (º C)	14	18

I. Tests at the Dove Marine Laboratory, UK

Two tests were performed at the Dove Marine Laboratory in May 2009. The storage tanks used for the treated and control water were rectangular and made of reinforced concrete, with the top open to the atmosphere as shown in Figure 4-12. The outlet valves from the treated and control tanks were 30 cm above the base and so it was not possible to completely empty the tanks via the outlet valves. There was also 5 – 10 cm of sludge/mud at the bottom of both tanks.

Figure 4-12: Control and treated tanks at Dove Marine Laboratory

The storage tank was filled with sand filtered seawater from Cullercoats Bay to which the test organisms, *A. salina* and *T. suecica* were added. The seawater was pumped firstly into the treated tank through the treatment system (Figure 4-10) while samples were collected at each sampling point for biological assessment. When the treated tank was filled, the remaining seawater in the storage tank was pumped into the control tank without any treatment. After five days, treated seawater from the treated tank was discharged through a second UV treatment as shown in Figure 4-11 and samples were collected before and after UV treatment for biological assessment. Samples were also taken directly from the control tank to evaluate the effect of five days storage of target organisms without any treatment.

II. Tests at the Port of Blyth, UK

Two similar tests were conducted at the Port of Blyth in August 2009. In these tests, cylindrical tanks made of steel were used to mimic, as far as practicable, a ship's ballast tanks. Unlike the tanks used at the Dove Marine Laboratory, these tanks were sealed and access to each of them was limited to a manhole located on the top surface of the tank. The discharge valves on the tanks were installed in the base, which made it possible to rinse and completely drain them. The tanks were cleaned at the end of each test to avoid any interference from one test to another. Figure 4-13 shows control and treated tanks at the testing site.

Figure 4-13: Control and treated tanks at the Port of Blyth

For these tests, the tanks were filled with seawater from the North Sea (Port of Blyth) to resemble a location from which ships would take their ballast water. The test organisms were added to the tank and the same sampling procedure was followed as described in test series conducted at Dove Marine Laboratory.

4.2.2.2 Sample Size

The volume and number of samples at each of the sampling points for biological analysis of *A. salina* and *T. suecica* were as follows:

Day 0 samples

Before filter samples:	3 ×1 litre for *T. suecica*
	3 ×20 litre for *A. salina*
After filter samples:	3 ×1 litre for *T. suecica*
	3 ×100 litre for *A. salina*
After UV samples:	3 ×10 litre for *T. suecica*
	3 ×1000 litre for *A. salina*

Day 5 samples

Control tank samples:	3 ×1 litre for *T. suecica*
	3 ×100 litre for *A. salina*
Before UV samples:	3 ×1 litre for *T. suecica*
	3 ×20 litre for *A. salina*
After UV samples:	3 ×10 litre for *T. suecica*
	3 ×1000 litre for *A.salina*

4.2.3 Biological Results

All operational parameters were measured online during the treatment process for each individual test. The delivered UV dose was determined using a calculated dose approach (4.6.2) for which the UV reactor was validated.

4.2.3.1 Results of Tests at Dove Marine Laboratory

The experimental conditions and biological results of all two tests are shown in Table 4-2. The parameters such as flow rate, UVT and UV lamp power in these test series were altered and set prior to the commencement of each test cycle to determine the UV does delivery for each test. All test cycles were conducted under different experimental scenarios in order to generate broader range of data for the modeling purpose.

Table 4-2: Experimental conditions of the UV/filter tests performed Port of Blyth All samples are the mean of three replicates ± standard Deviation. (AF = After Filter, BUV = Before UV, AUV = After UV).

Test Cycle	Flow rate Before UV(m^3/hr)	UVT (%)	UV Lamp Power (%)	Calculated UV Dose (mJ/cm^2)	Sample code	Live *A. salina* in 1 m^3 calculated (*n*±StDev)	Live *T. suecica* in 1 ml calculated (*n*±StDev)
1 Day(0)	38.3	82.9	100*	744.1	Control	25783.3±5268	5238.3±359
					Treated (AF)	27±20.8	3833±984
					Treated (AUV)	15±17.3	124.3±167.7
1 Day(5)	67.5	86.8	100	662.4	Control Tank	17.3±5.1	0±0
					Control (BUV)	0±0	14.7±16.8
					Treated (AUV)	29.7±14.5	0±0
2 Day(0)	66.2	92.4	100	904.3	Control	18400±4529	3714±4529
					Treated (AF)	43±25.2	2052±532
					Treated (AUV)	2±1.7	105.7±123
2 Day(5)	59.2	88.8	100	831.1	Control Tank	0.3±0.5	0±0
					Control (BUV)	0±0	24±20.8
					Treated (AUV)	0.3±0.5	0±0

* in this test two of UV lamps were switched off to lower the UV dose delivery.

The number of live microorganisms (≥50μm) present was significantly different between samples. The micro-filter showed 99.9% and 99.8% removal of *A. salina* individuals in the test cycles 1 and 2 respectively and so it is difficult to draw conclusion on the effectives of UV irradiation due to the low numbers of *A. salina* present after filtration. All the samples collected on day 5 for test cycles 1 and 2 also contained very low numbers of *A.salina* and so no conclusions could be made about the effect of the UV irradiation on the fifth day as well. Figures 4-14 and 4-15 show the number of live *A.salina* individuals present at each sampling point in test cycles 1 and 2.

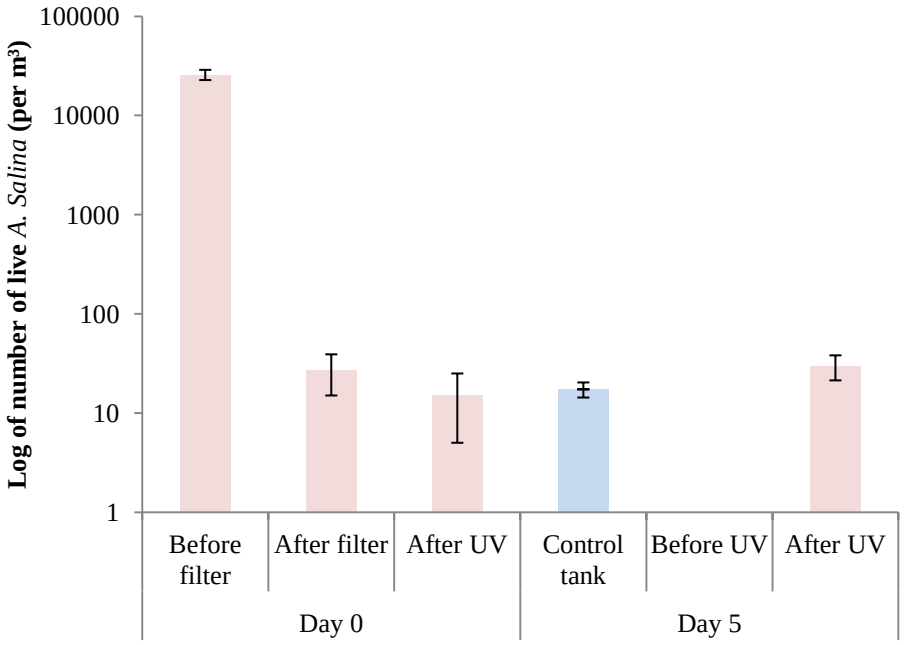

Figure 4-14: The total number of live *A. salina* (≥50µm) in 1000L in test cycle 1 at Dove Marine Laboratory. All data are the average of three replicates ± standard error.

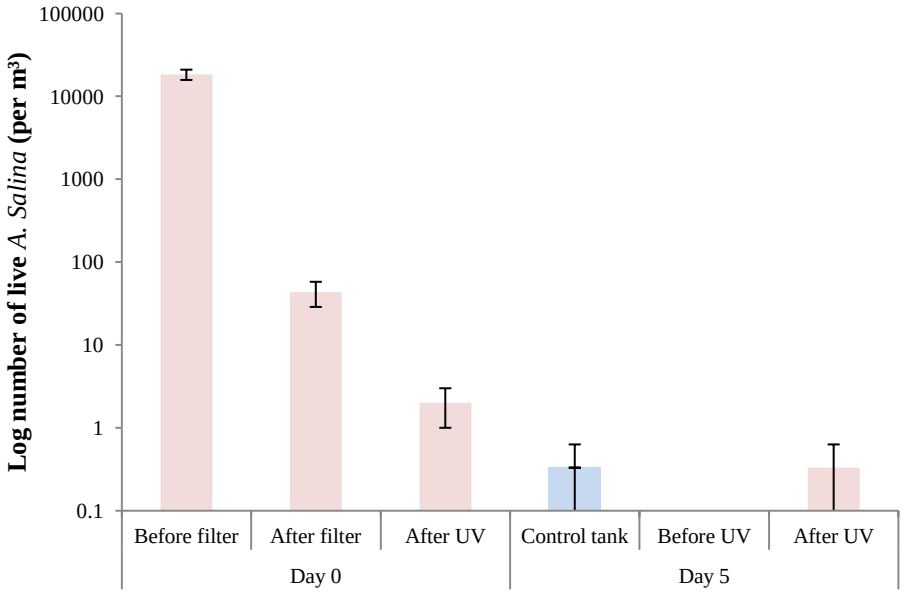

Figure 4-15: The total number of live A. salina (≥50µm) in 1000L in test cycle 3 at Dove Marine Laboratory. All data are the average of three replicates ± standard error.

The number of live microorganisms (≥10<50µm) present was significantly different between samples. Further analysis of the results of all three tests showed that the number of live *T. suecica* between before and after micro-filter samples on day 0 were not significantly different, meaning that there is no significant removal of this microorganism by micro-filter. *T.suecica* cells are actually between 10-20µm in size

which is smaller than the mesh size of the filter, therefore the filter was not expected to remove a large number of these cells. Contrary to micro-filter, UV irradiation has great impact on the mortality of *T.suecica* on the day 0 leaving very low number of live *T.suecica* on the fifth day. Figures 4-16 to 4-17 show the number of live *T.suecica* individuals present at each sampling point in test cycles 1 and 2.

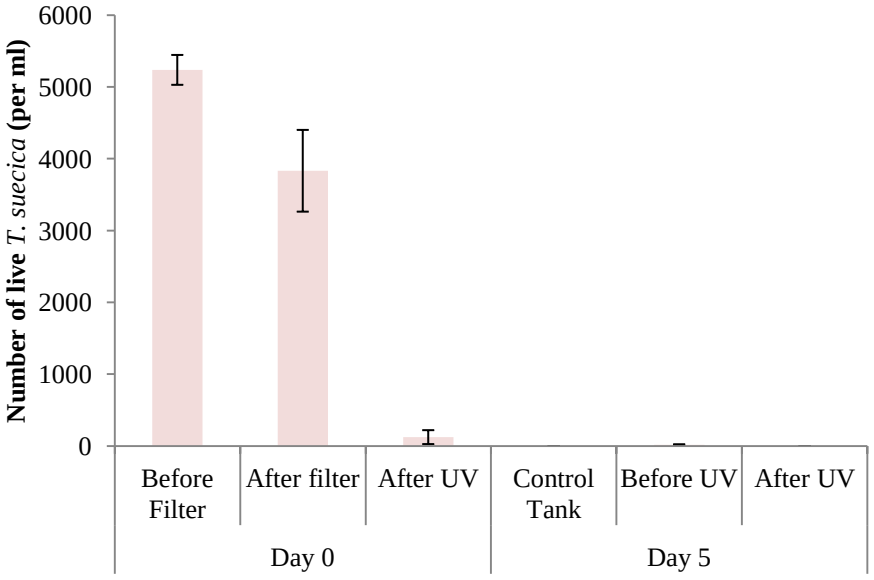

Figure 4-16: The total number of live *T. suecica* (≥10<50µm) in 1ml in test cycle 1 at Dove Marine Laboratory. All data are the average of three replicates ± standard error.

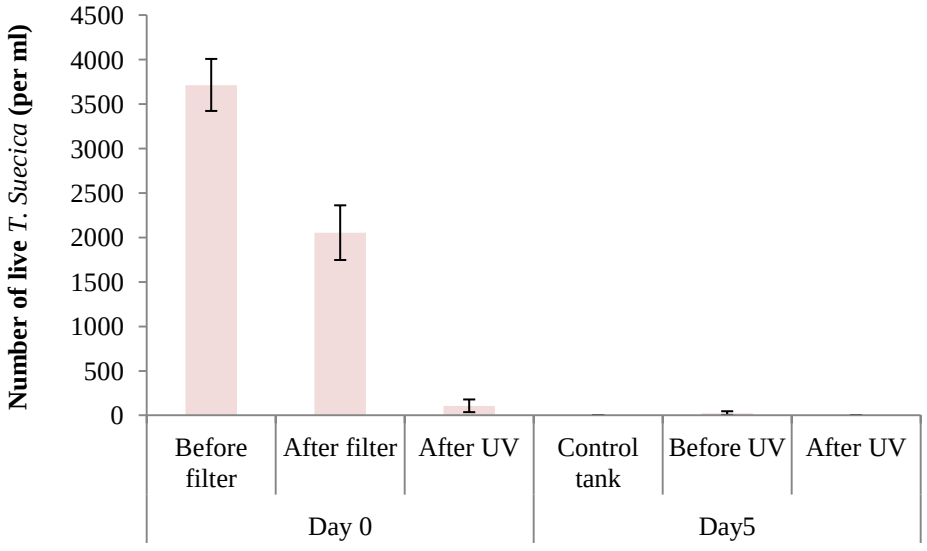

Figure 4-17: The total number of live *T. suecica* (≥10<50µm) in 1ml in test cycle 3 at Dove Marine Laboratory. All data are the average of three replicates ± standard error.

4.2.3.2 Results of Tests at Port of Blyth

The experimental conditions and biological results of both tests carried out at Port of Blyth are shown in Table 4-3. Similar to the tests conducted at Dove Marine Laboratory, parameters such as flow rate, UVT and UV lamp power were altered to determine the UV does delivery for each test. All test cycles were conducted under different experimental scenarios in order to generate broader range of data for the modeling purpose. A prominent difference observed in the test series conducted in the Port of Blyth as compared to the tests at Dove Marine Laboratory is the high number of live microorganisms in the control tank on the fifth day of the test. This can be attributed to the change in the holding tank configuration, which will be discussed later.

Table 4-3: Experimental conditions of the UV/filter tests performed Port of Blyth All samples are the mean of three replicates ± standard Deviation. (AF = After Filter, BUV = Before UV, AUV = After UV).

Test Cycle	Flow rate Before UV(m^3/hr)	UVT (%)	UV Lamp Power (%)	Calculated UV Dose (mJ/cm^2)	Sample code	Live *A. salina* in 1 m^3 calculated (*n*±StDev)	Live *T. suecica* in 1 ml calculated (*n*±StDev)
1 Day(0)	43.5	83.5	50	477.4	Control	32900±14086	1042±219
					Treated (AF)	33.3±5.7	951.3±275
					Treated (AUV)	0.3±0.57	252.3±77
1 Day(5)	64.5	70.5	100	371	Control Tank	2570±929.7	1197±399
					Control (BUV)	16.7±28.8	199.3±157
					Treated (AUV)	0±0	0±0
2 Day(0)	91.8	78.5	100	350	Control	50183±15846	1948±166
					Treated (AF)	16.7±15.3	1167±711
					Treated (AUV)	0.3±0.57	48.7±45.4
2 Day(5)	127	73.3	100	213.9	Control Tank	14136±3823	192±107
					Control (BUV)	16.7±28.8	0±0
					Treated (AUV)	0±0	0±0

The number of live microorganisms (≥50µm) present was significantly different between samples. The micro-filter showed 99.9% removal of *A.salina* individuals in both test cycles and so again it is difficult to make any conclusions about the effectiveness of the UV system due to the low numbers of organisms which were

present after filtration. Figures 4-18 and 4-19 show the number of live *A.salina* individuals present at each sampling point in test cycles 1 and 2.

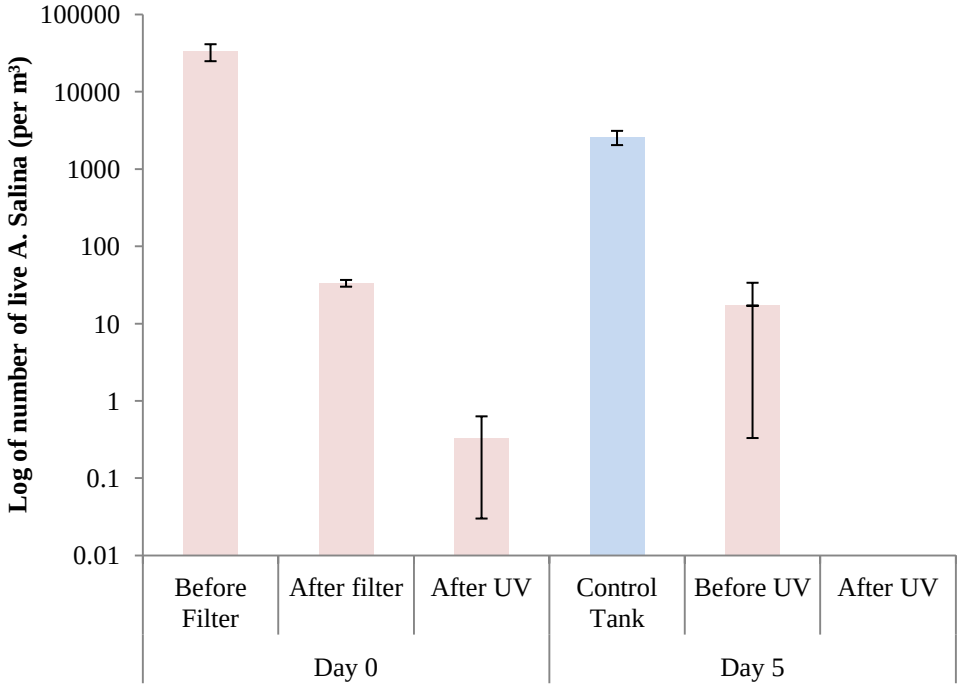

Figure 4-18: The total number of live *A. salina* (≥50µm) in 1000L in test cycle 1 at Port of Blyth. All data are the average of three replicates ± standard error.

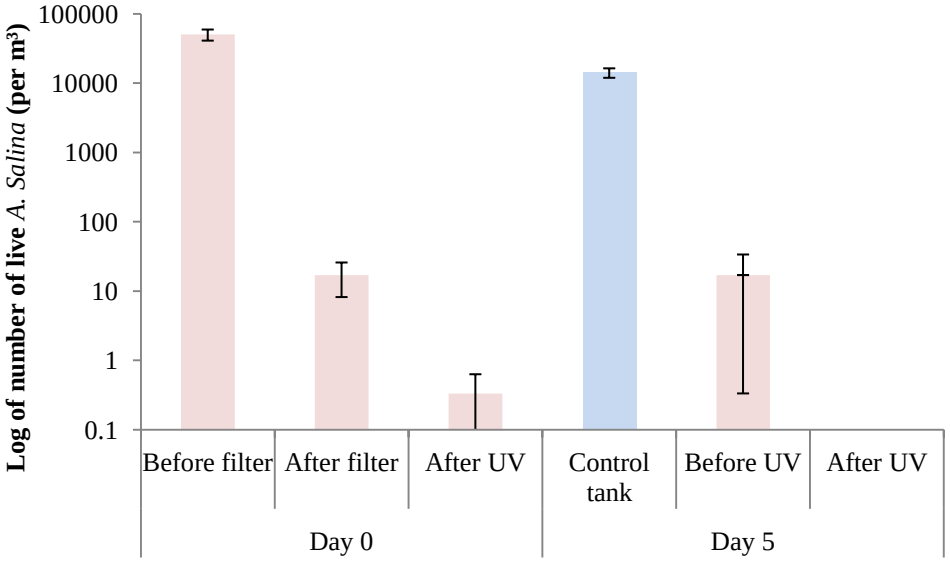

Figure 4-19: The total number of live *A. salina* (≥50µm) in 1000L in test cycle 2 at Port of Blyth. All data are the average of three replicates ± standard error.

The number of live microorganisms (≥10<50µm) present was significantly different between samples. Further analysis of the results of both test cycles showed again that the removal of live *T. suecica* by micro-filter was not considerable and there was no significant difference between before and after micro-filter samples on day 0. However,

the impact of UV irradiation, especially on day 0, was great in both test cycles even though the UV dose delivery was lowered approximately to 350mJcm^{-2}. Figures 4-20 and 4-21 show the number of live *T.suecica* individuals present at each sampling point in test cycles 1 and 2 respectively.

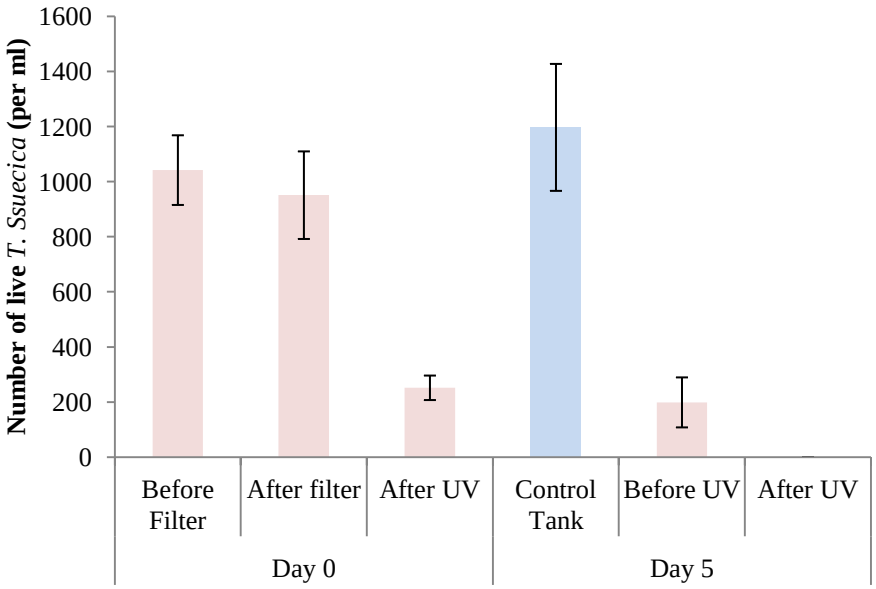

Figure 4-20: The total number of live *T. suecica* (≥10<50µm) in 1mL in test cycle 1 at Port of Blyth. All data are the average of three replicates ± standard error.

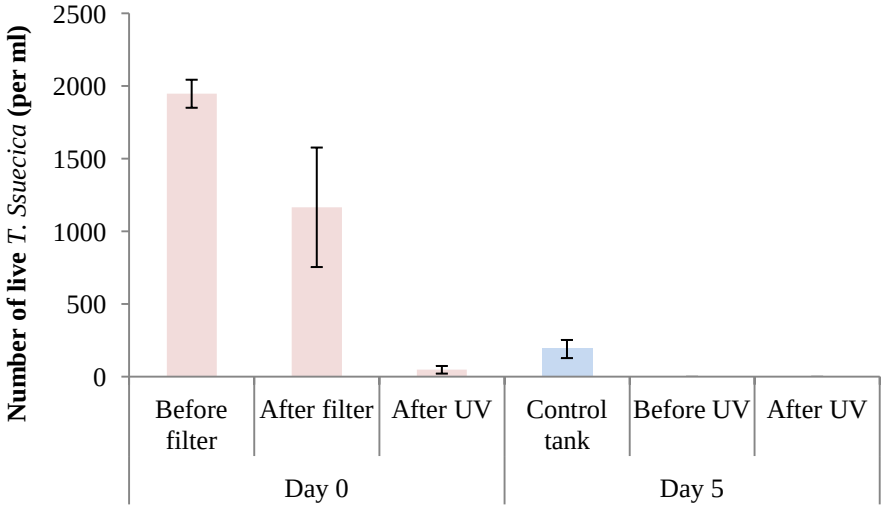

Figure 4-21: The total number of live *T. suecica* (≥10<50µm) in 1mL in test cycle 2 at Port of Blyth. All data are the average of three replicates ± standard error.

4.2.4 Discussion and Comparison of Biological Results

The results obtained from the experiments showed that micro-filter and UV technology would complement each other to remove/inactivate microorganisms of different size category. The combination of micro-filter and UV technology could provide the

discharge standard of the Convention for the size categories of >50 µm and ≥10<50µm after double exposure of UV irradiation and holding period of five days.

The experiment carried out in the case study, when UV technology was used as standalone technology to inactivate microorganisms for the size categories of >50 µm and ≥10<50µm in a similar setup (double UV irradiation and five days holding) the discharge standard was not achieved even at higher UV exposure. It was envisaged that the larger microorganisms shaded smaller ones from irradiation. Gregg et al., (2009) stated that higher doses of UV than bacteria and viruses are required to inactivate microalgae and zooplankton due to their large size and pigmentation. This is one reason why the inclusion of micro-filter is so important when using UV technology. It physically removes zooplankton and larger organic/inorganic particles, which could lead to lower required UV dose.

In other comparison, when two different test series carried out by ballast water treatment setup at different locations, distinctive difference was observed in the biological results of the number of live microorganisms in the control tank. Figures 4-13 to 4-20 clearly demonstrate this and reveal that the number of live microorganisms in the control tank of tests at the Dove Marine Laboratory is less than 10 viable microorganisms per m^3or per ml. In the test series at Port of Blyth, a high number of live microorganisms were present in the control tank after the five day storage period. A low concentration of organisms in the control tank for any test, e.g. tests carried out at Dove Marine Laboratory, suggests that the five days storage in the tank could possibly have detrimental effect on the organisms and resulted in mortality. However, for the tests performed at the Dove Marine Laboratory this may not be the only explanation. The position of the discharge valve, which is situated 30 cm from the base of tank means that the tanks cannot be completely drained and some water remains in the tank after each test. This remaining water, together with sediment at the bottom of tank, could provide a shelter for the organisms in which to settle during the five day storage period. Sediment at the bottom of ballast tanks has been reported to be species rich with organisms forming stable communities (Gollasch et al., 2000).

The biological results obtained from tests will be used to develop inferential measurement for the ballast water treatment setup.

4.3 Inferential Measurement for Ballast Water Treatment System

In all experiments carried out on ballast water treatment setups, off-line measurement procedure including sampling, preparation, enumeration and analysis by expertise were required to assess the performance of treatment system. Off-line laboratory analysis data can now be utilized to develop online inferential measurement for the treatment setup in order to monitor the performance of it. Figure 4-22 presents the structure of inferential measurement and shows the output from each inferential estimator predicts the number of live *A. salina* and *T. suecica* and hence the performance of the treatment system.

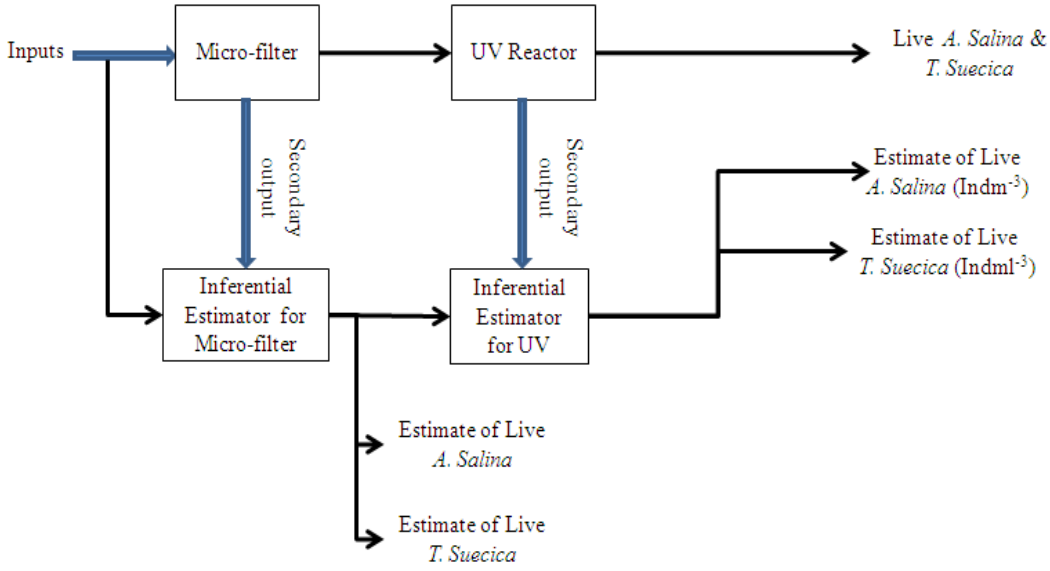

Figure 4-22: Inferential Measurement for ballast water treatment setup

Inferential measurement for the ballast water treatment setup consisted of two inferential estimators (soft sensors) for the involved technologies. Estimator for each treating technology that relates appropriate secondary output variable to the mortality of microorganisms will be developed using off-line data.

4.3.1 Inferential Estimator for Micro-Filter

Seawater flow rate is the operational variable that can influence the separation efficacy of micro-filter. Therefore flow rate can be used to infer the primary output (number of live microorganisms) of the micro-filter with the help of an appropriate model. Figure 4-23 presents the inferential estimator for the micro-filter. The input variables to the model are number of live microorganisms (*A. salina* and *T. suecica*) entering the micro-filter and the flow rate. The model will then estimate the number of live microorganisms exiting the micro-filter. ANN modelling technique is used to develop inferential

estimator for micro-filter.

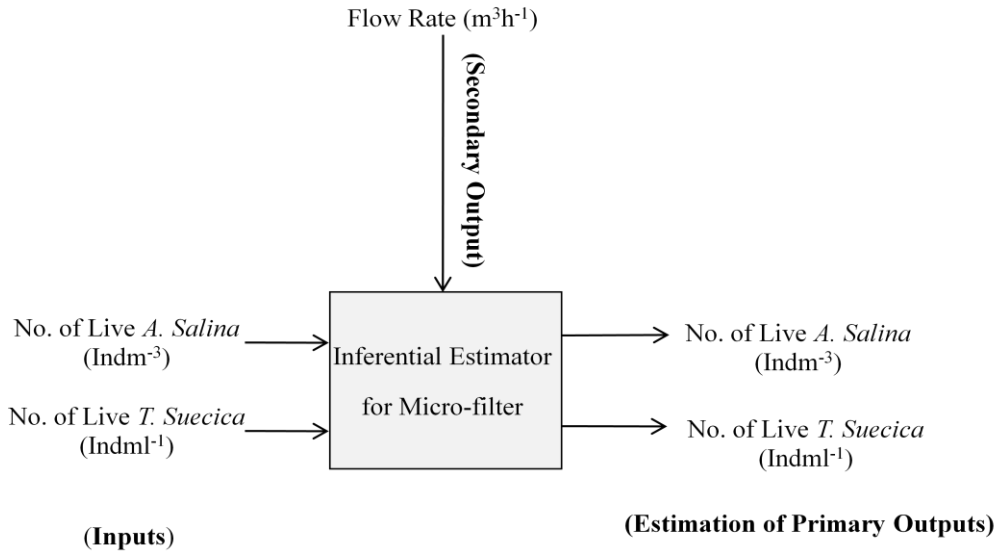

Figure 4-23: Inferential estimator for micro-filter

In order to model the inferential estimator, a feed-forward networks structure consisting three layers (input, hidden and output) with backpropagation as learning rule was used. Sigmoid function was selected as inactivation function for hidden and output layers. The weights during training were updated online (i.e. after each iteration), instead of at the end of the training (batch manner). Input layer contained 3 neurons and the output layer had 2 neurons. Five neurons were considered for the hidden layer and Networks trained with 3000 iterations. After successful training, the linear correlation coefficients of 0.999 and 0.999 for *A. salina* and *T. suecica* were obtained respectively.

The ANN model representing inferential estimator for the micro-filter was programmed in user-friendly interface environment, LabVIEW®, in order to integrate later into the program for the inferential measurement of large scale treatment setup. The results of separating performance of micro-filter revealed that it is much more efficient for larger microorganisms (*A. salina*) than smaller ones (*T. suecica*).

A single experiment was also carried out using micro-filter only. The developed inferential estimator was tested with a dataset obtained from single experiment, which was not used for modeling. The prediction by the model and actual biological results from the all experiments, including single test, are presented in the Table 4-4.

Table 4-4: Comparison of biological result of micro-filter test with ANN model prediction. (AF = After Filter).

Test Cycle	Flow rate before filter (m^3/hr)	Sample code	Biological Results		ANN Model Prediction	
			Live *A. salina* in 1 m^3 calculated (*n*±StDev)	Live *T. suecica* in 1 ml calculated (*n*±StDev)	Live *A. salina* in 1 m^3 calculated (*n*±StDev)	Live *T. suecica* in 1 ml calculated (*n*±StDev)
1 (Dove)	61.7	Control	25783.3±5268	5238.3±359	25783	5238
		Treated (AF)	27±20.8	3833±984	26.9	3798
2 (Dove)	71	Control	18400±4529	3714±4529	18400	3714
		Treated (AF)	43±25.2	2052±532	43.03	2062
1 (Blyth)	47.7	Control	32900±14086	1042±219	32900	1042
		Treated (AF)	33.3±5.7	951.3±275	33.3	945
2 (Blyth)	101	Control	50183±15846	1948±166	50183	1948
		Treated (AF)	16.7±15.3	1167±711	16.9	1143
Single test	86	Control	48650±18162	2039±879	48650	2039
		Treated (AF)	40±10	1212±528	23.2	1092

ANN model predicts very well when tested against datasets used for training. The maximum percentage errors for the training dataset are 1.12% and 2% for the prediction of live *A. salina* per m^3 and *T. suecica* per ml respectively. The prediction of ANN model for single test dataset was good, but not as accurate as training datasets; however the prediction showed similar log reduction for both *A. salina* and *T. suecica.* The accuracy of ANN model can be further improved if more experiment data is used for training.

4.3.2 Inferential Estimator for UV Reactor

Inferential estimator of UV system is the combination of UV dose calculation model and biological model. These two models are developed separately and then combined together to form inferential estimator. Figure 4-24 shows the structure of inferential estimator for UV treatment system of ballast water treatment setup.

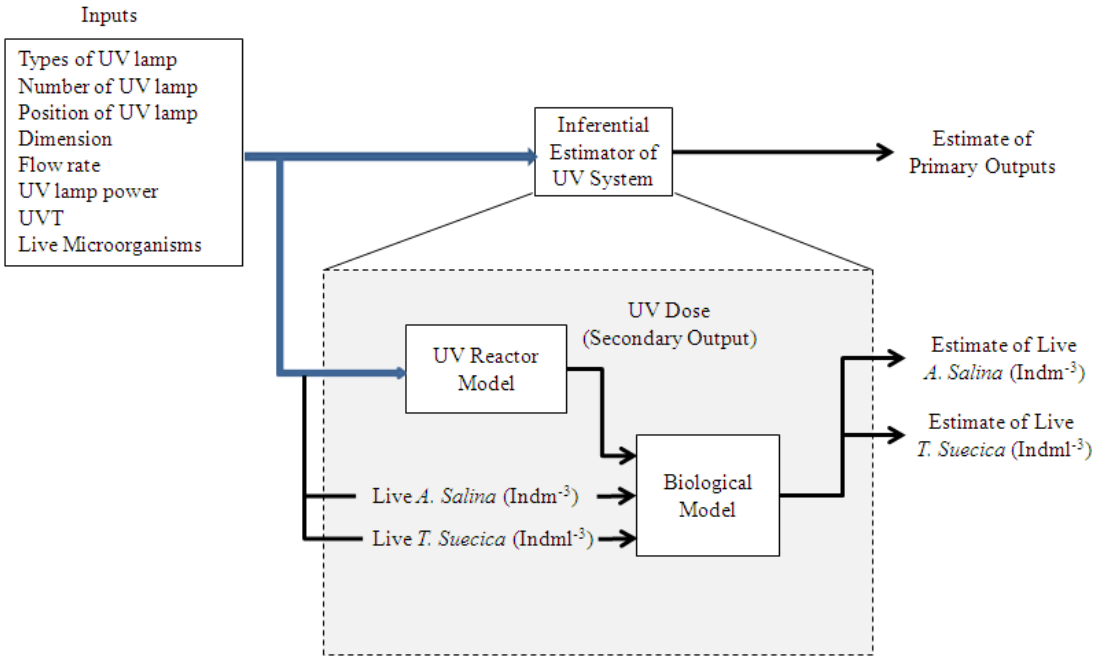

Figure 4-24: Inferential estimator for UV reactor of the ballast water treatment setup

4.3.2.1 UV Dose Calculation

This is simple to calculate how UV radiation enters the reactor and get attenuated by absorption and/or reflection if the UV radiation emits from a point source. However, it is more difficult when UV radiation source is a UV lamp with finite diameter and length. An approximation approach, called Multiple Point Source Summation (MPSS) that divides UV lamp into a series of *n* equally-spaced point sources along the axis of the lamp proves to be very satisfactory (Jacob and Dranoff, 1970; Scheible et al., 1985; Suidan and Severin, 1986). Blatchley (1997) extended MPSS by introducing a Line Source Integration (LSI) in which the MPSS model is taken to the limit of an infinite number of point source and Bolton (2000) adopted MPSS model with spherical emission from a series of point along the axis of the UV lamp for the calculation of UV intensity distribution in an annular reactor. For a cylindrical reactor with no absorption, refraction and reflection, Blatchley (1997) obtained UV intensity at the distance *x* from the UV lamp and a height *H* above the centre of the UV lamp of length *L*, which is given by:

$$I(x,H) = \frac{P(W)}{4\pi Lx}\left[arc\tan\left(\frac{L/2+H}{x}\right) + arc\tan\left(\frac{L/2-H}{x}\right)\right] \quad (4.2)$$

This can also be applied to the UV disinfection reactors consisting of multiple parallel lamps. For these reactors, the calculation of UV intensity in any small volume element

can be obtained by summation of the UV intensity contributions from each adjacent lamp (Bolton, J. R., 2000).

EPA adopted a method for calculating the average UV intensity of the UV reactor by considering 2D plane "Z" at the base of the lamps. In this method, "Z" plane is divided into number of small reception points "I_p" (maximum 4000). The intensity ($mWcm^{-2}$) at each reception point is calculated by summing up the contribution of each lamp to that point. Then the average intensity in the "Z" plane is calculated by dividing the sum of all reception point intensities by the number of points in that plane (USEPA, 1992). This method is used to model UV reactor used in the ballast water treatment setup in order to monitor UV dose delivery.

4.3.2.2 UV Reactor Model

The first step to model UV reactor is to determine the number of points "n" in a 2D plane "Z" at the base of the lamps, taking into account the size of reactor. In this case 3968 points were considered for the plane "Z". The reference point (values for x and y coordinates equal to zero) was considered in such a way that "x" and "y" coordinates of centre points of "Z" plane became 16 and 15.7 respectively. The next step was to locate the centre position of each lamp with respect to the reference point using the following formula.

$$X = \left(\frac{PCD}{2} \times \cos\theta\right) + 16 \qquad (4.3)$$

$$Y = \left(\frac{PCD}{2} \times \sin\theta\right) + 15.7 \qquad (4.4)$$

Where:

PCD = Pitch circle diameter of UV lamps,

θ = Angle of UV lamp position with respect to the horizontal line.

Once the coordinates of each lamp is determined, then the contribution of UV intensity of each lamp, I_p, in terms of Wcm^{-2} at each point "n" was calculated using Equation 4.5. It can be seen that in this Equation, the UV intensity of each lamp at each point depends on the distance from the lamp, UV transmittance and UV lamp power. As UV-C is the

most effective portion of UV light for disinfection, hence the UV-C efficiency of the Lamp has to be taken into account when calculating the UV intensity of each point.

$$I_{pi}=\sum_{j=1}^{m}\left(\frac{UVT^{D_j}}{D_j \times Arc \times 6.28}\right) \times P\ (W)\ \times \eta_{UVC}\ \times \eta_{quartz}\ \times UV\ decline \quad (4.5)$$

$$i = 1,2,3,\dots \& j = 1,2,3,\dots,m$$

Where:

I_{pi} = UV intensity of each lamp at each point in the "Z" plane

UVT = UV Transmittance

P = UV lamp Power

Arc = Disinfection diameter (cm)

D_j = Distance from each UV lamp to the respected point in the "Z" plane (cm), which is calculated by:

$$D_j=\left(\sqrt{(X_j-X_i)^2+(Y_j-Y_i)^2}\right)-R_{quartz} \quad (4.6)$$

Where:

X_j = Horizontal coordinate of UV lamp

X_i = Horizontal coordinate of point in the "Z" plane

Y_j = Vertical coordinate of UV lamp

Y_i = Vertical coordinate of point in the "Z" plane

R_{quartz} = Radius of UV lamp liner (cm)

And finally UV decline in the Equation 4.5 is the percentage drop of UV lamp performance depending on the intended running hours of usage.

To calculate the average intensity, "valid cells" have to be identified and counted. Valid cells are those points (n) in the "Z" plane, where UV intensity is not zero. For instance, depending on the physical dimension of UV reactor, those points within the UV lamps liners do not contribute to the disinfection as seawater cannot pass within the liner. These points are considered as zero intensity points and when taken away from the total number of points, then valid cells (points) will be determined. Example of UV intensity map is shown in Figure 4-25. The black points in the map are indicative of points with zero UV intensity.

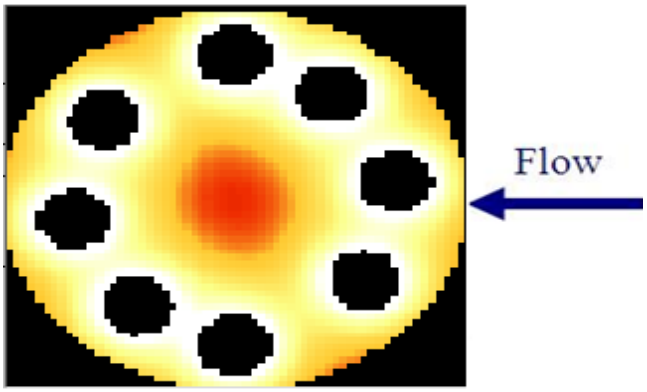

Figure 4-25: Example of intensity map

The map shows the regions of high (darker colour) and low (lighter colour) intensities. The average intensity is the sum of all intensities of reception points, I_p, divided by the total number of valid points (cells). The UV intensity depends on the physical dimension of disinfection chamber of UV reactor, power, position, type and number of UV lamps.

$$I_{Average}\ (Wcm^{-2}) = \frac{\sum_{i=1}^{n} I_{pi}}{Total\ number\ of\ valid\ points} \quad (4.7)$$

The next step is to calculate UV dose at each point and thus the average UV dose by considering retention time for passing particle through the reactor.

$$UV\ dose_{Average}\ (Jcm^{-2}) = I_{Average}\ (Wcm^{-2}) \times t\ (s) \quad (4.8)$$

Contact time, *t*, is calculated by:

$$t\ (s) = \frac{A(m^2) \times Arc(m)}{Q(m^3 s^{-1})} \quad (4.9)$$

Where:

A = Effective area of reactor

Q = Flow rate

The simulation model of UV reactor used in ballast water treatment setup was programmed in LabVIEW® based on the mathematical relationship presented earlier. Figure 4-26 illustrates the mathematical model of the UV reactor that relates the operational parameters to the average UV dose. It indicates that the average UV dose is a function of flow rate of water, UV lamp power and UVT of flowing water.

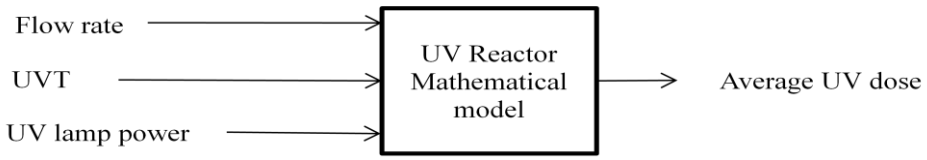

Figure 4-26: Mathematical model for the operation of UV reactor

Figure 4-27 shows the UV dose simulation, which displays the average UV intensity, UV dose and intensity map.

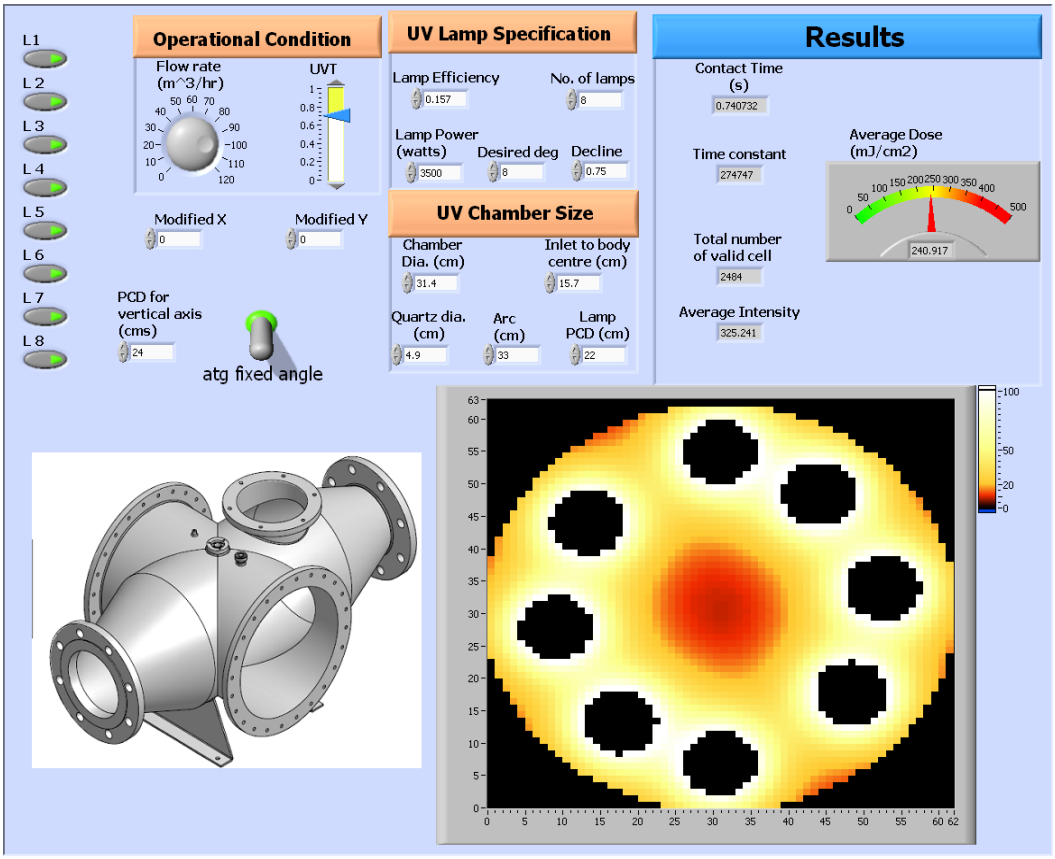

Figure 4-27: UV dose simulation and intensity map for the UV reactor

This simulation model is a soft sensor to measure the secondary output variable as part of the inferential estimator presented in Figure 4.24. The developed soft sensor feeds the calculated secondary output (average UV dose) into the biological model to form inferential estimator for the UV reactor. The soft sensor also provides online monitoring tool for the delivered UV dose throughout the disinfection process.

4.3.2.3 Biological Model for UV Reactor of Large Scale Setup

Experimental data obtained from the various tests conducted at two different locations are used to develop biological model as part of inferential estimator for the UV reactor of ballast water treatment setup. Figure 4-28 shows the biological model for the UV

reactor with corresponding inputs and outputs. This model has three inputs (shown in the Figure 4-27) and estimates the number of live *A. salina* (indm^{-3}) and *T. suecica* (indml^{-1}) exiting UV reactor based on the amount of applied UV dose.

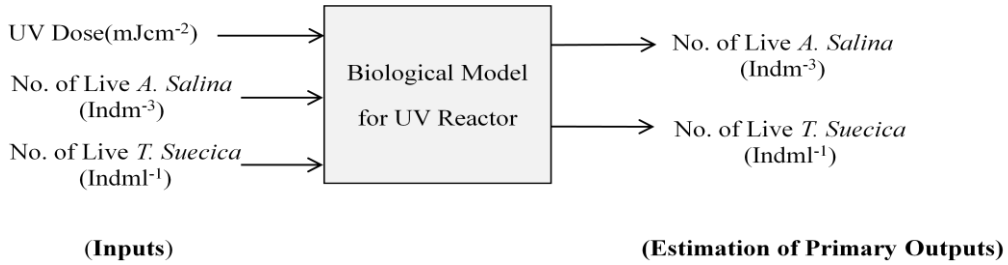

Figure 4-28: Biological model of UV reactor used in treatment setup

In order to model the biological model, a feed-forward networks structure consisting three layers (input, hidden and output) with backpropagation as learning rule was used. Sigmoid function was selected as activation function for hidden and output layers. Updating of weights was done in online manner instead of batch manner. Two disjoint sets of data were arranged from experimental data; one for training and the other for testing. Input layer contained 3 neurons and the output layer had 2 neurons. Five neurons were considered for the hidden layer and training carried out with 5000 iterations. After successful training the linear correlation coefficient of 0.998 and 0.999 were obtained for *A. salina* and *T. suecica* respectively.

The developed biological model for UV reactor was tested with datasets used for training and testing. The prediction by the model and actual biological results from the all experiments, including testing datasets, are presented in the Table 4-5.

Table 4-5: Comparison of biological result of UV reactor from experimental setup with ANN model prediction. (BUV = Before UV and AUV = After UV).

Dataset	UV Dose (mJcm^{-2})	Sample code	Biological Results		ANN Model Prediction	
			Live *A. salina* in 1 m^3 calculated (*n*±StDev)	Live *T. suecica* in 1 ml calculated (*n*±StDev)	Live *A. salina* in 1 m^3 calculated (*n*±StDev)	Live *T. suecica* in 1 ml calculated (*n*±StDev)
1 (training)	744	Control (BUV)	27±20.8	3833±984	27	3833
		Treated (AUV)	15±17.3	124.3±167.7	15	124
2 (training)	904	Control (BUV)	43±25.2	2052±532	43	2052
		Treated (AUV)	2±1.7	105.7±123	2	106
3 (training)	477	Control (BUV)	33.3±5.7	951.3±275	33	951
		Treated (AUV)	0.3±0.57	252.3±77	0	249
4 (training)	371	Control (BUV)	16.7±28.8	199.3±157	17	199
		Treated (AUV)	0±0	0±0	0	4
5 (training)	350	Control (BUV)	16.7±15.3	1167±711	17	1167
		Treated (AUV)	0.3±0.57	48.7±45.4	0	55
6 (training)	214	Control (BUV)	16.7±28.8	0±0	17	0
		Treated (AUV)	0±0	0±0	0	0
7 (testing)	831	Control (BUV)	0±0	24±20.8	0	24
		Treated (AUV)	0.3±0.5	0±0	6	0

The prediction by ANN model when compared to the actual results from experiments shows very good agreement. The maximum percentage error for training datasets is 12.9% for the prediction of *T. suecica* per ml. However the absolute error value for the same dataset is within standard deviation and percentage error for log reduction is only 3% (log reduction of actual result and ANN prediction are calculated as 1.37 and 1.32 respectively). The prediction result of ANN model for the testing dataset when compared to the actual result shows good agreement especially for the prediction of *T. suecica*.

The biological model of UV reactor was programmed in LabVIEW® and a performance map (Figure 4-29) was produced to observe the effect of applied UV dose on the mortality *T. suecica*. The graph clearly shows increase in mortality as UV dose exposure increases. The graph also shows downward trend for the number of microorganisms leaving UV reactor as the number of microorganisms entering reduces.

As explained earlier in the previous chapter this can be due to possibility of UV exposure on free floating microorganisms at further distance from the UV lamp. There is also a slight increase in the number of *T. suecica* leaving the UV reactor as UV dose delivery increases from 200 to 250mJcm^{-2} at the region of high number of microorganisms entering treatment reactor. Number of *T. suecica* leaving the UV reactor for the UV dose less than 250mJcm^{-2} may be considered the same as average UV dose of 250mJcm^{-2} as more experimental are needed to improve the accuracy of this range (between 200 to 250mJcm^{-2}) of UV dose exposure.

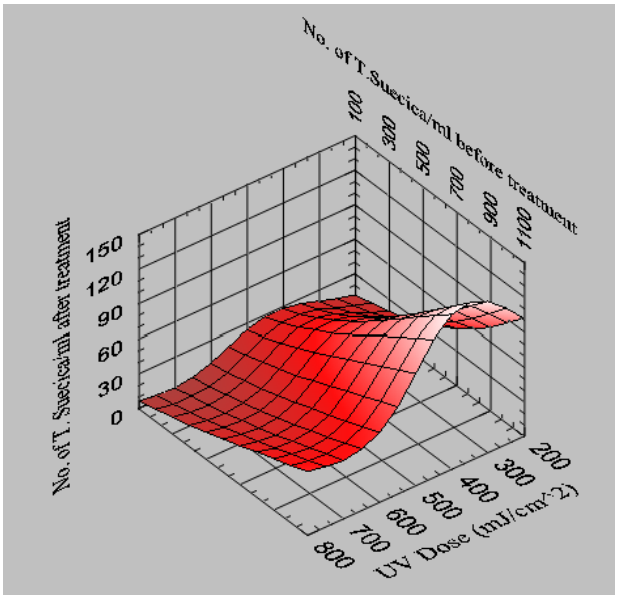

Figure 4-29: Performance of UV reactor used in large scale setup

The performances of two different configured UV reactors used in this thesis compared together by mapping their performances on the same graph. Figure 4-30 presents both performances and it can be clearly observe that the performance of UV reactor with perpendicular lamps to the flow requires less UV irradiation to inactivate the same number of *T. suecica* per ml especially at the lower range of UV dose. However the performance of both shows similar trend at region of high UV dose of around 800mJcm^{-2}. According to the graph, the performances of both reactors are approximately similar when the number of *T. suecica* before treatment is 300 per ml or lower.

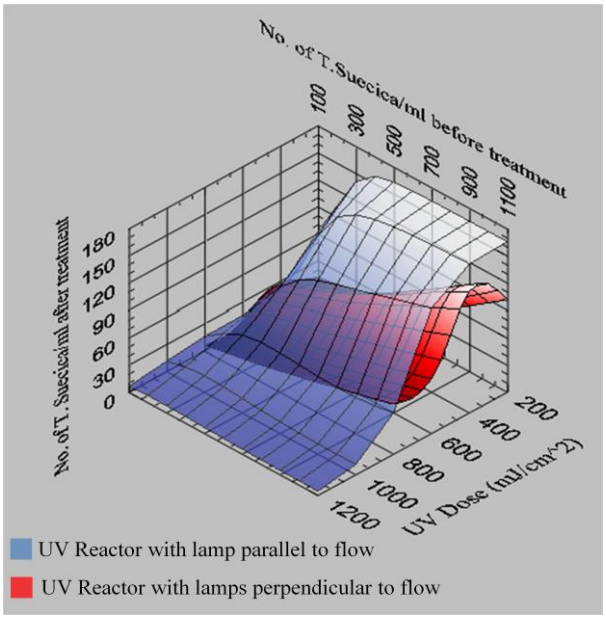

Figure 4-30: Comparison of performance of two UV reactors

Log inactivation rate of these two UV reactors with different configurations shows similar results observed from performance maps. Figure 4-31 shows the inactivation rate of both configurations.

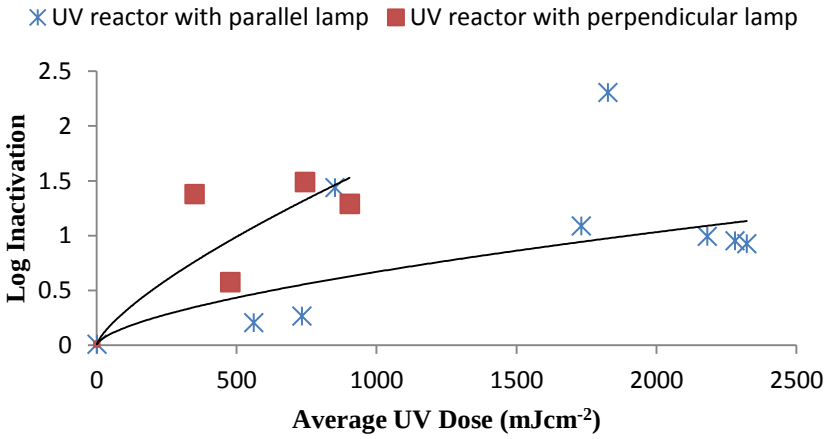

Figure 4-31: Log inactivation rate of *T. suecica* for two different configured UV reactors

Better performance of UV reactor with lamps perpendicular to the flow could be partly attributed to the hydraulic characteristics of the reactor and possibly partly due to the addition of UV absorbent substance (Kaolin) to the seawater in the case study. A better hydraulic characteristic of straight inlet/outlet configuration provides more uniform UV dose distribution. A comparison between the hydraulic characteristics and thus UV dose delivery of two different UV reactor configurations, similar to the ones used in this thesis, has been made using finite volume method by Baas, M.M. (1996) and concluded that velocity distribution is more homogeneous in the straight inlet and outlet

configuration with lamps perpendicular to the flow than the other one. The biological results of these two UV reactors also agree with the conclusion made by Baas, M. M. (1996).

Now in order to develop inferential estimator for UV reactor of large scale setup both UV dose calculation model (Figure 4-26) and ANN model (Figure 4-28) are combined together to form inferential measurement for ballast water treatment setup (Figure 4-32). The biological output from micro-filter is estimated by the ANN model and then fed into inferential estimator of UV reactor to predict the live *T. suecica* (indml^{-1}) and *A. salina* (indm^{-3}) exiting treatment setup. The inferential measurement model (Figure 4-25) shows the possibility of monitoring of performance at each section of treatment setup.

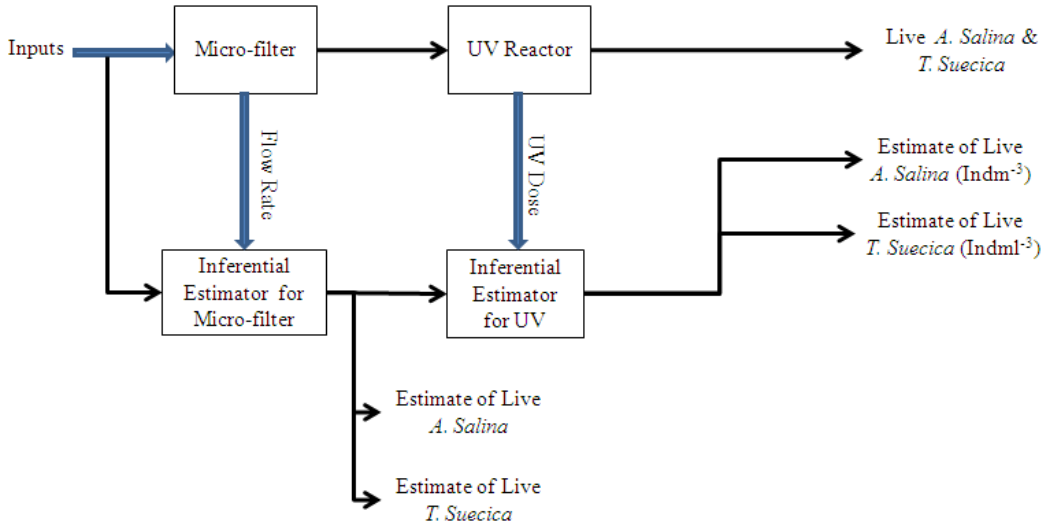

Figure 4-32: Inferential Measurement for ballast water treatment setup

4.3.3 Simulation model for Inferential Measurement

The model-based estimators of the inferential measurement for ballast water treatment setup (Figure 4-32) were programmed in the LabVIEW® environment. The simulation model (Figure 4-33) provides online monitoring of the immediate biological results of each section of the treatment setup under varying conditions.

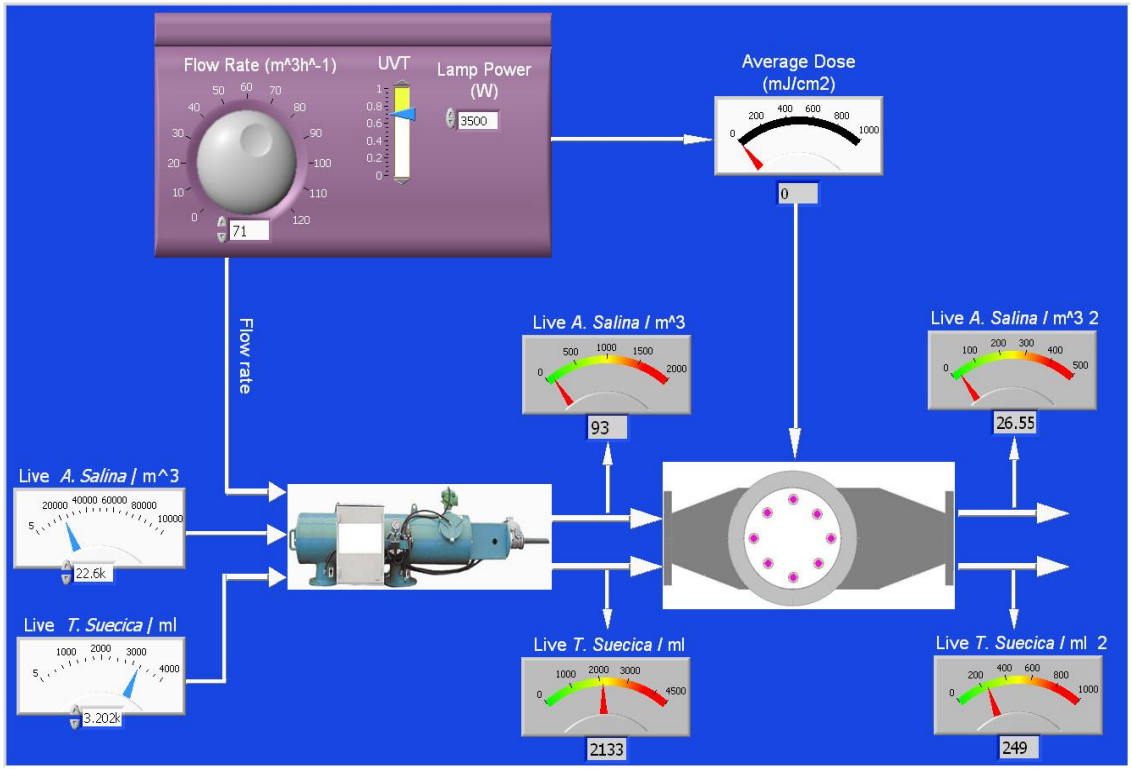

Figure 4-33: Simulation model for the inferential measurement of treatment setup

Currently, there is no measurement equipment that can detect and monitor the living status of microorganisms after treatment without the need for biological expertise. The procedure for detection of number of live microorganisms after treatment includes sampling, fixation, transportation to laboratory and long delay enumeration of live microorganisms of different size category. However, with the inferential measurement methodology developed in this thesis, monitoring for the performance of ballast water treatment setup, whose primary output measurement depends on the laboratory analysis, was provided through the model-based estimators. The simulation model can be a useful decision making tool to help the user understanding the performance of treatment system during operation.

The developed inferential estimator can also be used for up-scaling of treatment system using UV reactor in conjunction with micro-filter. From the performance map of large scale UV reactor, it can be observed that average UV dose of 250 to 300mJcm^{-2} should be delivered during uptake and discharge of ballast to meet the discharge standard of the Convention. Therefore, the UV reactor for higher flow rate can be designed to ensure delivery of average UV dose of 250 to 300mJcm^{-2} at low UVT of seawater for the intended flow rate. In order to up-scale the UV reactor for higher flow rate and achieve the above mentioned range of UV dose delivery, UV light intensity within reactor has to

be increased. The increased UV intensity can be obtained by considering installation of UV lamps with higher power or allocation of more number of UV lamps in the reactor for the same UV reactor configuration.

It is noteworthy to mention that the developed methodology for inferential measurement system is not confined to UV disinfection system and the same line of thinking can be adopted for other ballast water treatment systems, provided influential secondary variables are known. For instance, in the case of heat treatment, the possible secondary output variables are temperature and exposure time. Therefore, an inferential estimator can be developed, based on the results of comprehensive experiments, to predict the effectiveness of heat treatment system. This can then be used to find temperature and exposure time for effective treatment and relate them to the design of the size of heat exchanger and the amount of required heat source for the intended flow rate. In the similar way, an inferential estimator can be developed for a treatment system using chlorination. In this case, the influential secondary output variables are residual free chlorine after mixing and exposure time during retention treated ballast. The estimator should relate these two output variables with the mortality of microorganisms. This in turn can provide effective chlorination dose and time combination for the treatment of ballast water at intended flow rate.

4.4 Conclusion

Measurement of the live microorganisms exiting from a ballast water treatment system depends on laboratory assays with onerous preparations and long delay analysis. Therefore online monitoring of the performance of the treatment system cannot be established due to the long measurement delays limitations. In the previous chapter online measurement could be provided through model-based estimator for UV treatment system. The methodology was extended to develop inferential measurement for the ballast water treatment setup consisting of micro-filter and UV technology.

Series of experiments conducted to assess the effectiveness of developed treatment setup on target microorganisms (*A. salina* and *T. suecica*), as well as generating data for the development of model-based estimators. Followings are conclusions from these experiments:

- Micro-filter with 40 micron screen proved to be highly effective (> 98%) in removing microorganisms greater than 50μm in minimum dimension. The micro-

filter also had some effect on the removal of microorganisms ≤50 - >10μm, but not at the extent to provide significant difference between the samples.

- UV treatment showed to be effective but relying on the UV dose delivered during treatment process and of course number of microorganisms in the influent seawater. Operational parameters (flow rate and UV lamp power), turbidity of seawater in the form of UVT and physical configuration of UV reactor contribute to the calculation of delivered UV dose.
- Straight inlet/outlet configured UV reactor with perpendicular lamps to the flow was used in the ballast water treatment setup. Performances of two UV reactors with different configurations, used in this thesis, were compared on inactivation of *T. suecica*. Further analysis showed that the performance and log inactivation of straight inlet and outlet configuration with UV lamps perpendicular to the flow (UV reactor used in the ballast water treatment setup) was higher than the UV reactor used in the case study. More uniform dose distribution of UV reactor with lamps perpendicular to the flow was considered as main reason for better performance of this UV reactor.
- The number of live microorganisms in a control tank after the period of five days storage without any treatment is an important factor to ensure the credibility of the effectiveness of any treatment system. The number of live microorganisms in the control tank was very low for the tests conducted at Dove Marine Laboratory. One possible reason was the mud at the bottom of the control tank, which could allow microorganisms to shelter. This problem was solved in the second series of tests conducted at Port of Blyth by using different tanks. However, the low number of microorganisms in the control tank did not affect the data obtained from biological results of experiments.

The inferential estimators for micro-filter and UV reactor of the ballast water treatment setup were developed using ANN modelling technique. The estimator of micro-filter could predict the performance of actual micro-filter for the physical separation of *A. salina* and *T. suecica* under varying flow rates. The inferential estimator of UV reactor predicts the number of live microorganisms (*A. salina* and *T. suecica*) exiting real UV reactor depending on UV dose exposure.

The predictions of ANN model for micro-filter against datasets used for training were in very good agreement. The maximum percentage errors for the training dataset calculated to be 1.12% and 2% for the prediction of live *A. salina* per m^3 and *T. suecica*

per ml respectively. The prediction of ANN model for the test dataset was also good, but not as accurate as training datasets. The log reductions for the same dataset according to ANN model prediction were calculated 1.37 and 0.27 for *A. salina* and *T. suecica* respectively, which is approximately similar to the log inactivation of actual results (1.32 and 0.23 for *A. salina* and *T. suecica*). The accuracy of ANN model, however, can be further improved if more experiment data is used for the training of networks.

The predictions by UV reactor model when compared to the actual results from experiments found to be very close and in good agreement. The maximum percentage error for training datasets is 12.9% for the prediction of *T. suecica* per ml. However the absolute error value for the same dataset was within standard deviation and percentage error for calculated log reduction was only 3%. The log reduction of actual result and ANN prediction were calculated as 1.37 and 1.32 respectively. The prediction result of ANN model for the testing dataset was also very close to the actual result from biological experiment. Similarly, more experimental data would improve the prediction ability of ANN models.

Both micro-filter and UV reactor inferential estimators combined together to form software-based inferential measurement to provide online monitoring capability of the treatment setup. The inferential estimators developed in this chapter are based on the offline data for two types of microorganisms. The accuracy and versatility of estimators can be enhanced by incorporating more data for different microorganisms and wider ranges of experimental conditions. This methodology can also be extended to the different treatment technologies and systems where on line measurement of primary output is not possible and requires long measurement delays.

Online measurement for the ballast water treatment setup was made possible through model-based estimation (soft sensing); hence the treatment setup can be operationally optimised and controlled. Operational optimisation and controlling of UV reactor by online inferential measurement will be discussed in the next chapter.

Chapter 5 Optimisation and Inferential Control of Ballast Water Treatment System

Summary

The main goal of this chapter is to develop inferential control for ballast water treatment setup, using ANN model based estimators and optimisation program for the operation of UV reactor. Different optimisation algorithms were compared for accuracy and suitability of online application. An ANN optimisation model was developed to incorporate into inferential control algorithm.

Chapter 5's objectives may be briefly summarised as:

- *To define optimisation and review deterministic and stochastic optimisation methods,*
- *To define and formulate objective function for the operation of UV reactor,*
- *To apply optimisation algorithms including ANN technique and compare the accuracy and execution time of each method,*
- *To develop optimisation program suitable for online application.*
- *To develop decision making tool for the inferential control of ballast water setup.*

5.1 Introduction

The high performance of micro-filter when combined with UV treatment system has shown promising way forward for the treatment of ballast water system. Optimisation and thus controlling of the treatment system ensure less energy consumption for the effective operation. Due to the high and almost constant separating efficacy of micro-filter especially for larger microorganisms (*A. salina*), optimisation and control of treatment setup was concentrated on the operation of UV reactor. Online model-based measurement of live microorganisms after treatment was provided through inferential estimator using secondary measurable variables. The estimator for UV reactor can be further used in a controlling concept to estimate the required UV dose delivery for effective treatment. UV dose delivery is a function of operational variables (flow rate and UV lamp power), UVT and physical configuration of the reactor. Different combinations of operational variables and UVT can provide the same UV dose, which reflect the need for the operational optimisation of UV reactor.

This chapter presents optimisation scheme based on ANN methodology for the

operation of UV reactor and propose an inferential control concept for the ballast water treatment setup.

5.2 Optimisation

5.2.1 Definitions and Formulation

Optimisation is a method to find the best solution (maximum or minimum values) of some objective functions subject to any possible resources and/or other constraints (Bertram, V., 2003). Based on this definition, operational optimization can be defined as finding the optimum operating conditions of a system or a process for a productive, low operating cost (energy consumption) and robust operation. In order to find the optimal operating conditions, the followings have to be defined:

- An objective function, which expresses the quality of the system's operation;
- Decision variables (also called free variables), describing the characteristics of the operation of the system, which are allowed to be changed during the operation of a system; and
- Constraints, which guarantee the practicality of the operation of a system.

Optimization can be mathematically represented by:

$$Optimise \;\; y = f(x_1, x_2, \cdots, x_n)$$

$$Subject\ to \;\; g_j(x_1, x_2, \cdots, x_n) \begin{Bmatrix} \leq \\ = \\ \geq \end{Bmatrix} b_j \quad j = 1, 2, \cdots, m \tag{5.1}$$

Where x_1, x_2... x_n represents the set of decision variables and "y" is the objective function expressed in terms of these variables. The term optimise used for objective function means either maximise or minimise the value of it and depends on the nature of objective function. The Equation 5.1 also indicates how each constraint can be formulated in the form of equalities or inequalities.

To implement the optimisation algorithm in to a system the following steps needs to be considered:

- Define the objective (e.g. minimising the capital/operational costs of maximising the productivity). Sometimes there is more than one objective to achieve for a

particular system, which without assumptions it may not be possible to accommodate them in a single objective function.

- Define the decision or free variables, which are changeable and influence the operational behaviour of the system.
- Define and formulate the objective function, which embraces the defined objective/s.
- Define and formulate the constraints either in the form of equalities or inequalities or both.

To find the best solution for an optimisation problem, an algorithm needs to be taken into account before calculation starts. Figure 5-1 illustrates the procedure in the form of a block diagram.

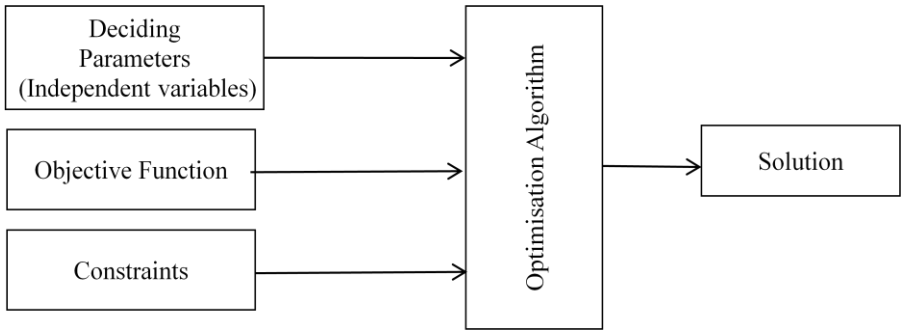

Figure 5-1: Components of optimisation

5.2.2 Optimisation Algorithms

Optimisation problem may be classified in different ways. If the optimisation problem is subjected to equality and/or inequality constraints, then the problem can be classed as "constrained optimisation problem" or otherwise it is classed as "unconstrained optimisation problem". In the other aspect, when the objective function and constraints are linear function then they need to be solved using Linear Programming (Birk, L., 2003). Although, there are very important applications for LP and some special algorithms are available for this type of optimisation problems, but the majority of engineering problems are non-linear and requires non-linear programming (NLP) algorithm to solve them.

Generally, to solve the optimisation problem (Equation 5.1), initial values of free variables should be selected as starting point. Then series of free variables are created by iteration process, which satisfy the criteria defined in the objective function. The

general form of the iteration process is:

$$\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \Delta\mathbf{x}^{(k)}: \quad k = 0, 1, 2, \cdots \tag{5.2}$$

In the above equation k is the iteration number and $\Delta\mathbf{x}^k$ is a change in the current point. This change can be further decomposed into two parts:

$$\Delta\mathbf{x}^k = \alpha_k \mathbf{d}^k \tag{5.3}$$

where $\mathbf{d}^k$ is a desirable direction vector and the parameter α_k represents a step size.

Ideally the most suitable algorithm is the one, which can find the optimal solution with minimum number of iterations. Optimisation algorithm can also be categorised into two basic classes of deterministic and stochastic algorithms. In the deterministic algorithm, the space of viable solutions can be searched analytically by iteration from one set of variables $\mathbf{x}^{(k)}$ to the next set of variables $\mathbf{x}^{(k+1)}$. The moves in this search are predictable and rely on the information of previous steps. Stochastic algorithm incorporates probabilistic elements either in objective function or in the algorithm itself or both. In this approach some viable solutions are traded in for shorter runtime (Birk, L., 2003; Weise, T., 2009).

5.2.2.1 Deterministic Algorithms

Deterministic algorithm is subdivided into gradient and search methods (Birk, L., 2003).

I. Gradient Method

In the gradient methods, the search direction (**d** in Equation 5.3) is based on the gradient of the objective function. The gradient method (the steepest descent method) is the first order derivation of objective function to evaluate the search direction **d** at the current iteration in which the objective function decreases rapidly. Following equation shows how gradient (vector **c**) of the objective function $f(\mathbf{x})$ can be calculated:

$$\mathbf{c}^{(k)} = \mathbf{c}\left(\mathbf{x}^{(k)}\right) = \left[\frac{\delta f\left(\mathbf{x}^{(k)}\right)}{\delta x_i}\right]^T \tag{5.4}$$

Important to know that when the direction of gradient at a point **x** is towards increasing the objective function, the negative gradient vector then represents the direction of

steepest descent for the objective function.

$$\mathbf{d} = -\mathbf{c} \qquad \text{or} \quad d_i = -\, c_i = \frac{\delta f}{\delta x_i}: \; i = 1, 2, \cdots, n \qquad (5.5)$$

Once the search direction is determined, then step size can be analytically determined using methods such as line search. In theory the gradient methods (Steepest descent method) show linear convergence, which means in reality they move in zig-zag direction along narrow valleys of the objective function. This reflects high number of iterations until optimum point is reached. If second order derivation of objective function is possible then, Newton's method (Newton – Raphson) can be used to yield the poor performance of gradient method. This method uses the Hessian of the function and has quadratic rate of convergence, which reduces the number of iterations and reaches to minimum point at faster rate.

This method, however, has very good convergence, but the method can be inefficient due to calculation of $n(n + 1)/2$ second order derivatives to generate the Hessian matrix where n is the number of free variables. This calculation would be tedious or may be impossible when there is high number of free variables in the objective function. Quasi-Newton methods can be used to overcome the drawbacks of Newton method by using first derivative only to approximate for the Hessian matrix or its inverse (Arora, 2004). The gradient method requires the knowledge of the curvature of the objective function in order to calculate its gradient. However, in many cases of practical applications an explicit mathematical model of objective function does not exist and hence approximate derivatives are considered.

II. Search Method

Contrary to gradient methods, search methods do not rely on gradient and sometimes curvature information, but they rely on objective function values. Search methods have been developed widely from the work of Hooke and Jeeves in the 1960s and early 1970s. The advantages of this method stated by Brik (2003) are:

- Perform well even with lack of theoretical knowledge,
- Can be applied to various problems,
- User's input and preparation of problem are low, and
- Straightforward to apply.

Most of the algorithms of this class of optimisation have been based on heuristics with no formal proof of convergence. Lack of convergence proof made search methods less favourable compared to the gradient methods from theoretical point of view. Recently Lewis et al. (2000) discussed why these methods are being used and provided references for convergence proofs for search methods. Brik (2003) subdivided search methods into pattern search, simplex and conjugate directions methods:

a) Pattern Search

The name of pattern search has come from the pattern, which are created during search in the solution space. The most simple and widely used search pattern is the coordinate search algorithm. In this algorithm, search is started by adding/subtracting a step size $\Delta x_i^{(k)}$ to each variable along its corresponding coordinate for a decrease in objective function. Each free variable is replaced by new variable in corresponding coordinate for which the objective value is lower.

In the case of no descent direction is found then the step size is reduced by a factor α ($\alpha \in (0,1)$) and next step size becomes $\Delta x_i^{(k+1)} = \alpha \Delta x_i^{(k)}$. This process is repeated until the step size becomes smaller than threshold. This algorithm requires, in the worst case, 2*n* objective evaluations to complete the search for improvement on iteration. It is simple to implement, but not necessarily the most efficient method (Brik, 2003).

b) Simplex Search

Simplex search method is an algorithm to numerically solve linear programming problems. Contrary to the pattern search method, the simplex method requires no more than *n* + 1 values of the objective function in *n*-dimensional space, $\Re^n$, to determine the descent or ascent direction. That means in simplex method, *n* + 1 design points (simplex) are considered in a *n*-dimensional space (for instance a triangle in a 2-dimensional plane, and a tetrahedron in 3-dimensions space). The idea in this method is to compare the value of the objective function at each vertices of simplex and move the simplex toward the optimum point by iterative process. The worst design point (the highest objective value in case of minimisation) is replaced by a new point (new set of free variables) calculated by the reflection of the worst point through the centroid of all the other design points. If new point has improved the objective value, then a new simplex is formed and search continues until no improvement in the objective value is observed and the best point of final simplex contains the optimal values of free

variables. In some cases when the objective value of the new point is worse than the original point, then the new point will be reflected back and search continues with reflecting "next worst" point in the same way. Ultimately in such case, when there was no improvement in objective values of new reflected points as compared with the best point, then either best point is reflected or it is the candidate for optimum (Lewis et al., 2000; Rao, 1996).

Nelder and Mead (1965) have turned simplex search into an optimisation algorithm commonly used for non-linear problems by introducing additional moves to accelerate the search. Their proposed additional move, expansion and contraction, accelerated the search by deforming the simplex (Rao, 1996).

c) Conjugate Directions Methods

Conjugate directions methods rely on the values of objective function while trying to gather the information of curvature during iterations. Powell (1964) showed that by searching along conjugate directions, minimum can be found for convex quadratic functions with finite number of iterations. In this method the initial set of conjugate directions is equal to the set of coordinate axes (x_1. x_2,..., x_n) and the search is performed in stages. Each stage consisted of $n + 1$ one-dimensional line searches that find the exact minimiser of a convex of a quadratic interpolant computed for each direction. The first n searches are along each single variable direction and the last one is along the direction connecting obtained points from the first n searches. At the end of each stage, one of the first n search directions is replaced by the last search direction. The process is repeated until no further improvement of objective function is obtained (Brik, 2003).

d) Direct Search Method

In the context of optimisation, Volker Bertram (2003) also described Concept Exploration Models (CEMs) as an alternative for solving optimisation problems. The principle of CEMs is to generate a large set of viable solution by systematic varying the free variables. It was stated that the initial starting point, in search algorithm, is vitally important to avoid trapping in the local optima when global one is demanded. However, in CEM the entire viable space is explored through an iterative procedure and hence risk of trapping in local minima due to wrongly selected initial starting point is eliminated. Each viable solution can then be evaluated and compared to find the most promising solution. The drawback of this method as stated by Erikstad (1996) is the computation time to find the optimum solution when free variables are many. There are various

techniques proposed to deal with this problem such as early rejection of some solutions that do not comply with basic requirements (Georgescu et al., 1990), multiple step methods (Nethercote et al., 1981) and reducing the number of free variables (Erikstad, 1994).

III. Branch and Bound

In the Branch and bound methods the idea is to divide the viable region into sub-regions, so called Branch, and compute the upper and lower bounds of the objective function of sub-regions (bound). The procedure in finding the global optimum in this approach is to compute both upper and lower bounds of viable region and if they are different, the region is split into sub-regions. Then the computing process of upper and lower bounds continues for each sub-region until both bounds in a sub-region match. That means a local minimum or in other words a candidate for global optimum has been found. This information can be used to prune the other sub-regions with their lower bounds higher than the candidate. The search continues until all sub-regions are pruned. The success of this method depends on the reliability of computing of upper and lower bounds of sub-regions.

The performance of each algorithm in deterministic approach is dependent on the nature of the problem itself. The main advantage of gradient methods is their mathematically proven concept and convergence, but they need smoothly defined, continuous and twice differentiable objective function. This requirement cannot be generally met in the practical engineering problems. The search algorithms, on the other hand, do not rely on the gradient of objective function, but the value of it. The drawback, however, is they are calculation-intensive and there is a risk of trapping in local optima rather than finding global one. However, in the direct search method (CEM), where entire viable space is explored for optimal point, the risk of trapping into local optima is eliminated, but it is computationally intensive especially when there are many free variables involved. On the other hand Branch and bound method is simple to implement and can guarantee global optima. However, depending on the number of free variables, it is also exhaustive search and computationally expensive even for moderate size problem.

5.2.2.2 Stochastic Algorithms

Stochastic methods are popular and being used today for finding the global optimum of the non-linear problems. In these methods, the knowledge on the mathematical properties of objective function and constraints is not required and they are generally

easier to implement.

I. Genetic Algorithm

Genetic Algorithm that inspired from the principal of genetics and natural selection has been first proposed and applied by Holland (1975). In GA, as Brik (2003) stated, there is no general convergence proof for this optimisation algorithm and it is based on the heuristics. Nonetheless, the algorithms have been successfully applied to many engineering disciplines. Volker Bertram (2003) describes that the general procedure in GA is to create an improved new set of solutions from a population representing multitude of solutions. The fitness of each solution is determined by comparing its value with the rest of solutions. The unfit solutions are filtered out in this approach and new sets of solutions are created by pairing the remaining data using an appropriate cross-over technique. Some marine application examples of using GA are automatic optimisation of the hull form in order to reduce the ship resistance as well as the wake wash by Koushan (2003) and optimisation of ship collision avoidance trajectory considering different navigational conditions in inland waterways by Cheng et al. (2006).

II. Simulated Annealing

Similar to GA, Simulated Annealing (SA) mimics the natural process. It is originally introduced by Kirkpatrick et al. (1983) and Cerny (1982, 1985). The name of this algorithm is derived from simulation of thermal annealing of critically heated solids. The process of reaching to optimum solution in this approach is to select an initial design as well as high initial temperature. New designs points will be generated by moving along each coordinate in turn and evaluate each with initial design. With high temperature, those designs that are much worse than current one are rejected and subsequently by reducing the temperature only those designs with small increase in objective function will be accepted. The acceptance of those designs with higher objective function values makes it different with the deterministic approach and it is probably the main reason why this algorithm can leave local minima and reach the global minimum (Birk, L., 2003).

III. ANN Method

The other optimisation technique, which has been used in the last decade, is based on the Artificial Neural Networks. The ANN based optimisation technique has been introduced by Rao (1996) to minimize the structural weight of the three bar truss. This

technique has also been used in marine application by Danisman et al. (2002) for the optimisation of Catamaran's hull form for minimum wave resistance and Koh et al. (2004) for the hydrodynamic optimisation of high speed hull form.

Similar to deterministic approach, algorithms under stochastic approach have their own strengths and weaknesses.

- The GAs take the advantage of their robustness and the use of genotype rather than phenotype to move in search space makes them more probable to find global optima. The drawbacks of GAs are intensive computation process, which makes them to converge slowly and there is also lack of proof for the optimal solution.
- Simulated Annealing optimisation technique benefits from its ability to optimise functions with random degrees of non-linearity, boundary conditions, stochasticity and constraints. This method can find the global optimum even for the functions with numerous local optima. However, this algorithm is also computational intensive and consequently converges slowly.
- It is worthwhile to mention that the accuracy and performance of the ANN optimisation technique depends on the quality of the data used for training.

5.3 Operational Optimisation of UV Reactor

The important points in any optimisation problems are the interfacing features such as precision and speed. Speed and precision are conflicting objectives, meaning that improving in accuracy of optimisation problem is possible at the expense of more time. In some examples such as design optimisation, time is not so important and problem can be solved *offline* and within days. In contrast, when there are continuous changes in free variables during operation of a system or process, the problem then needs to be solved *online* and in a short period of time. (Weise, T., 2009).

The operational optimisation of UV reactor is an example of *online* optimisation problems. The operation of UV reactor is influenced by some design parameters, which remain constant after design and some operational parameters such as UV lamp power, flow rate and UVT. Different combinations of these three variables can yield the same average UV dose. The optimisation algorithm should find the optimal combinations of operational variables for minimum energy consumption, if there is a change in UVT of seawater.

The defined criteria for the optimum operation of UV reactor are:

- To maintain the biological effectiveness of UV treatment system.
- To maximise the flow rate
- To minimise the power consumption

These criteria should be turned into meaningful objective function and subjected to boundaries or constraints if any. The last two criteria can be formulated in one objective function, which calculates the overall energy consumption of treatment system. However, the first criterion is turned into constraint in order to avoid complexity of multiple objective functions. The other constraints in this particular case were minimum operational power of the UV lamps and the feasible boundaries of flow rates that treatment system can safely operate. These boundaries are considered after consultation with UV reactor manufacturer.

Once criteria are defined, the next step is to identify free variables with which objective functions can be formulated. The operational parameters (UV lamp power and flow rate) and UVT of seawater are considered as free variables. Operational variables are controlled variables, which can be manipulated while UVT is an uncontrolled variable.

Once free variables are identified then objective function and constraints need to be defined and formulated. The main goal for the treatment of ballast water using UV reactor is to minimise the overall power consumption of an effective UV treatment system. In the ballast water treatment system using UV technology, two major power consumers are seawater pump and UV reactor. The power required for the operation of seawater pump is a function of the flow rate and determined by the pump's performance characteristics. Equation 5.6 expresses the relationship between power and flow rate of the seawater pump used in the large scale setup.

$$P_{pump} = -0.0002 \times Q^2 + 0.0828 \times Q + 3.5766 \qquad (5.6)$$

where:

P_{pump} = Seawater pump's power in kW

Q = Flow rate in m^3h^{-1}

UV power can also be determined by the number (n) and power of UV lamps as expressed in the Equation (5.7).

$$P_{reactor}(kW) = P_{UV\ lamp}(kW) \times n_{UV\ lamp} \qquad (5.7)$$

The overall power consumption for ballast water treatment using UV technology can then be calculated using the following formula:

$$P_{Consumption}(kWh) = \left(P_{pump}(kW) + P_{reactor}(kW)\right) \times Time\ (h) \qquad (5.8)$$

Where time of treatment can be calculated using following Equation (5.9)

$$Time(h) = \frac{Ballast\ Capacity(m^3)}{Q(m^3h^{-1})} \qquad (5.9)$$

The objective function is to minimise the Equation (5.8), which satisfies both defined criteria of minimum UV lamp power and maximum flow rate simultaneously. All constraints including effective UV dose delivery are defined in the following and formulated in the form of inequalities.

- Calculated UV dose has to be greater or equal to desired UV dose.
- Flow rate should be equal or less than 110 and equal or greater than 50 m^3h^{-1}.
- UV lamp power varies between 50 to 100%.

The above can be represented by:

Minimise Power Consumption = f (UV lamp power and Flow rate)
Subject to:
Calculated UV Dose ≥ Desired UV Dose
50 ≤ Flow rate ≤ 110
50% ≤ UV lamp power ≤ 100%

Objective function plays an important role for the selection of appropriate optimisation algorithm. In this case, the function is not a straight forward relationship between free variables. For instance, UV lamp power needed for the calculation of objective function value is determined through iterative procedure by running the simulation program of UV reactor (chapter four). This means the required values for the evaluation of objective function should be supplied from the simulation program prior to the application of optimisation algorithm. In such cases, simulation-based optimisation method should be adopted. The simulation-based optimisation method includes a simulation model and optimisation algorithm to search for the best set of variables values that give optimal objective value. Due to the possible variation in the operational parameters of UV reactor or UVT of seawater and need for online application, the algorithm should find optimal combination in a short period of time. Three different algorithms were used for the operational optimisation of UV reactor.

5.3.1 Direct Search Method

In this approach, a large viable set of candidate solutions is first created by systematic

changing of free variables. Each of these solutions will then be evaluated by exploring the entire set to find the optimal operating combinations. In the light of above, a database of possible solutions for the selected UVT (uncontrolled variable) and desired UV dose will be generated by varying the controlled free variables systematically in certain steps. Then each operational combination will be ranked based on the calculated value of the defined objective function. The most promising operating combination that yields minimum overall consumption will be selected and displayed as optimal combination. The block diagram of this approach is shown in the Figure 5-2.

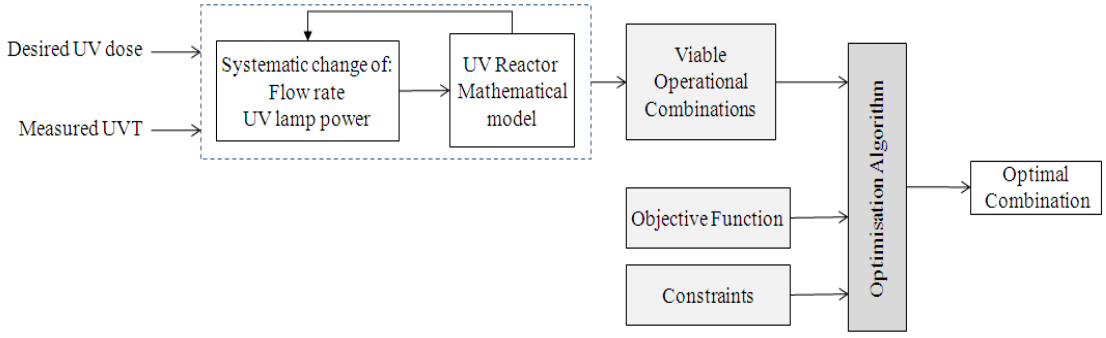

Figure 5-2: Components of operational optimisation of UV reactor

The accuracy of results in this approach depends on the steps in systematic change of parameters. The smaller steps in search algorithm lead towards the more accurate result in the optimal solution, but at the expense of longer search time.

A program in LabVIEW® based on the methodology presented in the Figure 5-2 was developed in order to generate database of viable candidates and search for the best combination within that database. Three UV doses of 200, 300 and 400 $mJcm^{-2}$ and three UVTs of 70, 75 and 80% were arbitrarily selected. The surfaces of the viable solutions (Figures 5-3 to 5-5) for the selected UV doses, in which the program explore and find the optimal solution, were also produced. Each point on the surface carries the data for flow rate and UV lamp power at particular UVT to provide the desired UV dose. The program was then run to find the optimal combination for each set of selected UVTs and UV doses. The running time to find the optimal combination for every chosen UVT and UV dose was noted five minutes approximately.

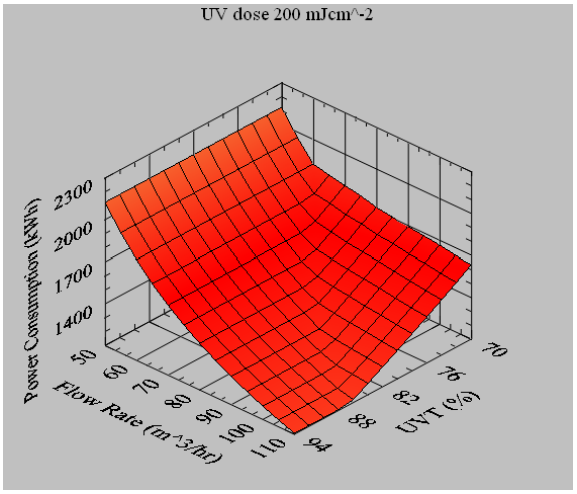

Figure 5-3: Search surface for average UV dose of 200mJcm^{-2}

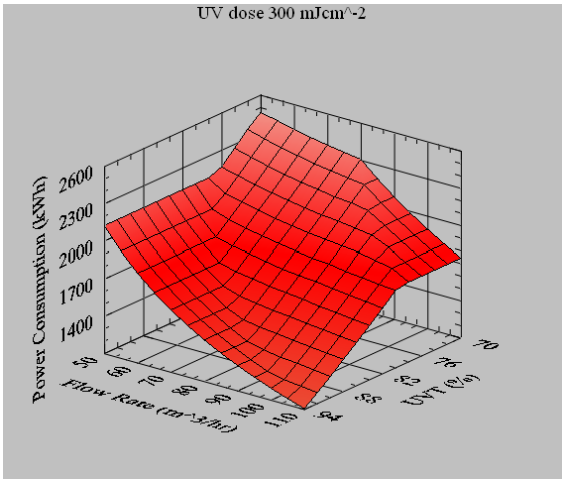

Figure 5-4: Search surface for average UV dose of 300mJcm^{-2}

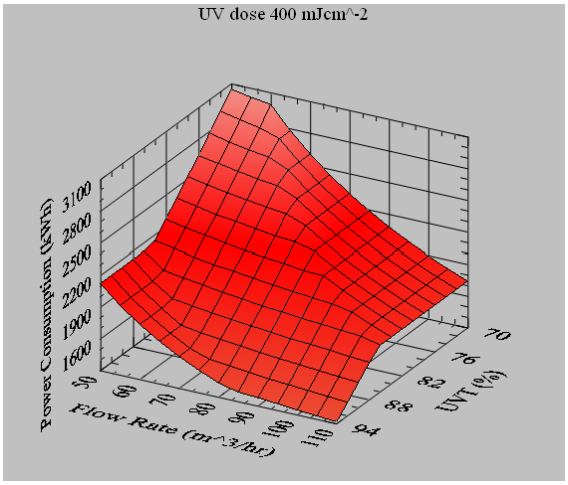

Figure 5-5: Search surface for average UV dose of 400mJcm^{-2}

The results of optimal combinations of operational parameters (flow rates and UV lamp power) and the respected power consumption for the selected UV doses and UVTs are presented in the Table 5-1.

Table 5-1: Optimal combinations for various UVT and UV dose

		Direct search algorithm (CEM)			
Desired UV dose ($mJcm^{-2}$)	UVT (%)	Flow rate (m^3h^{-1})	UV lamp Power (%)	Calculated UV dose ($mJcm^{-2}$)	Power Consumption (kWh)
200	70	110	91.5	200.4	1631.1
	75	109	77.5	200.3	1464.5
	80	109	65	200.2	1303.9
300	70	79	98.5	300.4	2306.9
	75	92	98	300.07	2007.6
	80	110	98.5	300.6	1720.2
400	70	59	99	400.1	2983.5
	75	70	99.5	400.4	2589.5
	80	83	99	400.4	2216.3

The results of optimal combination shows that as UVT improves, the overall power consumption reduces for the same UV dose delivery. It also shows that the flow rate and thus time of treatment improves as UVT increases. Unfortunately, UVT is an uncontrolled variable and may change during treatment process. The optimisation algorithm should, therefore, find new optimal combination for any changes in the UVT. The speed of finding optimal combination for the operation of UV reactor should be faster than frequency of variation in UVT. As the frequency of variation in UVT is unknown then the speed of optimisation should be fast enough to cater for any possible change. Optimisation speed can be improved through lesser number of iterations. Therefore another optimisation algorithm incorporating ANN is used to reduce the computational time.

5.3.2 Direct Search Approach using ANN models

One way of speeding up the process of optimisation is to reduce the number of iterations by increasing the step size, which would be possible but at the expense of accuracy of the result. The other way is to somehow reduce the number of free variables. Artificial Neural Networks has been used in optimisation problems in one way or another in the last decade. Rao (1996) trained the networks by ANN modelling

technique to map the input into the desired output of the four-bar mechanisms and used the ANN model in his optimisation algorithm to minimise the structural weight. Danisman et al. (2002) firstly trained the networks to develop an ANN model representing the Numerical Flow Solver to predict a set of output variables such as wave resistance, Wave elevation, significant wave elevation displacement and WSA of a catamaran. Then they used this model to "blind search" in the all possible values of input space by using a continuous loop to calculate all possible output values. In their optimisation program the corresponding input values, rendering minimum output values, were saved as optimum result. Alternatively they used the ability of ANN modelling technique to inverse model the problem and moved backwards from output to input. Danisman et al. (2002) stated that this procedure of optimisation would guarantee the convergence and it could find the local minimum. In another attempt Koh (2006) optimised the deep-VEE hull form of a large and fast ship using ANN model coupled with the direct search method. Later Ana Mesbahi (2007) used the same technique to optimise the hull form of high speed craft for each of the responses for the different headings.

ANN technique can be implemented here to improve the computational time for the operational optimisation of UV treatment system. With the capability of ANN, the mathematical model of the operation of UV reactor can be reversed in such a way that the average UV dose becomes input to the new model while considering either flow rate or UV lamp power as output. Using ANN, two single output variable models (Figures 5-6 and 5-7) can be developed to predict either flow rate or UV lamp power. Each of these models can then be used in a blind search algorithm through iterative procedure to find the optimal operational combination. In this approach, number of free variables has been reduced to one variable only. Therefore, incorporation of either of ANN models in the blind search algorithm will consequently reduce the computational time and thus improves the speed of optimisation process.

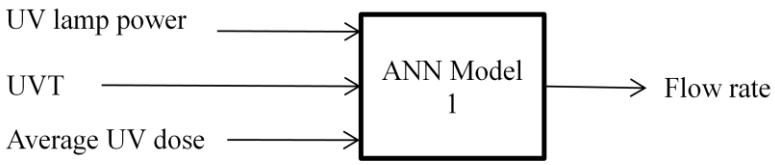

Figure 5-6: ANN model to predict flow rate

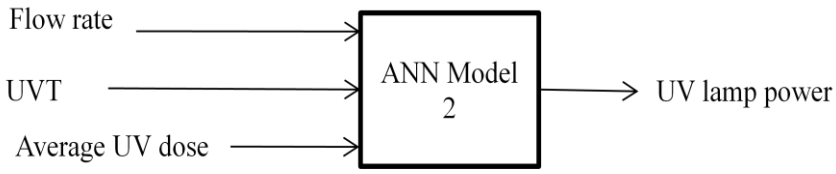

Figure 5-7: ANN model to predict UV lamp power

Comprehensive dataset were generated using mathematical model of UV reactor in order to develop ANN models. Feed-forward multilayer networks with backpropagation algorithm as learning method was used to develop both ANN models. One hidden layer was used for each ANN model and number of neurons in hidden layer of first (Figure 5-6) and second (Figure 5-7) models were 23 and 25 respectively. Sigmoid function was selected as activation function for all the neurons in hidden and output layers of both models.

In total, the number of data arranged for the training of the networks to predict flow rate was 1122 sets. All datasets randomised and 950 of them were used for training while 150 and 22 datasets allocated for cross-validation and testing. Training of networks started with 1000 and 3000 iterations and linear correlation coefficients of 0.997 and 0.999 were obtained respectively. When both trained networks tested against datasets put aside for cross-validation and testing, more accurate predictions were observed from the trained networks with 3000 iterations.

Unlike training of networks for flow rate prediction, all values of the UV lamp power in the database were first normalised to a relevant number from 0.5 to 1 accordingly, before being arranged for networks training. All arranged data were randomised and appropriate input and output variables were tagged. Training of the networks performed with allocation of 1000 datasets for training, 100 for cross-validation and 22 for testing. Training began with 1000, 5000 and 10000 iterations and after successful training linear correlation coefficients of 0.995, 0.997 and 0.9972 were achieved. When these trained networks tested against cross-validation and testing datasets, the networks with 10000 iterations found to be the most accurate one.

In order to validate both ANN models, five different datasets were randomly selected and the predicted results of ANN models were compared with the mathematical model

of UV reactor. The results from these simulation models are presented in the Tables 5-2 and 5-3.

Table 5-2: Prediction and comparison of results of ANN model for flow rate

Input			Output	UV reactor mathematical model	
UVT (%)	UV lamp power (kW)	Desired UV dose (mJ/cm^2)	ANN Predicted flow rate (m^3h^{-1})	Calculated flow rate (m^3/hr)	Calculated UV dose based on ANN prediction ($mJcm^2$)
70	16.8	200	72.3	72.2	199.9
76	20.72	220	99	98	217.7
81	14	310	55.7	56.2	312.9
73	28	335	78.9	78.8	334.8
87	25.2	402	101.2	100.8	400.5

Table 5-3: Prediction and comparison of results of ANN model for UV lamp power

Input			Output	UV reactor mathematical model	
UVT (%)	Flow rate (m^3h^{-1})	Desired UV dose ($mJcm^2$)	ANN Predicted UV lamp power (kW)	Calculated UV lamp power (kW)	Calculated UV dose based on ANN prediction ($mJcm^2$)
70	81	200	18.48	18.88	196.3
76	90	220	18.76	19.04	216.8
81	95	310	23.8	23.68	312
73	60	335	21.28	21.36	334.5
87	110	402	27.16	27.52	397.3

The results of both ANN models prediction show excellent accuracy with 1% error when compared to the results from mathematical model of UV reactor.

Each valid model with the respective search algorithm was then programmed in LabVIEW® to develop optimisation program. Figures 5-8 and 5-9 present the schematic flow chart of the search procedure to find the optimal operational performance of UV treatment system under defined conditions. Each ANN model will produce the predicted value based on the systematic changes of relevant independent variable to calculate the objective value. Each viable combination of operational parameters will be ranked based on the calculated objective value and the most promising one will be saved and

presented as the optimal combination. The number of iterations, in this method, is limited to one independent variable only.

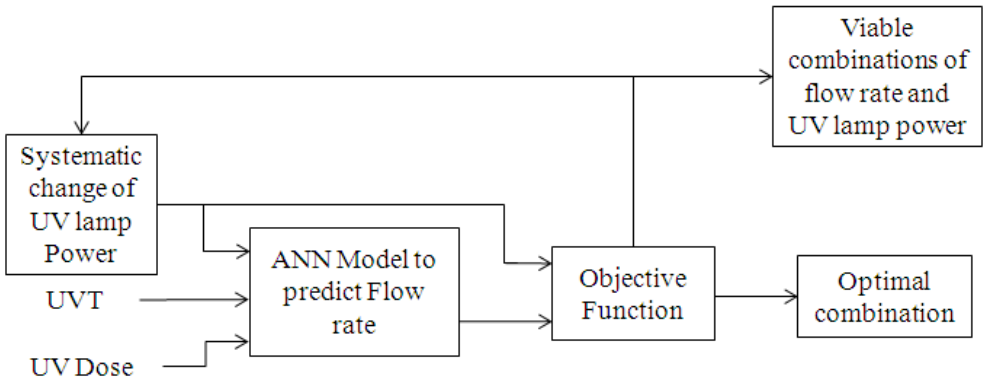

Figure 5-8: Optimisation flow chart using ANN model to predict flow rate

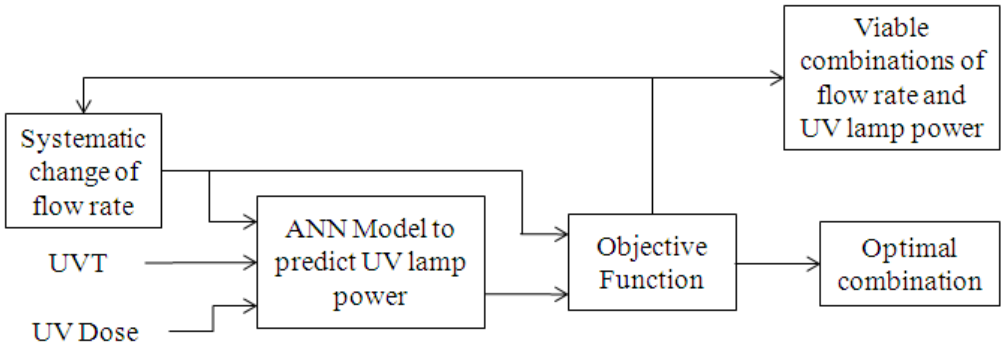

Figure 5-9: Optimisation flow chart using ANN model to predict UV lamp power

The possibility of running both search algorithms simultaneously in the program will also allow comparison of the optimal results without increasing the number of iterations. The results from each search can now be compared and the most promising objective value will be considered and presented as the optimal combination. Figure 5-10 presents the flow chart of optimisation procedure using both ANN models in parallel.

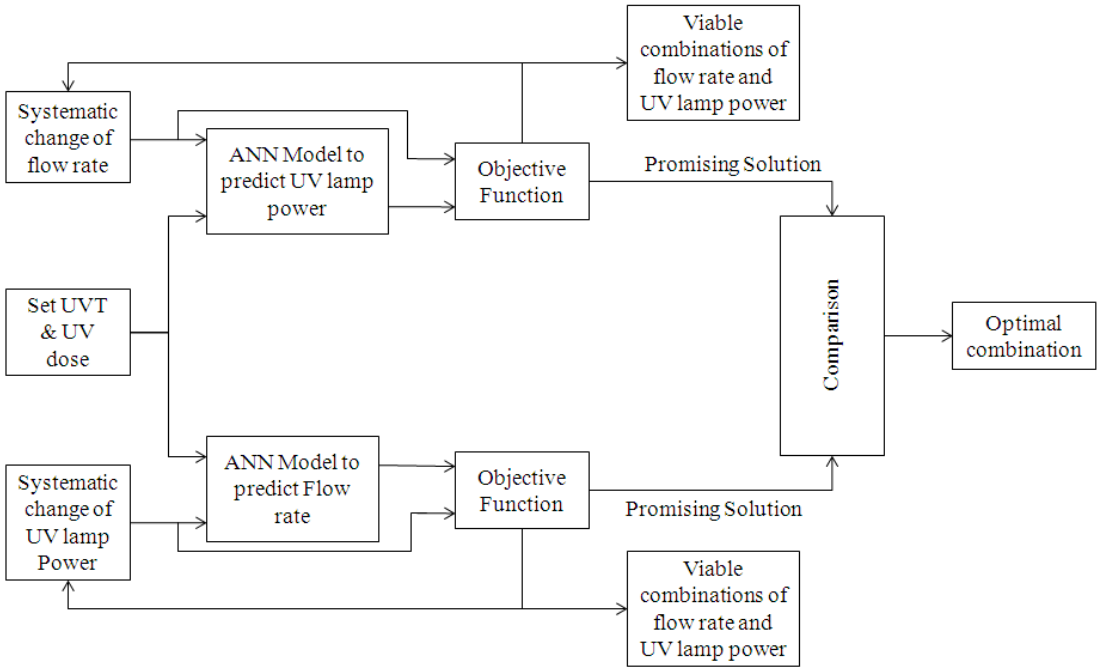

Figure 5-10: Schematic flow chart of optimisation procedure using two ANN models

Similar 9 datasets, used in the previous optimisation algorithm, were applied in the program and results of optimal combinations for each dataset from each direct search are presented in the Table 5-4. Comparing the results shows that direct search using "ANN model 1", in some of the cases, could find the combinations with higher flow rates that result in lower overall power consumption. Although in some cases the optimal results found by each search might not be the same, but parallel running of both searches simultaneously would allow the program to select the better of two solutions. That means both optimisation processes in the program complement each other in finding the optimal solution without increasing the number of iterations. The results from the optimisation program using ANN models show similar or very close results when compared to the previous algorithm (5.3.1). The computational time to find the optimal solution by the program is noted 15 seconds approximately, which is much lower than the other method. This optimisation technique, due to its fast execution time, can be used for online application of UV treatment system.

Table 5-4: Optimal combination results by direct search using ANN models

Input Variables		Direct search approach using ANN model 1			Direct search approach using ANN model 2			Direct search approach using both ANN models in parallel		
Desired UV dose ($mJcm^{-2}$)	UV Transmittance (%)	Flow rate (m^3h^{-1})	UV lamp Power (%)	Power Consumption (kWh)	Flow rate (m^3h^{-1})	UV lamp Power (%)	Power Consumption (kWh)	Flow rate (m^3h^{-1})	UV lamp Power (%)	Power Consumption (kWh)
200	70	110	91.5	1631.1	110	92	1637.4	110	91.5	1631.1
	75	107	76	1468.5	107	76	1468.5	107	76	1468.5
	80	109	65	1303.9	94	56	1344.3	109	65	1303.9
300	70	80	100	2307.5	77	96	2314.7	80	100	2307.5
	75	93	99.5	2011.1	88	94	2024.6	93	99.5	2011.1
	80	105	94	1732.6	106	95	1731.4	106	95	1731.4
400	70	59	98	2983.5	57	95	3004	59	98	2983.5
	75	63	89.5	2623.7	64	91	2620	64	91	2620
	80	82	98.5	2231.8	73	87	2254.4	82	98.5	2231.8

5.3.3 Optimisation using Multi-output variables ANN Model

For this approach, ANN modelling technique was again used to develop the multi-output variable model. The input variables in this model were the desired UV dose and UVT while flow rate and UV lamp power were assigned as output variables (Figure 5-11).

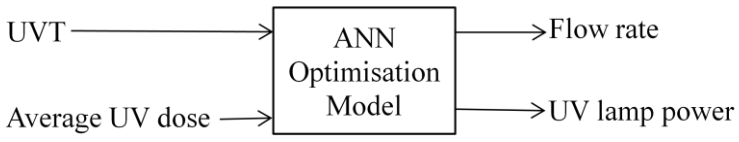

Figure 5-11: Multi-variable ANN model for the operational optimisation of UV reactor

In this way ANN model predicts the optimal combination without the need to iterate and search for it. Similarly an appropriate database has to be generated for training of the networks. In this light, the database for the training was compiled by generating data from running the optimisation program mentioned in the 5.3.1 section. All datasets in the generated database were optimal operational combination of UV lamp power and flow rate for the selected average UV dose and UVT. The generated database is used to train the networks and develop multi-variable optimisation model. Figure 5-12 illustrates the process of development of ANN optimisation model.

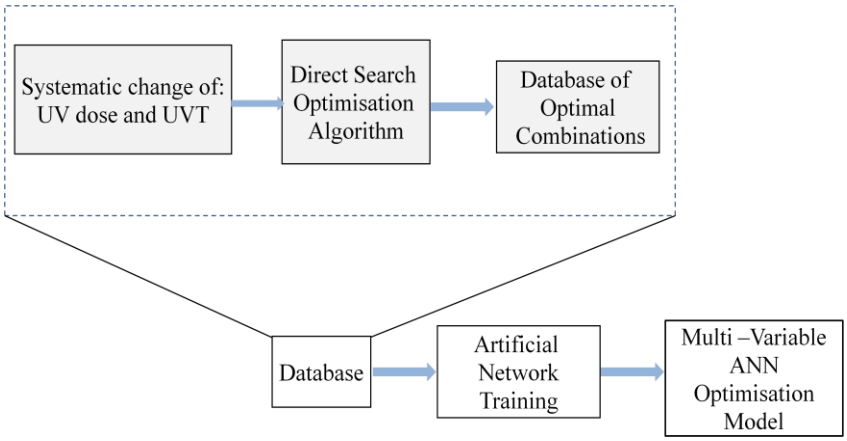

Figure 5-12: Process of ANN optimisation model

Feed-forward multilayer networks with backpropagation algorithm as learning method was used to develop this model. Four networks were structured with four different numbers of neurons (from 9 to 15) in their hidden layers. For each network three training runs were performed initially with 3000 iterations in each run and then number of iteration increased to 10000 and the best training results were saved. The best trained one was tested with cross-validation datasets and linear correlation coefficients of 0.998 for flow rate and o.999 for the UV lamp power were obtained. The simulation model of best trained networks was developed in LabVIEW® to predict the optimised operational values for flow rate and UV lamp power. The same nine datasets presented in the table 5-1 and 5-4 applied into the ANN optimisation model for comparison with the other algorithms and the results of all three algorithms are presented in the Table 5-5.

Table 5-5: Comparison of optimised results of different optimisation approach

Input Variables		Direct search approach			Direct search approach using ANN models			Mullti-variables ANN model		
Desired UV dose ($mJcm^{-2}$)	UV Transmittance (%)	Flow rate (m^3h^{-1})	UV lamp Power (%)	Power Consumption (kWh)	Flow rate (m^3h^{-1})	UV lamp Power (%)	Power Consumption (kWh)	Flow rate (m^3h^{-1})	UV lamp Power (%)	Power Consumption (kWh)
200	70	110	92	1631.1	110	92	1637.4	108	93	1677
	75	109	77.5	1464.5	107	76	1468.5	108	76	1456.7
	80	109	65	1303.9	109	65	1303.9	109	65	1303.9
300	70	79	98.5	2306.9	80	100	2301.7	80	100	2307.5
	75	92	98	2007.6	93	99.2	2007.5	89	98	2067.5
	80	110	98.5	1720.2	106	95	1731.4	110	97	1701.1
400	70	59	99	2983.5	59	98	2983.5	59	100	3030.9
	75	70	99.5	2589.5	70	100	2587	69	98	2592.5
	80	83	99	2216.3	81	97	2222	82	99	2240.3

The results in the Table reveals that prediction of optimal combinations for the selected input conditions by multi-variables ANN optimisation model are very close to that of found by direct search method (CEM). The values, which are presented in red, indicate lower power consumption when compared to direct search method. The predicted operational parameters in these cases, however, yield marginally lower average UV dose (the percentage errors in providing average UV dose are 0.9 and 1.3% respectively). The search for the optimal operating combination in the viable surface is eliminated in this method and thus computational time becomes very short. The ANN optimisation model becomes fast responsive to the change of input conditions, which makes it suitable for online application. However, integration of multi-variables ANN model for optimal operation of UV reactor requires provision for modulating both UV lamp power and flow rate. For some UV treatment systems modulating of UV lamp power is not possible during operation and it is set prior to the operation. Referring to

the Equation 5.8, if UV lamp power is considered constant, then the overall power consumption will be minimised as flow rate increases. The UV reactor used in the ballast water treatment setup did not have the provision of gradual changing of the UV lamp power during operation, but the flow rate in the treatment setup could be varied by the operation of discharge valve. In this case, developed "single variable ANN model 1" can be used as optimisation model. The model predicts the highest possible treatment flow rate to maintain the desired UV dose under varying conditions of UVT or UV lamp power.

In the control scheme for UV treatment system, effective treatment can be manipulated by the flow rate of seawater passing through the UV reactor. Therefore, the developed single variable ANN model can be incorporated as part of inferential control scheme to provide direct signal for the setting of control flow valve. Next section will present the proposed inferential control scheme for the ballast water treatment setup using estimators and single variable optimisation model.

5.4 Inferential Control Concept

The control system configuration, as stated earlier, consists of a sensor, a process under control, a controller and an actuator. A sensor, which can measure the primary output (quality) variables online, is the key element to monitor the performance of the system and can be used to control the output quality of the system. The monitoring and control of many treatment systems (e.g. ballast water treatment system) is difficult because reliable measurement of output variable depends on the long delay analysis. Previous chapter addressed how primary output of ballast water treatment setup can be inferred by the measurement of secondary output variable and with the help of a mathematical model. In the inferential control concept, the estimated primary output can be used to improve and control the operation of the system. There are two ways to use inferential estimator in a control scheme (Tham, M. T., 2000):

- Using the inferred value of the primary output variables as a feedback signal to an external controller. In this case the inferential estimator acts as a "soft sensor" as shown in the Figure 5-13.

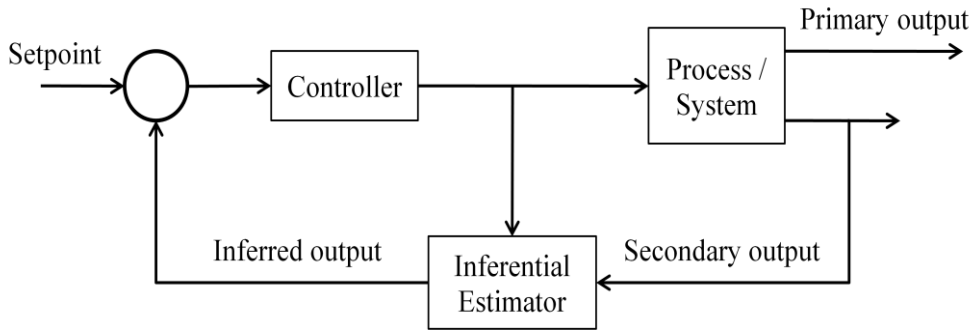

Figure 5-13: General structure for inferential control scheme

- Using inferential estimator to design an appropriate controller and combine them together to develop integrated inferential measurement and control.

The estimators used in this thesis are developed using ANN modelling techniques. The information characteristics of ANN such as nonlinearity, parallelism and fault tolerance have made ANN suitable for dynamic modelling, plant optimisation, forecasting, fault diagnostics and process control. In the area of process control, ANNs have been applied as dynamic model and/or the controller through adaptive control or model-based control (Fernandez de Canete et al., 2008). In the former (adaptive control), ANN is used to update/adjust the controller parameters by monitoring the online data of a process. In the model-based control, ANN model estimates the process variables that have to be implemented to the process for optimal performance.

5.4.1 Adaptive Control

In adaptive control the parameters of controller are adjusted in real time as the controlled parameters vary or are initially uncertain. By this control method a desired level of performance of a control system can be obtained. Figure 5-14 shows the schematic of an adaptive control.

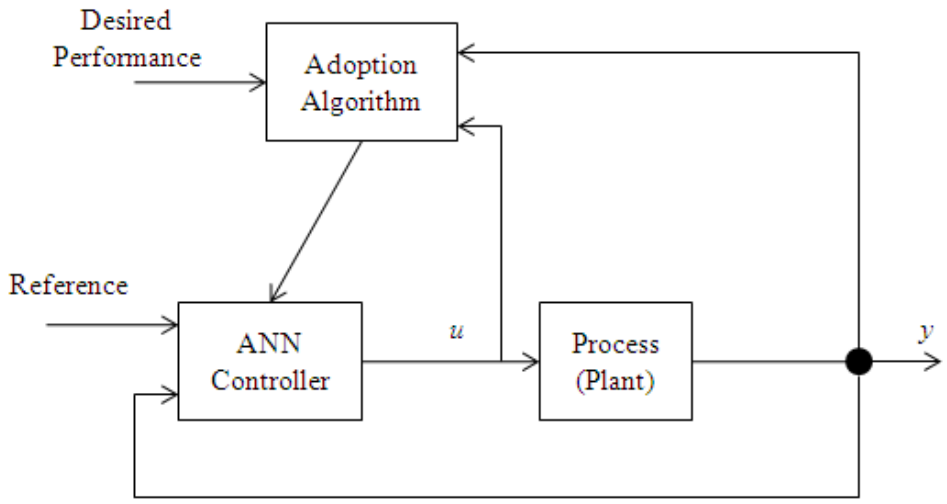

Figure 5-14: General structure of an adaptive control system

In this control structure, the weights and bias of ANN controller is modified in real time by an adoption algorithm. It is done by conducting additional training cycles until the performance criteria are met. One important issue in this control system is the difference in time scales between the dynamic response of the process/plant and the adoption process of ANN controller upon receiving changes in the process variables. The problem occurs when the adoption period is long enough so that the deviation of process/plant from desired set point is significant. In such cases a back-up controller to keep the system close to the set point in needed until adoption is completed. Some applications of adaptive ANN controller are: Lu and Markward (1997) developed an integrated neural system, comprising two multilayered feedforward neural networks and a neural adaptive controller, for the control of coating weight of modern hot dip coating line in a steel mill; Mesbahi (2000) successfully developed Neuro-Governor in controlling the speed of the high speed diesel engine at two modes of identified and unidentified load signal; Diaz et al., (2001) investigated the application of adaptive ANNs to control the exit temperature of a compact heat exchanger. They finally implemented the ANN controller for an air-water compact heat exchanger and showed that the neurocontroller was able to adapt to new conditions for disturbances in the air and water flow rates; Zeynelgil et al., (2002) applied ANN controller to automatic generation control of four-area interconnected power system. In their study, they used back propagation through time algorithm as ANN learning rule.

5.4.2 Model-Based Control

In this control structure, the ANN model of the plant (forward model) and the inverse ANN model are two important components. Two approaches that use ANN in the

model-based control strategy are the direct inverse control and the internal-model control techniques. In the former, the inverse model acts as controller in cascade with the system without using any feedback. In this control scheme, the ANN model supply the control parameters at its output upon receiving desired target as input. The internal-model control technique (Figure 5-15), however, has the forward ANN model in parallel with the process and the error between ANN prediction and the process actual output is taken away from desired output before being fed into the inverse model. The other inputs to the inverse ANN model are the previous process inputs and outputs while the output of the inverse ANN model is the future actuator signal (Varshney, K. and Panigrahi, P.K., 2004; Hussain, M. A., 1999).

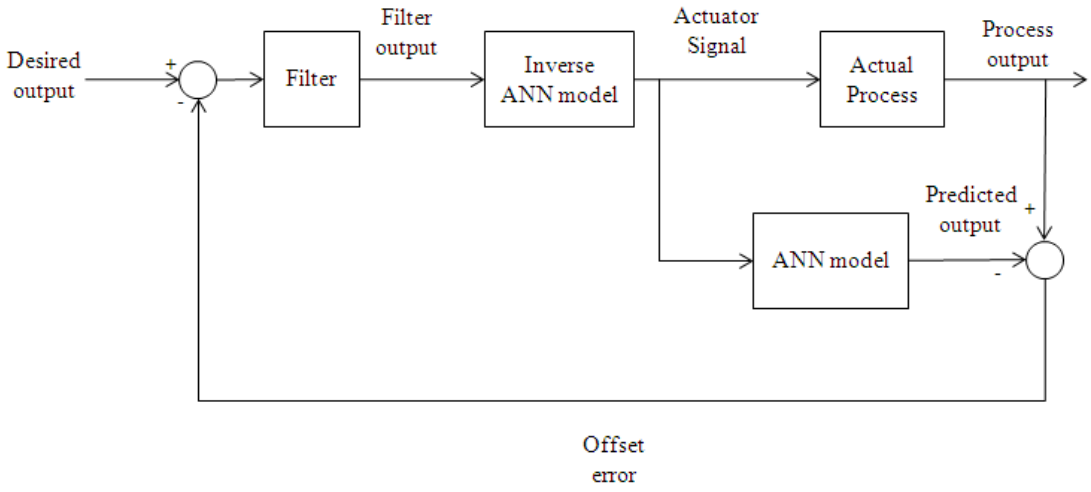

Figure 5-15: The general ANN control structure (Varshney, K. and Panigrahi, P.K., 2004)

In this control structure, the ANN model is trained to learn the dynamics of the process and the required data for training is provided through either experiments or in some cases by running the valid, but computational intensive, mathematical model of the process. The inverse ANN model can then be trained off-line to learn the inverse dynamics of the process in order to act as controller. The issue for this control structure is when the trained networks do not cover the full operating range of the process. To avoid such problem, broad range data covering the full operating range should be collected for the training of the networks. This control structure using ANN as controller has been used in many processes. Some example of Ann applications in controlling the processes are: Nahas et al., (1992) used ANNs to control a continuous stirred tank reactor and a pH neutralisation process; Fernandez de Canete et al., (2008) applied ANN for identification and control of a lab-scale distillation column; Varshney, K. and Panigrahi, P.K., (2004) investigated the control of a heat exchanger in a closed

flow air circuit using ANN-based control and compared it with the PID control. They concluded that ANN-based control showed faster speed and response with less steady state error; Umair, S.M. and Usman, R (2009) applied ANN-based control system for automatic and effective irrigation scheduling system.

5.4.3 Inferential Control Scheme for Ballast Water Treatment Setup

Online measurement of treatment output is required in order to apply control scheme for the ballast water treatment setup. As discussed in the previous chapter, secondary output measurements such as flow rate, UV lamp power and UVT are used to calculate average UV dose delivery and then infer the number of live microorganism exiting UV reactor. The control strategy for the ballast water treatment system should have the potential for modulating either flow rate or UV lamp power or both to maintain the desired UV dose delivery. It means that it is possible to adjust UV lamp power or alter flow rate to maintain the desired UV dose. However, as it was stated earlier, there will be a time delay before the UV lamp reach required power output. This may result in undue delay for the control of the ballast water treatment system when there is a demand for UV power change. Additionally, UV reactor and its control panel should allow for minute setting of UV lamp power while in operation. The UV reactor used in this thesis did not have the provision of minute UV lamp power change during operation and hence flow rate was selected as controlled variable to ensure the delivery of required UV dose at the set UV lamp power.

The control system configuration of ballast water treatment then consists of a flow sensor, a UV treatment process, a flow control valve as actuator and a controller. The developed ANN estimators (Soft sensors) as well as direct inverse control strategy are used to control the flow rate of treatment setup in order to maintain the average UV dose for effective treatment. Three assumptions were considered in the inferential control scheme of ballast water treatment setup:

- The density of live microorganisms of the port area from where ballast water is taken should be known or otherwise minimum IMO standard for test procedure is applied as input to the treatment system,
- The variation in power supply to the UV reactor and ballast pump, due to the cargo operation and or operation of treatment, is considered negligible,

- The size of ballast pumps considered during the design stage of ship's ballast water system are good enough to provide required flow rate as demanded by the inferential control scheme.

Figure 5-16 presents the inferential monitoring and control concept for the ballast water setup. In this concept, the monitoring of the performance of micro-filter and UV reactor is provided by two ANN model estimators and the control of UV treatment is performed by software-based "Decision Making Tool", which sends appropriate signal to the flow control valve for modulating the treatment flow rate.

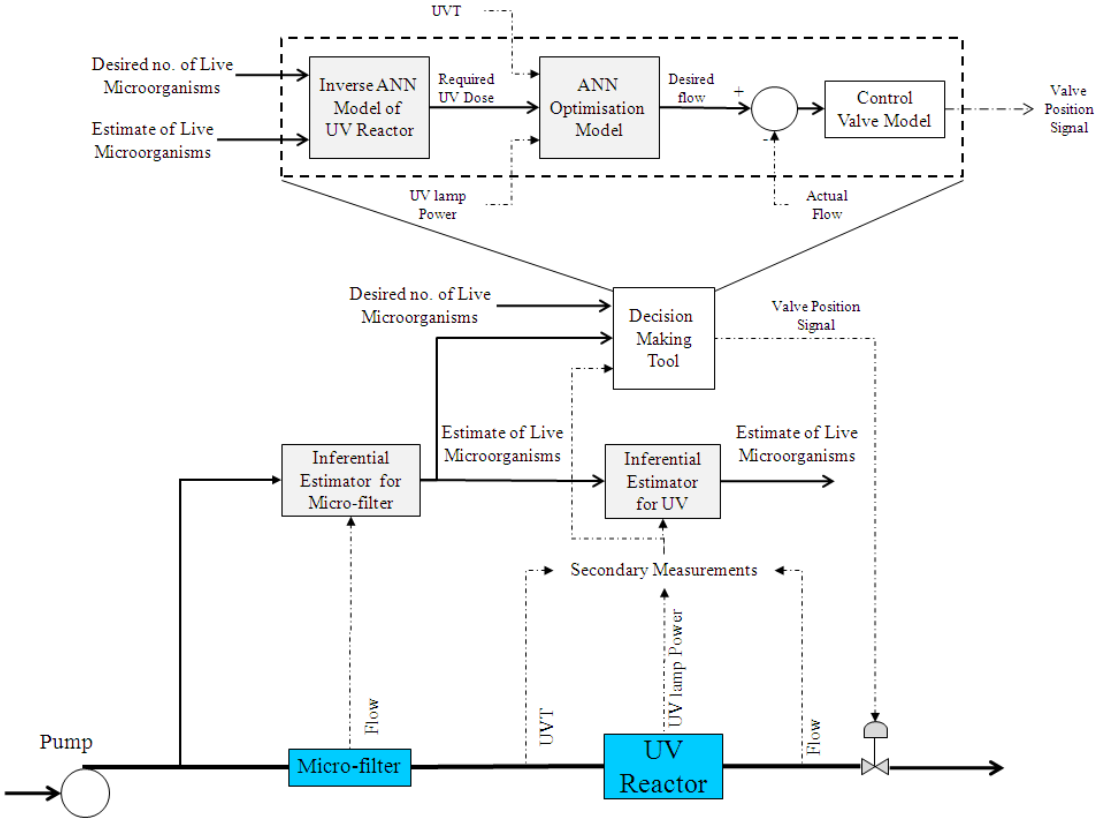

Figure 5-16: Inferential monitoring and control of ballast water setup

As shown in the Figure 5-16, "Decision Making Tool" consists of Inverse biological model of UV reactor, ANN optimisation model for the operation of UV reactor and control valve model. The estimation of live microorganisms from micro-filter and desired number of live microorganisms are fed into Inverse ANN model to predict the required UV dose for such inactivation. The output from this model together with UV lamp power and UVT are inputs to the ANN optimisation model to predict the desired flow rate for the effective UV treatment. Combination of two ANN models in the "Decision Making Tool" provides set-point for the flow control system. The feedback is

also provided through flow control system by comparing actual flow of treatment system and predicted flow by ANN model.

The same networks structure (feed-forward multilayer networks with backpropagation algorithm) was used to develop the inverse ANN model for the UV reactor. All off-line experimental data obtained from the various tests were used to train the networks. In the networks, live microorganisms before and after treatment were selected as input and applied UV dose as desired output. Five neurons were considered for hidden layer and sigmoid function was also considered as activation function for neurons of both hidden and output layers. Training of networks was performed with 5000 iterations and after successful training, linear correlation of 0.996 was obtained when networks tested.

The final control element in this inferential control scheme is control valve, which regulates the flow rate based on the received signal from the "Decision Making Tool". There are also three common types of valve characteristics for the control flow valve: the quick-opening, linear and equal percentage. The last two characteristics (linear and equal percentage) are normally used to regulate the flow rate (Smith, C. A. and Corripio, A. B., 1997). Recommendations for the selection of valve characteristics depend on the types of control loop. For instance Shinskey recommends the use of linear characteristics valves for all flow, level and pressure control applications (except vapour pressure) and the use of equal percentage valves for heat transfer control (Liptak, B., 2006). It is usually sufficient to model the control valve as first order lag whose transfer function is (Smith, C. A. and Corripio, A. B., 1997):

$$G_v(s) = \frac{k_v}{\tau_v s + 1} \qquad (5.10)$$

where:

k_v = Valve gain

τ_v = Time constant of valve actuator.

The final control valve used in the ballast water setup has linear characteristic and capable of receiving DC input signal for the actuation of the valve. The transfer function of final control valve is:

$$G_v(s) = \frac{6.7}{2.5s + 1} \qquad (5.11)$$

All ANN and control valves mathematical models were programmed in the LabVIEW®, according to the inferential control structure presented in the Figure 5-16, to develop simulation model of ballast water treatment setup. Figure 5-17 shows the graphical representation of inferential monitoring and control of ballast water setup.

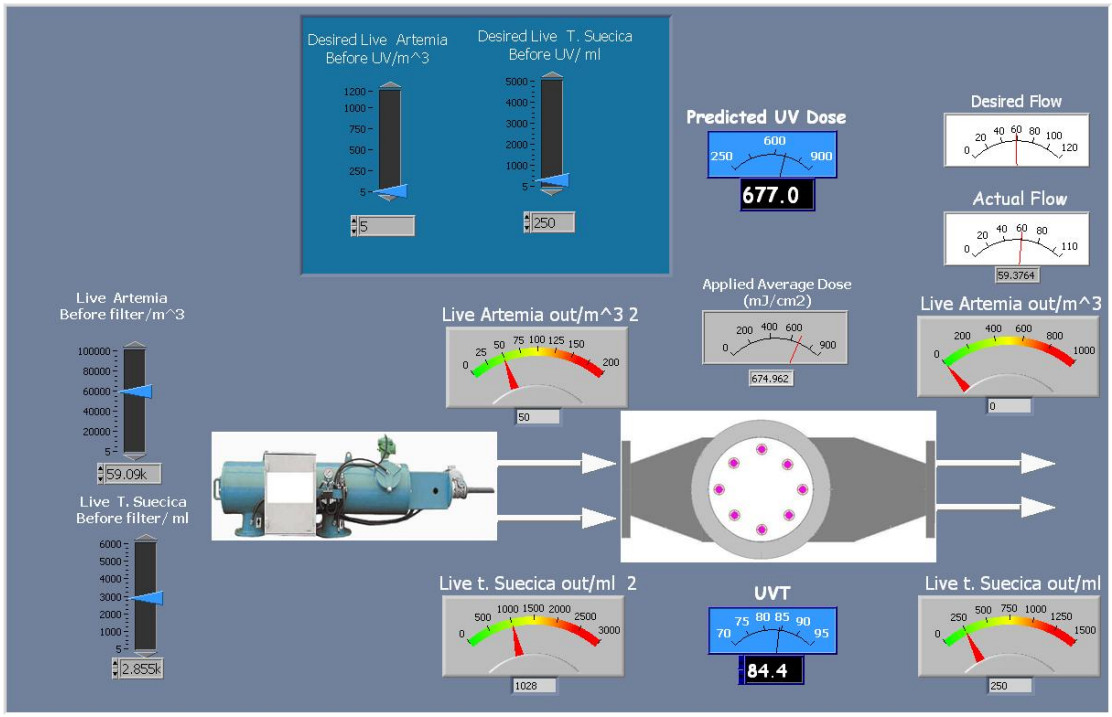

Figure 5-17: Simulation program for inferential monitoring and control

A treatment scenario was defined in which the numbers of live microorganisms going into the micro-filter were arbitrarily chosen. Then the desired number of microorganisms leaving the UV reactor was also set and the program started with setting UVT value as 85%. The UVT value was then changed, as if the seawater turbidity was changed during treatment process, in four steps between 85 to 75%. During the simulation predicted and actual flow rates and UV doses were plotted to see the response of flow control system against simulated changes in UVT of seawater. Figures 5-18 and 5-19 present demand changes and responses of UV dose and flow rate of the simulated scenario.

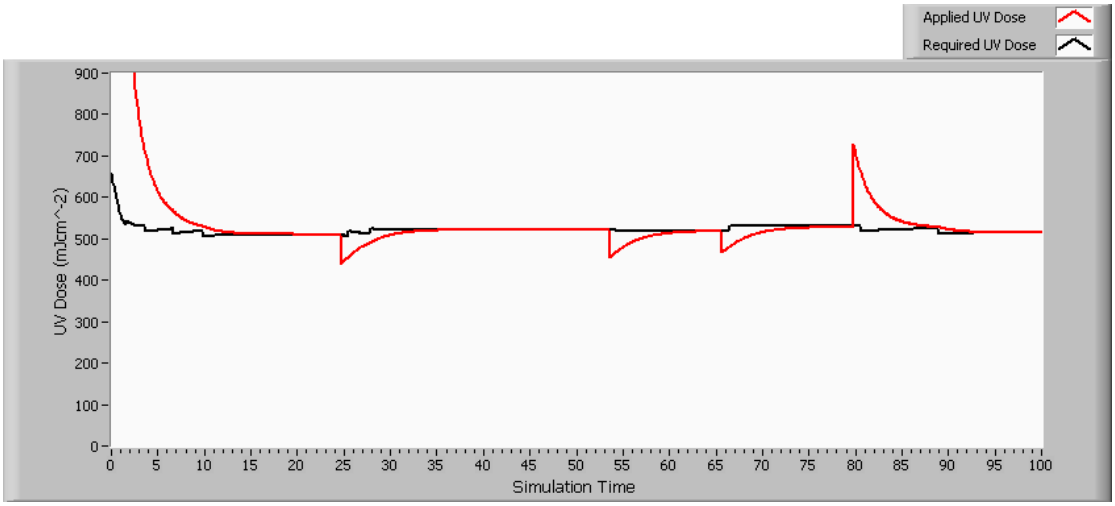

Figure 5-18: Comparison between predicted and applied UV doses in simulated scenario

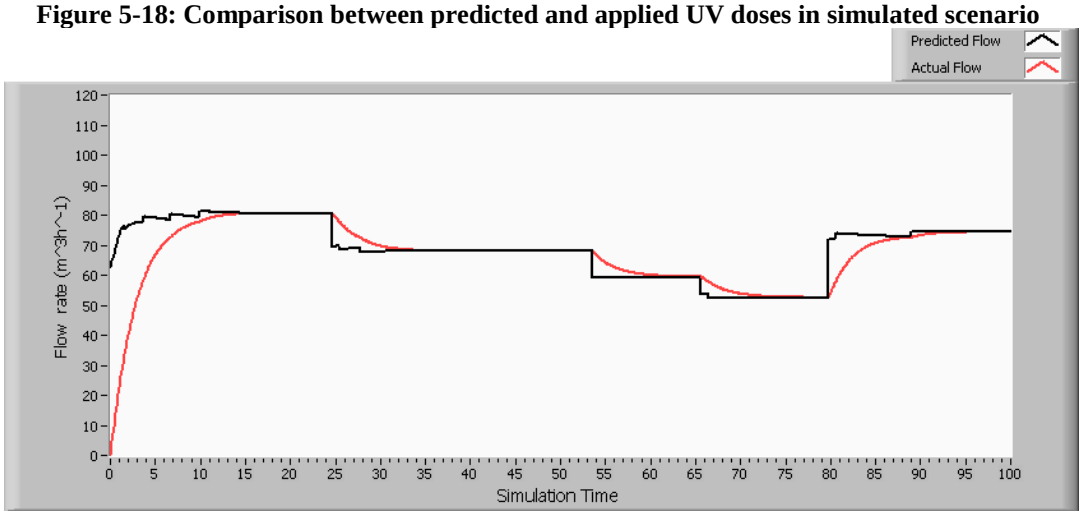

Figure 5-19: Comparison between predicted and actual flow rates in simulated scenario

The Figures show that as soon as treatment flow rate increases, the required UV dose for the inactivation of microorganisms deceases and vice versa. This can be due to improved performance of micro-filter at higher flow rate, meaning that when flow rate of treatment setup goes up, then the separation efficacy of micro-filter improves.

Therefore, lower number of live microorganisms will be available for the UV treatment and thus the required UV dose deceases accordingly. This trend can also be observed when there is a change in the UVT value. It can be observed from the Figures that when UVT is changed to some lower value, the instantaneous prediction of UV dose by the inverse ANN model is slightly lower than the time it has reached to the stable running condition. The similar trend, but in reverse direction, can be observed when UVT value increases.

After successful simulation of the inferential monitoring and control of ballast water setup, a wet test was performed in order to observe the flow control system of treatment

setup. In this light, all measuring sensors were wired up to the computer simulation program via data acquisition card. In return, the computer was connected to the control valve through an amplifier to send the appropriate signal to the control valve. For the wet test, the number of live microorganisms entering UV reactor and the desired number live microorganisms after treatment were set in the simulation program in such a way that the desired UV dose predicted by the inverse ANN model showed 350mJcm^{-2}. The disturbance was applied to the treatment system by changing the value of UVT from simulation program. Changes of UVT in the wet test were as follows:

- UVT was set 80% at the beginning.
- UVT changed to 75% after few minutes.
- UVT changed to 71%
- UVT changed back to 80%

All predicted and actual flow rates and average UV doses were recorded and plotted to observe the behaviour of flow control system and thus delivered average UV dose with respect to the variations in UVT. Figures 5-20 and 5-21 show the actual flow rate and delivered UV dose of the wet test respectively.

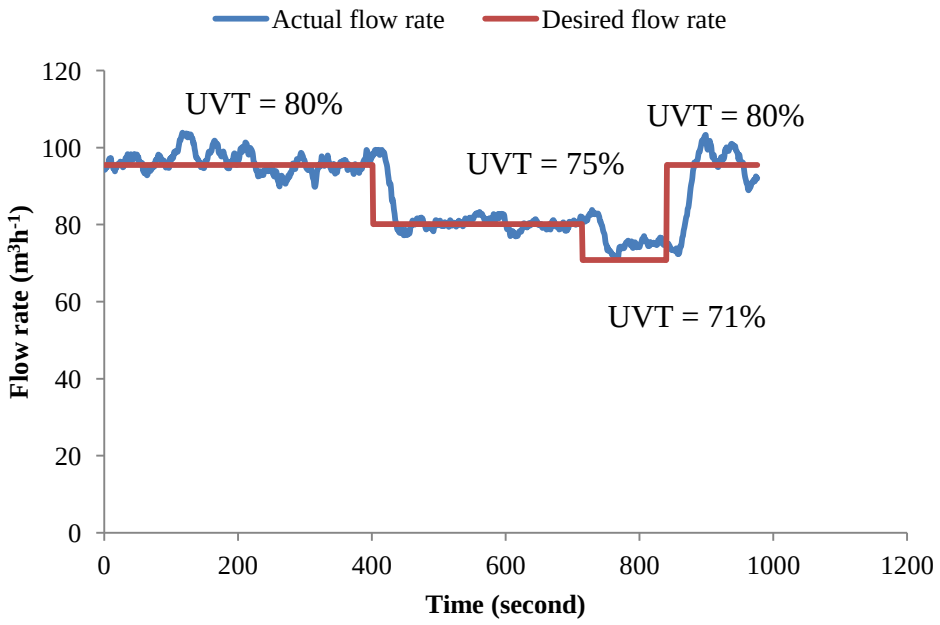

Figure 5-20: Comparison between actual and desired flow rates in real wet test

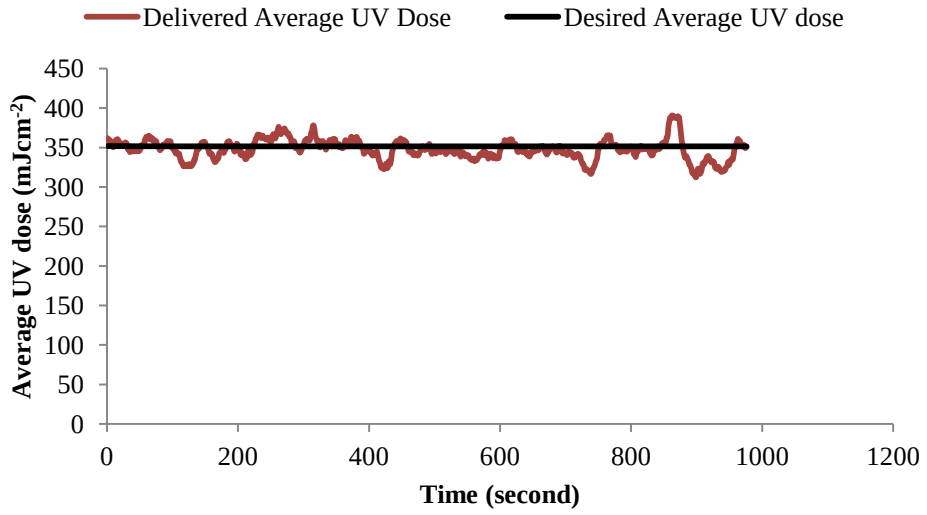

Figure 5-21: Comparison between delivered and desired average UV dose in real wet test

Figure 5-20 shows that the actual flow rate conforms well to the desired flow rate as predicted by ANN optimisation model. This reflects that the average UV dose delivery can be maintained as desired, despite of intentional variations in UVT (Figure 5-21).

The proposed methodology showed that monitoring and control of the ballast water setup can be achieved by using the inferential measurement concept and direct inverse control strategy. The proposed inferential control scheme for the ballast water treatment setup benefits from early detection of deviation from desired output and hence remedial action can be taken before it is too late. It is, however, worthwhile to mention that the accuracy of this concept relies on the accuracy of ANN models. To achieve excellent degree of accuracy, more data will be required through broad range of experiments. In this thesis, the main concentration was focused on the ballast water treatment system, specifically UV treatment system. The proposed inferential measurement and control concept, however, can be extended to the other treatment technologies or systems for which online measurement of primary output does not currently exist.

5.5 Conclusion

Operational performance of UV reactor, based on its mathematical model, showed various combinations of operational variables that can provide the desired average UV dose. A suitable online optimisation algorithm is the way forward to improve the operational performance of UV treatment system. Accuracy and computational time were considered as important factors when comparing optimisation algorithms. The optimisation problem was defined as finding the optimal operational combination (flow

rate and UV lamp power) to yield the least power consumption while ensuring the delivery of desired UV dose. Due to the requirement for running simulation program to find values for independent variables in an iterative way, direct search and ANN algorithms were used as optimisation methods to optimise the operation of UV reactor.

The possibility of variations in the UVT of seawater during the course of treatment causes the optimal solution to move from one point in the surface of viable solutions to another point. In this case, the optimisation method should start searching for the optimal solution from the beginning for every change in the UVT. A developed program based on direct search algorithm (CEM) could accurately find the optimal operational combination subject to the defined constraints. The computing time for this algorithm was noted 5 minutes approximately. This computational time, though short, may not be suitable for online application if change in the uncontrolled independent variable (UVT in this case) is more frequent than the computing time.

Alternatively, ANN was used to reverse model the operation of UV treatment system in order to reduce computing time. Using this technique, two single variable models were developed for the prediction of flow rate and UV lamp power. In this reversing technique, one of the objectives (average UV dose) was considered as input to the model. Each ANN model needs to iterate for one independent variable only, which reduce the number of iteration and thus computing time. These two models complemented each other when used in an optimisation computer program with the same objective function. The results obtained from this program was either the same or very similar to the results of optimisation programme using mathematical model of UV reactor. The accuracy of finding optimal operating combination was similar to the direct search algorithm (CEM) and it also benefits from short computing time of 15 seconds approximately. High accuracy of the result and very short computing time of this optimisation algorithm makes it suitable for online application.

By the ANN modelling technique, multi-output variables for the operational optimisation of UV reactor was developed. This optimisation model could predict the optimal operational combination for varying input variables (average UV dose and UVT) within the specified boundaries. There is no need for any searching algorithm in this model and the optimal results are found instantaneously with good auuracy. The

optimisation model is suitable for online application of UV treatment system where both flow rate and UV lamp power can be modulated.

Single variable ANN model that predicts the flow rate was considered as operational optimisation model for UV reactor used in the ballast water setup, as modulating of UV lamp power was not possible during operation. This model was integrated into inferential measurement and control scheme to estimate highest possible flow rate for the desired UV dose.

An inferential measurement and control concept was proposed for the ballast water treatment setup. In this concept, the monitoring of the performance of micro-filter and UV reactor is provided by two ANN model estimators developed in the previous chapter and the control of UV treatment is performed by software-based "Decision Making Tool".

The software-based "Decision Making Tool" consisted of inverse biological model of UV reactor, single variable ANN optimisation model and control valve model. The "Decision Making Tool" provides appropriate signal to the flow control valve for modulating the treatment flow rate and hence ensuring effective treatment.

The simulation model of inferential monitoring and control concept was programmed in LabVIEW® and tested for the defined scenario. The result of simulation showed the actual flow rate tracks the desired flow rate and thus the delivered average UV dose.

The flow control system of the ballast water treatment setup was tested in a real wet experiment by varying UVT from simulation program. The result of experiment showed that the actual flow rate of the real experiment conforms well the desired flow rate and UV dose delivery was maintained throughout the experiment irrespective of changes in the UVT.

Even though the proposed inferential measurement and control concept was used for the UV treatment system in this thesis, but this concept can be applied to the other treatment technologies and similar processes whose primary output cannot be measured online and depends on laboratory assays with long delays analysis.

As stated earlier, ANN modelling technique is data hungry and requires large datasets for training in order to learn the behaviour of the actual system. Although, ANN models developed as inferential estimators were accurate within the ranges of experimental data, but the accuracy of these models, in particular, and the inferential measurement and control concept, in general, can be improved by performing more experiments and thus providing more biological data for training the networks.

Chapter 6 Conclusions and Recommendations for Future Work

6.1 Conclusion

The interaction of ship, as a complex mobile structure, with her surrounding environment has turned ship and shipping into one of the major pollution contributors. The transportation of seawater from one geographical location to another provides a platform for the marine microorganisms to break through natural barriers and results in marine bio-invasion. Chapter two of this thesis reviews the consequence of ship's interaction with the surrounding environment, and the possible measures to stop or mitigate the marine bio-invasion. Shipboard treatment systems are predominantly considered as mitigating technologies for marine bio-invasion. However, lack of online measurement sensor and need for laboratory assays with long delays analysis has turned ballast water treatment system into a non-observable system. The overall aim in this thesis is to develop a methodology, through mathematical algorithm, to turn ballast water treatment system into observable system for which monitoring and control can be provided.

Within the frame of this overall aim, the research carried out had two main objectives to achieve, which were:

- To develop a methodology that can provide reliable measurement for a system with immeasurable output,
- To propose and develop inferential measurement and control system for ballast water treatment system.

These objectives were accomplished through the research work presented in this thesis from chapter 3 to 5 and the following main conclusions were obtained:
As the first main objective was to develop a methodology, which provides measurement for immeasurable system such as ballast water treatment system, different methodologies were investigated in the chapter 3. The suitability of applying each methodology for monitoring ballast water treatment systems was also reviewed. The conclusions drawn in this chapter are:

- Observability provides evidence of the actual behaviour of a system under observation from the knowledge of its state variables. Therefore to observe the actual behaviour of a system, reliable measurement devices are required to measure the data proportional to certain variables of interest.
- Two well-known techniques of kalman filter and Luenberger observers for the reconstruction of unmeasured state variables were reviewed and found to be linear in nature and to some point can be extended to deal with nonlinearity. In both techniques, the output variables of the system together with the disturbance noises should be available to estimate the state variables.
- Inferential measurement system infers immeasurable primary outputs by using secondary measurements and appropriate model of the system. This methodology can provide observability for the ballast water treatment system in which the measurement of primary output variables (number of live microorganisms per specified unit volume) requires laboratory assays with long delays analysis.
- Case study was conducted to validate the concept of inferential measurement for ballast water treatment system. Three different data driven modelling techniques (MLR, MNLR and ANN) were used to develop an estimator model for the inferential measurement system. The linear correlation coefficient of ANN, MLR and MNLR models were calculated as found to be 99.94%, 61.5% and 98.5% respectively. In the other statistical comparison, the RMSE values of ANN, MNLR and MLR models were 1.26, 13.7 and 28.26 respectively. Both of these statistical analysis showed that the ANN prediction was more accurate than the other two techniques.
- The software-based inferential measurement provided observability for the UV treatment system used in the case study. This concept showed how the performance of each section of treatment can be monitored.

The conclusions obtained from chapter 3 lead to use inferential measurement system for ballast water treatment system consisting of micro-filter and UV technology. Various experiments were conducted on the treatment setup to generate required data for modelling of treating technologies. The conclusions drawn from chapter 4 are in two folds:

1. Conclusions drawn from biological performance of the ballast water setup:

- Micro-filter with 40 micro screen was highly effective (> 98%) in removing

microorganisms greater than 50μm in minimum dimension. Contrary to larger microorganisms, there was no significant removal of smaller microorganisms (≤50 - >10μm) by micro-filter,

- UV treatment showed to be effective especially on smaller microorganisms (≤50 - >10μm), but relying on the UV dose delivered during treatment process and of course number of microorganisms in the influent seawater.
- Performances of two different configured UV reactors used in this thesis showed that log inactivation of straight inlet and outlet configuration with UV lamps perpendicular to the flow (UV reactor used in the ballast water treatment setup) was higher than the UV reactor used in the case study. The better performance was attributed to the more uniform dose distribution of UV reactor with lamps perpendicular to the flow.

2. Conclusion drawn from development of inferential measurement system:

- ANN was successfully used to develop inferential estimators for micro-filter and UV reactor of the ballast water treatment setup. The predictions of ANN model for micro-filter against datasets used for training were in very good agreement. The maximum percentage errors for the training dataset were 1.12% and 2% for the prediction of live *A. salina* per m^3 and *T. suecica* per ml respectively. The prediction of ANN model for the testing dataset was also in good agreement with the actual result.
- The predictions by UV reactor model when compared to the actual results from experiments found to be very close and in good agreement. The maximum percentage error for calculated log reduction was only 3%. The log reduction of actual result and ANN prediction were calculated as 1.37 and 1.32 respectively. The prediction result of ANN model for the testing dataset was also very close to the actual result from biological experiment especially for the prediction of *T. suecics*.
- Online measurement and monitoring for the ballast water treatment setup was developed through model-based estimators (soft sensing) of both technologies. The inferential estimators developed were based on the offline data for two types of microorganisms. More experimental data would improve the predictability of ANN models, which leads to more accurate inferential measurement system.

Chapter 5 focussed on the second main objective of this research and propose the

inferential control concept for the ballast water treatment setup. In this chapter a methodology is addressed, using ANN technique, to develop operational optimisation model for the UV reactor. The conclusion drawn for this chapter were:

- Single-variable and multi-variables optimisation models were developed for the operational optimisation of UV reactor using ANN modelling technique. ANN optimisation model for UV reactor could find the optimal solution without the need for iterative procedure and with good accuracy. The ANN optimisation model is suitable for online application of UV treatment system where either flow rate or UV lamp power or both can be modulated.
- An inferential measurement and control concept was proposed for the ballast water treatment setup. In this concept, the monitoring of the performance of micro-filter and UV reactor is provided by two developed ANN model estimators and the control of UV treatment is performed by software-based "Decision Making Tool".
- The software-based "Decision Making Tool" consisted of inverse biological model of UV reactor, single variable ANN optimisation model and control valve model, controls the flow rate of treatment system and thus ensures the effective treatment.
- The developed inferential measurement and control system was successfully tested in the simulation environment and real wet test. The observation from the test showed that the proposed inferential control system for the ballast water treatment setup benefited from early detection of deviation from desired output due to the arbitrary changes in UVT and sent corrective signal to control flow rate accordingly.
- ANN modelling technique, which used to develop inferential estimators, is data hungry and requires large datasets for training in order to learn the behaviour of the actual system. Although, ANN models developed as inferential estimators were accurate within the ranges of experimental data, but the accuracy of these models, in particular, and the inferential measurement and control concept, in general, can be improved by performing more experiments and thus providing more biological data for training the networks.

In this thesis, it was shown how important it is to have a mechanism to measure the performance of a system with immeasurable quality outputs. It was also stated that the

developed measurement mechanism can be utilized for further monitoring and optimal control of non-observable systems. Immediate measurement of output quality variable for a ballast water treatment system, at current practice, is not possible. However, this was made possible through mathematical algorithm in this thesis. The new contribution and novelty of this thesis is the development of a methodology, using inferential measurement system, to provide a reliable measurement system for a non-observable system such as ballast water treatment system. The developed reliable measurement system will guide ship operators for effective treatment and early detection of reduced performance.This methodology can not only be utilised for any other ballast water treatment systems, but also can be extended further for other similar non-observable systems. Important to note that the other new contribution of this thesis is the proposed computer based decision making tool for monitoring and optimal control of ballast water treatment system. Additional contribution of this thesis is the new approach, using ANN algorithm, for the development of online operational optimisation without the need for iterative procedure. It is also noteworthy to mention that the key important points of this thesis are its practicality of the developed methodology and applicability to other disciplines.

6.2 Recommendations for Future Work

From the conclusions given above following recommendations are proposed for future research:

- Currently there is no online device to provide the knowledge of the status of microorganisms (dead versus alive) before and after treatment upon which the effectiveness of treatment system can be assessed. Inferential measurement system, using ANN estimators, provided performance monitoring for the treatment technologies used in this research. Even though the inferential measurement system was used for the UV treatment system in this thesis, but this concept can be applied to the other treatment technologies and similar processes whose primary output cannot be measured online and depends on laboratory assays with long delays analysis.
- The proposed inferential measurement and control concept can be extended further for the shipboard ballast water treatment system. This can not only provide performance monitoring of the treatment system for the shipboard personnel, but ensures effective treatment irrespective of changes in variables.

Furthermore, the shipboard application of inferential measurement and control system with ability to record data can provide evidence of proper treatment.

- The concept of inferential measurement system can be used to develop software-based estimator to predict the density of live microorganisms in the port area from where ships takes their ballast water. This, however, requires massive data and field research to understand the influencing parameters that affect the density of microorganisms and their distributions.

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Chapter 7 List of Microorganisms in the Ballast Tanks

Table A-1: List of microorganisms in the ship's ballast tanks at various ports

Study site and period	Sampling regime	Bacteria and viruses	Type of species	Reference
Australia 1973	Plankton sample from ballast water from 1 ship		Polychaetes, copepods, amphipods, ostracods and chaetognaths	Medcof 1975
Australia 1976-78	Ballast water tanks of 23 bulk cargo vessels sailing between Japan and Australia was investigated over two years		Most common species found: copepods, molluscs, larvaceans and barnacles	Williams *et al.*, 1988
Australia 1976-78	Sediments from 9 bulk carriers sailing between Japan and Australia		Crustaceans and polychaetes	Williams *et al.*, 1988
Coos Bat, OR 1986-91	Samples from 159 ships (woodchip carrier) from Japan		402 species in 24 animal, plant and protest phyla	Carlton & Geller 1993
Australia 1987-93	Sediment from ballasted cargo holds of 12 Japanese woodchip carrier		56 phytoplankton species, including dinoflagellates cysts in 7 ships	Hallegraeff *et al.*, 1990
Australia 1987-93	Sediments from 31 of 83 bulk carriers arrived at Australia		Dinoflagellates and toxic species in four of those ships	Hallegraeff & Bolch 1991
Great Lakes and upper St. Lawrence River 1990-91	Samples from 86 ships ballast tanks	110 species of zooplankton in 11 phyla. 100 species of bacteria, phytoplankton and protists mainly diatoms and dinoflagellates		Locke *et al.*, 1991, 1993; Subba Rao *et al.*, 1994
Washington state 1991	Samples from ballast water and sediments of 6 Japanese bulk carrier		21 species of phytoplankton and protists (sediment) and at least 8 organisms from ballast water	Kelly 1992, 1993
Gulf of Mexico 1991-1992	Ballast water sampled from 19 ships	5 ships ballast water included *Vibrio cholerae*		McCarthy & Khambaty 1994
Germany 1992-95	Samples taken from ballast tank, sediment and fouling on tanks wall of 189 ships		Samples included over 350 species mainly unicellular algae, copepods, other crustaceans and molluscs	Gollasch *et al.* in press
Chesapeake Bay 1993-94	Samples taken from ballast tanks and bottom sediments of 70 ships		Ballast water sample included 275 plant, protest and animal species. 4 species in sediment from 5 ships	Smith *et al.*, 1996
Hong kong 1994-95	Ballast water sample from 5 ships from both sides of North Pacific		Ballast water sample included 82 species of invertebrates and protists	Chu *et al.*, 1997
Baltimore, MD	Ballast water sample		Included 23 species	Wonham *et*

1995	taken from 1 coal carrier		of dinoflagellates and invertebrates	*al.*, 1996
New Zealand 1995-97	Ballast water and sediment samples taken from 50 different ships		Included live phytoplankton in 80% of tanks and live invertebrates in 83% of tanks	Hay *et al.*, 1997
Valdez, AK 1996	Ballast water samples from 16 domestic and 1 foreign oil tanker		Included 68 taxa	Ruiz & Hines 1997
Israel 1996	Ballast water and sediment samples of 17 ships		Included at least 198 heterotrophs plus diatoms and other species	Galil & Hulsmann 1997
Canada, Ports of Toronto and Hamilton and the Welland canal. 1995	Total of 71 ballast water samples taken from 59 ships	*Fecal Coliform* and *E. Coli* found in 31 ships; *Enterococci* found in 47 ships		Whitby 1998
Great lakes and St. Lawrence, 1997-98	Ballast water and sediment samples from 28 Transoceanic vessels	*Fecal Coliforms, vibrio cholerae, Enterococci* and *Salmonella*		Knight *et al.* 1999
9 Brazilian Ports 2002	99 samples taken from ships calling Brazilian ports	*Vibrio, Fecal Coliforms, E. Coli, Entrocci fecal, V. Cholerae, coliphage, Clostridium perfringens*		Anvisa 2003
Chesapeake Bay and North American Great Lakes 2002	Samples taken from ballast tanks biofilm	*V. Cholerae, Vibrio alginolyticus*		Drake et al., 2003
Chesapeake Bay and Great Lakes 2002	Ballast water and sediments samples taken from 200 ballast tanks	Rare to occasional presence of viruses, bacteria and protists pathogenic to humans and fish		Dobbe *et al.*, 2003
Ship ballast water travelling between Japan and Qatar. 2002-03	Samples from ships ballast tanks	*Vibrio* Species		Mimura *et al.*, 2005

Appendix B. UV Technology

B.1. Introduction

Disinfection property of UV irradiation has been well researched and treatment technologies adopting UV irradiation technique have been developed and served in the water system. Conversely to chemical disinfection, like chlorination, little toxic residual or disinfection byproducts (DBPs) would be produced and discharged to new receiving location (Ward and DeGrave, 1978 as cited in Guo Lin, 2005; Whitby and Scheible, 2004 as cited in Guo Lin, 2005). Therefore, it is worthwhile to study and research on this technology for disinfection of ballast water. In this chapter, details of UV treatment system will be explored.

B.2. UV Treatment System

UV treatment system is an established disinfection technology and supported by decades of research. Historically, germicidal properties of sunlight discovered by Downes and Blunt in 1877, followed by development of mercury lamps as artificial UV light sources in 1901 and usage of quartz as a UV transmitting material in 1906 until the first drinking water disinfection by UV was developed in Marseilles, France in 1910. In the 1950s, considerable research carried out on the mechanisms of UV disinfection and inactivation of microorganisms (Dulbecco, 1950; Kelner, 1950; Brandt and Giese, 1956; Powell, 1959; USEPA, 2006). Despite of low cost of drinking water disinfection by chlorine and operational problems with early UV disinfection equipment, the first reliable drinking water disinfection system using UV light was used in Switzerland and Austria in 1955 (Kruithof and van der Leer, 1990; USEPA, 2006). UV disinfection became more popular, when by-products from chlorinated disinfection were discovered.

Successful treatment of municipal drinking water, wastewater and swimming pool by UV disinfection drew the attention of researchers to consider this technology as viable solution for ballast water problem. This technology has been tested against targeted microorganisms in ballast water from laboratory scale to shipboard experiments. As a result, a type approved two stage system using UV technology has been developed and installed, but technology still demands more research work for optimum performance.

B.3. UV Light Generation and Transmission

The use of UV light for disinfection and/or inactivation of microorganisms involve generation of UV light with the desired germicidal properties as well as transmitting it

to the targeted pathogens or microorganisms. In the following, how UV light is generated and the water condition that can affect its propagation to the targeted particles will be discussed.

B.3.1 Nature of UV Light

UV light is the part of electromagnetic spectrum that lies between the X-ray portion of the spectrum and visible portion as shown in the Figure B-1.

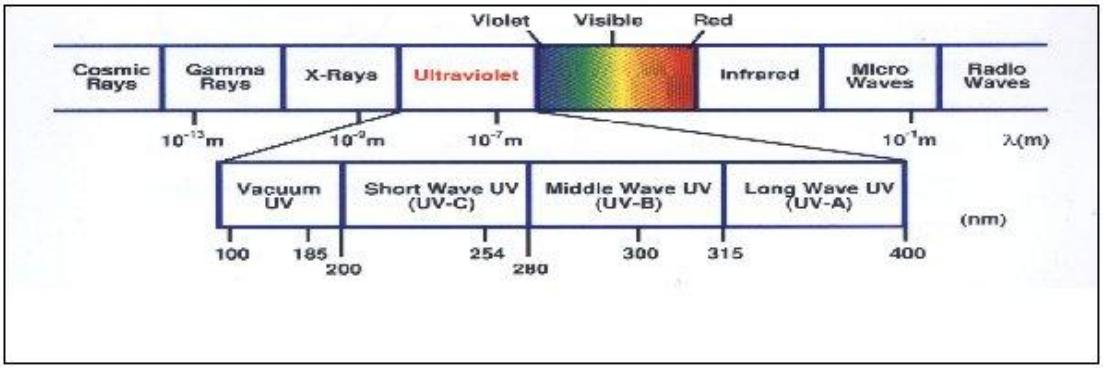

Figure B-1: UV Light in the electromagnetic spectrum

The UV light is commonly referred to black light as it cannot be seen by human eye. As can be seen from figure 3-1, the UV portion of light is subdivided into four regions based on their range of wavelengths: vacuum UV covers the portion with the wavelength ranges from 100 to 200 nanometers (nm); UV-C from 200 to 280 nm; UV-B from 280 to 315 nm; and UV-A from 315 to 400 nm (Meulemans, 1986). When germicidal actions of these four regions are compared, UV-B and UV-C light have higher disinfection action on organisms than UV-A light; therefore very long exposure time is required for UV-A light to become effective. Germicidal action of light in the range of vacuum UV said to be effective on microorganisms, but it is impractical to use it for water disinfection applications. In fact vacuum UV light rapidly dissipate in the water over very short distances (Munakata et al., 1991). As a matter of fact, to obtain practical application of UV disinfection, artificial source of UV (e.g. UV lamp) is required. Typically, UV light is generated by the application of a voltage across the gas mixture, resulting in discharge of photons. The specific wavelengths of the light emitted from discharged proton depend on the composition of gas mixture in the UV lamp's tube and the power level of the lamp. The most common types of UV lamps available are low and medium pressure mercury arc lamps. The reason to use gas mixture containing mercury gas is its ability to emit light in the germicidal wavelength range. The concentration of mercury atoms, which directly related to the vapour pressure inside the tube, decides the light output from mercury filled UV lamps. The most energy

efficient lamps used for UV disinfection are the low pressure – low intensity (LP-LI) lamps. In these lamps, the tube contains mercury vapour and argon gas at the pressure of 2×10^{-5} to 2×10^{-3} psi and operates at the temperature between 40 °C and 60 °C. These lamps produce monochromatic UV light at 253.7 nm wavelength, which is near the peak for germicidal effectiveness (Christopher P. Martin et al., 2004; USEPA, 2006). The power of the LP-LI lamp is around 88 watts and the germicidal output is approximately between 20 to 25% of the lamp's rating (Christopher P. Martin et al., 2004; Thampi, 1990). These lamps emit approximately 0.2 Wcm^{-1} germicidal radiations (Hanzon and Vigilia, 1999). The next commercially available UV lamp is low power – high intensity lamp, which is the modified version of LP-LI lamp. These lamps operate at the pressure similar to low intensity lamps, but at higher operating temperature ranging from 180 to 200 °C (Hanzon and Vigilia, 1999). The power for these lamps is about 250 Watts and the germicidal output is approximately 13 Wcm^{-1} (Christopher P. Martin et al., 2004). Another UV lamp modified from LP-LI is medium pressure – high intensity (MP-HI) lamp, which operates at the temperature between 600 and 800°C. These lamps produce polychromic radiation throughout the germicidal wavelength region. The power for these lamps is 2800 W or more and its germicidal output is about 16 Wcm^{-1} or more depending on power of the lamp (Christopher P. Martin et al., 2004; USEPA, 2006). The higher intensity of MP-HI lamps reduces the required number UV lamps significantly for adequate disinfection (Christopher P. Martin et al., 2004; Hunter et al., 1998).

B.3.2 Propagation of UV Light

In disinfection application, UV light propagates from it source and interacts with the materials it comes in contact through absorption, reflection, refraction and scattering. These interactions occur between the emitted UV light and UV reactor components (e.g. lamp envelope, lamp sleeve and reactor wall) as well as particles in the water. It is very important to assess the quality of the water in order to quantify the UV light propagation. In the following the phenomena influencing the UV light propagation will be described.

B.3.2.1 Absorption

Absorption can be defined as transformation of UV light energy into another form of energy as it passes through a substance. UV absorbance of a substance depends and varies with the wavelength of the UV light. For instance, dissolved iron can absorb UV light significantly (Jacangelo et al., 1995) and precipitate on the UV system quartz tube.

Other substances such as organic humic acids and dyes can also absorb UV light (Christopher P. Martin et al., 2004). As a result of this phenomenon, the absorbed UV light is no more available to disinfect microorganisms.

B.3.2.2 Refraction

Refraction is the change of direction of light as it passes through the interface between one object and another. In the context of UV disinfection reactor, refraction will occur when UV light emitted from the source and passes through the interface between air and quartz sleeve and then at the time it just enters water as shown in the Figure B-2.

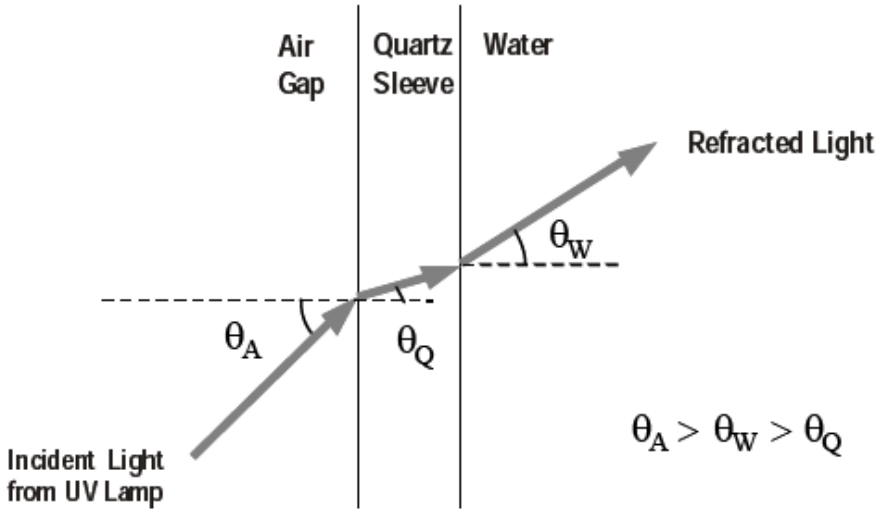

Figure B-2: Refraction of light in UV reactor (USEPA, 2006)

B.3.2.3 Reflection

Reflection is the change of direction of light propagation when it hits a surface and reflected back at the same angle of incident (specular) or different (diffuse) depending on the surface roughness (Figure B-3). Specular reflection occurs when the light hits the smooth surface, whereas diffuse reflection occurs from rough surfaces. In UV reactor, reflection occurs at the interfaces that UV light cannot pass through (e.g. UV reactor wall) as well as UV transmitting interfaces (e.g. the inside wall of UV lamp sleeve). The type of reflection of UV light and its intensity depends on the roughness and the material of the surface.

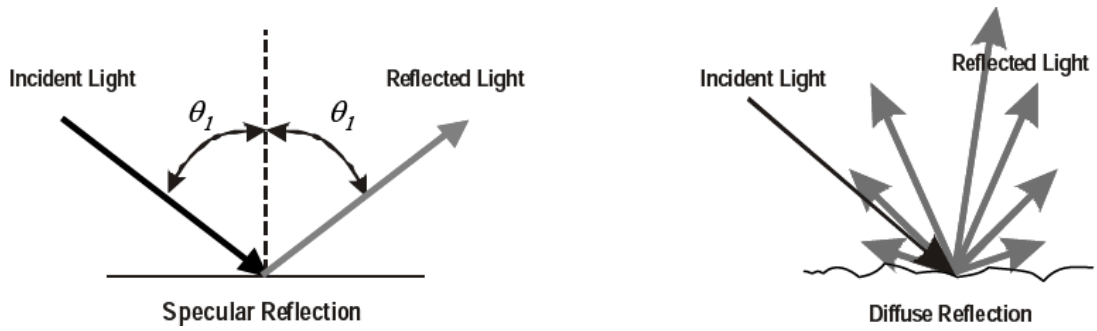

Figure B-3: Reflection of light (USEPA, 2006)

B.3.2.4 Scattering

Scattering is the change of light propagation when it hits a particle (Figure B-4). In this case light can be scattered in all directions even back toward the light source. Particles can scatter UV light or shade the targeted microorganisms by blocking the UV light. As a consequence, these organisms are more difficult to inactivate than non-shaded ones (Christopher P. Martin et al., 2004; USEPA, 2006).

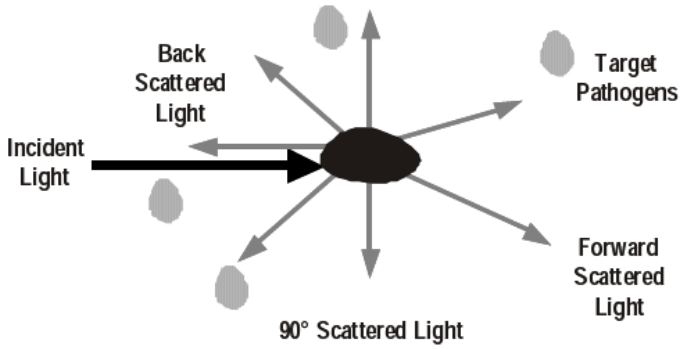

Figure B-4: Scattering of UV light (USEPA, 2006)

It is worthwhile to mention that from disinfection point of view, absorption differs from the other phenomena such as refraction, reflection and scattering. In the case of absorption, UV light and consequently UV energy is no more available for disinfection, whereas after occurrence of the other phenomena, UV light is still present, but at different directions.

B.3.2.5 UV Transmittance (UVT)

UV transmittance measures the ability of a medium (in this case ballast water) to transmit UV light. It represents the percentage of UV energy in the water available for disinfection of microorganisms after a specified distance of UV light penetration (e.g. 1 cm). For instance, when UV transmittance is said to be 0.9, it means 10% of UV energy has been absorbed, as the UV light passes through the water over the distance of 1 cm

and 90% of UV energy remains for disinfection of microorganisms beyond that distance. This would indicate that the lower the transmittance, the lower amount of UV light reaches the targeted microorganisms and additionally, the organisms free-floating at the longer distance away from UV irradiation source; receive less UV energy than nearer ones. The UVT can be calculated by the following Equations:

$$\%\boldsymbol{UVT} = \mathbf{100} \times \mathbf{10}^{-\boldsymbol{A}} \qquad \text{(B.1)}$$

where

UVT = UV transmittance at a specified wavelength (e.g. 254 nm) and path length (e.g. 1cm)

A = UV absorbance at a specified wavelength and path length (unitless) and calculated as follows:

$$A = \log(I_o/I) \qquad \text{(B.2)}$$

I_o = Intensity of reference beam

I = Intensity of sample beam

Figure B.5 represents a working principle of typical spectrometer, which measures the UVT of sample of water at specified wavelength and path length of 1 cm.

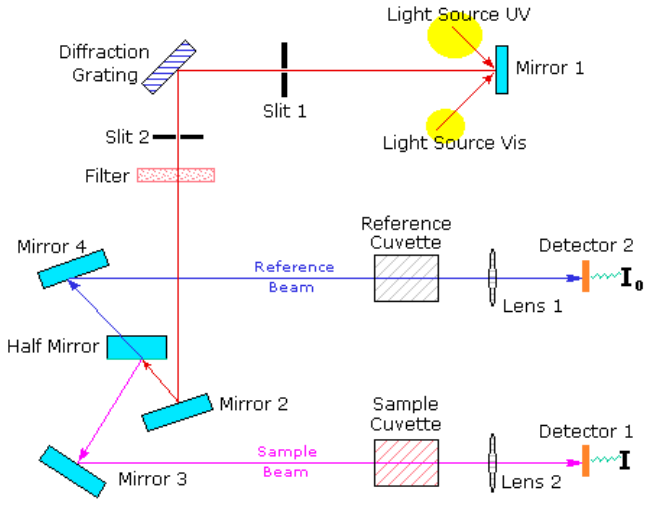

Figure B-5: Working principle of a typical spectrometer (Source internet)

B.4. Mechanisms of UV disinfection

The disinfection mechanism of microorganisms by UV light is different with the mechanisms of chemicals such as chlorine and ozone. In chemical disinfection, inactivation of microorganisms is caused by destroying or damaging cellular structure,

interfering with metabolism and hindering biosynthesis and growth (Snowball and hornsey, 1988), whereas UV light damages their nucleic acid and hence preventing them from reproducing (USEPA, 2006). UV absorption by nucleotides, the building blocks of DNA and RNA, is wavelength dependent with peaks at or near 260 nm (Figure B-6). This means that UV light has maximum effectiveness at the wavelength of 260 nm. There is, however, no efficient way of producing UV light at this wavelength and mercury can produce UV light at the wavelength of 254 nm very efficiently, hence the latter is considered as standard effective wavelength (USEPA, 2006).

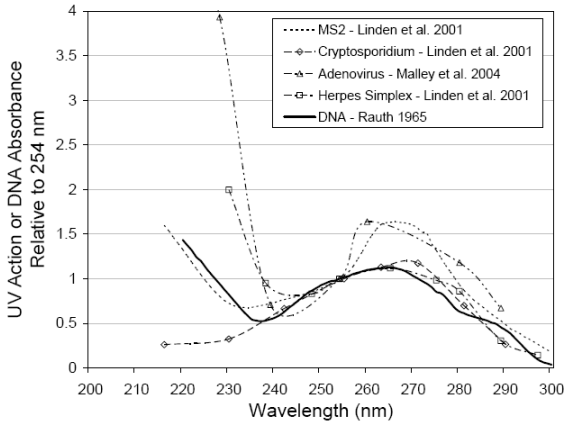

Figure B-6: Comparison of microbial UV action and DNA absorbance (USEPA, 2006)

As a result of exposure to the UV light at this wavelength, microorganisms are either killed or rendered inactive. However, some microorganisms have enzyme systems that enable them to repair the damage done by UV light. Repair mechanisms are classed as photo-repair or dark-repair (Knudson, 1985). This capability of microorganisms to repair under either of circumstances causes increase in the required UV dose to achieve a given degree of inactivation.

In photo-repair, exposure of microorganisms to light with the wavelength between 310 and 490 nm (near and in the visible range) energizes the enzymes and break the covalent bonds that formed resulting from UV disinfection. Conversely, in dark repair process, the presence of light is not required. However, the term dark repair does not mean that it cannot be occurred in the presence of light. In this repair process, the damaged section of DNA is removed and then regenerated by using the existing complementary strand of DNA (USEPA, 2006).

B.5. UV Intensity

UV intensity is a fundamental property of UV light, which is defined as the amount of

UV light falling on a unit area of surface and hence has the units of Watts per meter squared (Wm^{-2}) (Holliday and Resnik, 1978). The intensity of a position in a UV reactor can then be calculated by knowing the intensity and UVC output of the UV mercury lamp. The total UV intensity at a point in space of the reactor is the sum of the intensity of UV light from all directions (USEPA, 2006).

There are two different methods for calculating the intensity adopted by EPA in the USA and Berson UV (USEPA, 1992; Baas, M.M., 1996). Both methods use similar parameters in their calculation, which are:

1. Number of segments, N
2. Distance from the lamp, R
3. UV Lamp power, P
4. UV Transmission for the path length of 1 cm
5. Multiple reception point, I_p

Both methods consider the contribution of each lamp to the intensity (Wm^{-2}) at a point in the UV reactor. In the EPA method, the intensity at each point "n" is calculated in a plane "Z" at the base of the lamp as shown in the Figure B-7. Then the average intensity in the "Z" plane is calculated by dividing the sum of all reception point "I_p" intensities by the number of points "n" in that plane. Finally to calculate the average intensity of UV reactor a correction factor, F_z, is arbitrarily considered and multiplied with average intensity of the plane "Z".

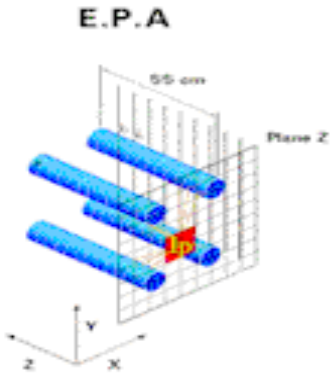

Figure B-7: Calculation of UV intensity in UV reactor by EPA method (Baas, M.M., 1996)

The Berson UV-technique method calculates the intensity at each point "n" in the UV reactor and considers contribution of all lamps to the intensity of point with respect to the distance and UVT of water (Figure B-8). The average intensity is the sum of the reception point intensities "I_p" divided by the number of points.

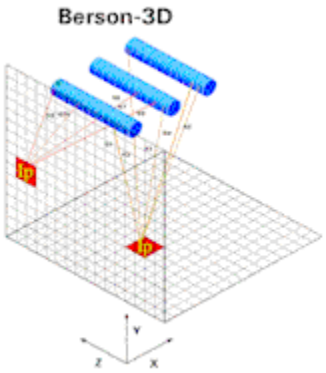

Figure B-8: Calculation of UV intensity in UV reactor by Berson 3-D method (Baas, M.M., 1996)

B.6. UV Dose

UV dose is the integral of UV intensity during the exposure time, but if the UV intensity is considered constant over the exposure time, then it is defines as the product of UV intensity (Wm^{-2}) and the exposure time (s). Units commonly used for UV dose are $mJcm^{-2}$ (or $mWscm^{-2}$) in North America and mJm^{-2} in Europe.

One accurate way to determine the delivered dose on target microorganisms is the collimated beam study (Figure B-9). In this study a petri dish containing target microorganism is stirred and a collimated UV light beam is applied on to microorganisms. In this case, the average UV intensity is calculated by measuring the UV intensity incident on the surface of water containing microorganisms (test water), the depth and the UV absorbance of the test water. Then UV dose is determined by multiplying the average UV intensity delivered to target microorganism and the accurately measured exposure time.

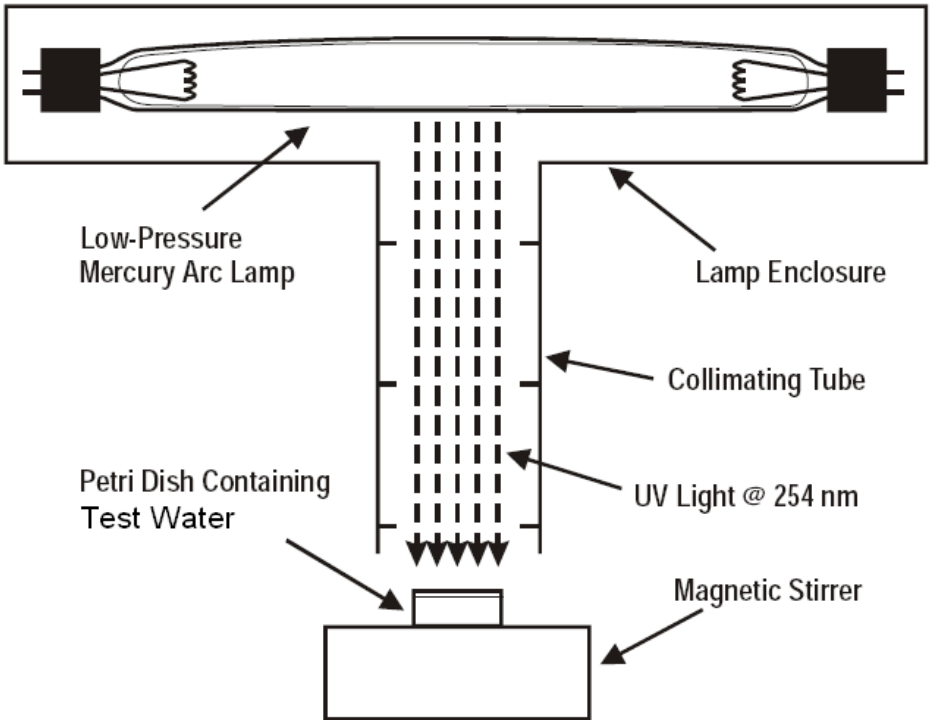

Figure B-9: Collimated beam apparatus (USEPA, 2006)

In case of using polychromatic light source (e.g. MP-HI lamps), UV dose calculation incorporates the intensity at each wavelength and germicidal effectiveness at the associated wavelength. It is worthwhile to note that in order to measure the intensity of UV light; a calibrated radiometer replaces the petri dish and is positioned below the collimating tube (USEPA, 2006).

Collimating beam study and associated UV dose calculation is an example of completely mixed batch system. In ballast water treatment system, however, a continuous flow UV reactor should be used. Dose delivery in such system is considerably more complex than in a completely mixed batch reactor. In continuous flow system, some microorganisms move near UV lamps, where intensity is highest, and some other travel close to the reactor wall and receive comparatively lower dose. Some microorganisms take the shorter path while travel through the reactor, whereas the other may take circuitous path. Therefore, the result would be different UV dose applied on the microorganisms leaving the UV reactor. Cabaj et al. (1996) stated that the best way of describing delivered UV dose is to use a dose distribution as opposed to a single dose value. The dose distribution of a UV reactor can be estimated by mathematical models using computational fluid dynamic (CFD) and the light intensity distribution (LID). CFD and LID are used to predict the trajectories of microorganisms and the intensity of each point within the reactor respectively. UV dose can then be

calculated by integrating the UV intensity over the microorganisms' trajectory through the reactor (USEPA, 2006).

Currently, EPA recommends measuring the delivered dose by using a technique called biodosimetry, with which the log inactivation of a surrogate microorganism is measured through the UV reactor and related to a dose value, using the UV dose-response curve of the surrogate microorganisms. Figure B-10 shows examples of UV dose-response curves for some bacteria and virus.

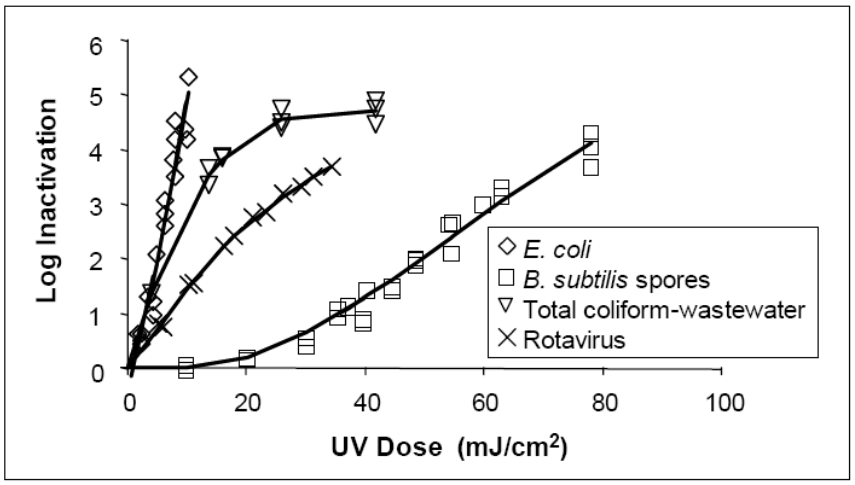

Figure B-10: Shapes of UV Dose-Response Curves (USEPA, 2006)

Microbial response to UV light can vary significantly, as shown, depends on types of microorganisms (Rauth, 1965; USEPA, 2006). Microbial UV response-curves are available and many studies have been carried out for the pathogens of interest in drinking water, waste water treatment and swimming pool applications. Similar curves, however, do not exist for larger microorganisms such as those of interest for ballast water disinfection.

UV dose-response is generally independent of some factors such as UV intensity, temperature and pH. In general, UV dose-response follows the Law of Reciprocity over the UV intensity range of 1 to 200mWcm^{-2} (Oliver and Cosgrove, 1975). This means that to achieve the dose delivery of 100 mJcm^{-2}, for inactivation of certain microorganisms, a combination of either UV intensity of 2 mWcm^{-2} and high exposure time of 50 seconds or intensity of 5 mWcm^{-2} and lower exposure time of 20 seconds is required. Effects of temperature on dose-response are also considered negligible. Malley

(2000) reported that the dose-response of MS2 was independent of the temperature from 1 to 23°C and pH from 6 to 9.

It is worthwhile to mention that UV absorbance of the water is considered when calculating UV dose, hence UV response-curve is independent of it. Nonetheless, in order to maintain the required UV dose, increasing intensity or exposure time may be necessary as the level of absorbance of the water changes (USEPA, 2006).

B.7. UV Disinfection Equipment

The main goal in designing a UV reactor for disinfection purposes in drinking water, waste water and swimming pool application is to efficiently provide the required dose delivery to inactivate pathogenic microorganisms of interest. The same line of thinking must be adopted for ballast water disinfection and hence required dose should not only be delivered for inactivation of pathogenic microorganisms, but for larger ones such as phytoplankton and zooplankton. Commercial UV reactors consist of open or closed-channel vessels, UV lamps, lamp sleeve, UV sensors, and temperature sensors. In some cases, automatic cleaning mechanisms to clear the lamp sleeve from deposits, flow meter and UVT analyser for monitoring the dose delivery are also included.

B.7.1 UV Reactor Configuration

UV reactors are generally classified as open or closed-channel and are being used depending on the application. For instance, closed reactors are employed in drinking water application, whereas open basins with channels containing racks of UV lamps are commonly used in wastewater applications.

UV reactors are designed in such a way to provide efficient and cost effective dose delivery. The optimum hydraulic/flow characteristic for UV disinfection said to be turbulent flow with mixing while minimising head loss (Christopher P. Martin et al., 2004). In theory, optimal dose delivery will be obtained with plug flow hydraulics through the reactor, but in practice UV reactors do not have such flow characteristics. Some manufacturers insert baffles to improve hydrodynamics in the reactors. Lamp location, baffles, inlet and outlet conditions affect mixing within the reactor and, of course, dose delivery (USEPA, 2006).

The lamps in the reactor are either fixed vertically in the reactor, perpendicular to the flow, or horizontally (parallel to the flow) or diagonally to the flow direction (USEPA, 2006). The lamp placement in the reactor influences the dose delivery. Most of the UV

systems currently produced for disinfection of wastewater application have their lamps fixed in a position that the flow lines are running parallel to the lamp axes (Christopher P. Martin et al., 2004). Some manufacturing companies, however, claim that the vertical arrays (perpendicular to the flow) are more efficient and it is less probable that the exiting water has not received adequate dose (Infilco Degremont, Inc., 1996; Christopher P. Martin et al., 2004).

The other factor influencing the dose delivery is the space between the lamps and between the lamps and the reactor wall. If the thickness of water layer in these spaces is too thin, then the reactor wall and other lamps in vicinity will absorb UV light and in case of being too thick then microorganisms passing through this layer will receive lower UV dose.

Finally the inlet and outlet conditions of UV reactors can have significant influence on the hydrodynamics of UV reactor and UV dose delivery. For instance, perpendicular inlet and outlet to the flow direction within the reactor promotes sort-circuiting, eddies and dead zones in the reactor. In contrast to perpendicular inlet and outlet configuration, straight inlet and outlet configurations with smooth gradual changes in cross sectional area will improve the flow characteristics for optimal dose delivery (USEPA, 2006).

B.7.2 UV Lamp

UV lights can be produced by various lamps as listed below:

- LP mercury vapour lamps
- Low-pressure high-output (LPHO) mercury vapour lamps
- MP mercury vapour lamps
- Electrode-less mercury vapour lamps
- Metal halide lamps
- Xenon lamps (pulsed UV)
- Eximer lamps
- UV lasers
- Light emitting diodes (LEDs)

Generally, in some applications like drinking water, LP, LP-HI and MP-HI are being used. These lamps, as shown in the Figure B-11, consists of lamp envelop, electrodes, mercury (amalgam in case of LPHI and liquid elemental mercury for LP and MPHI lamps) and inert gas (typically argon).

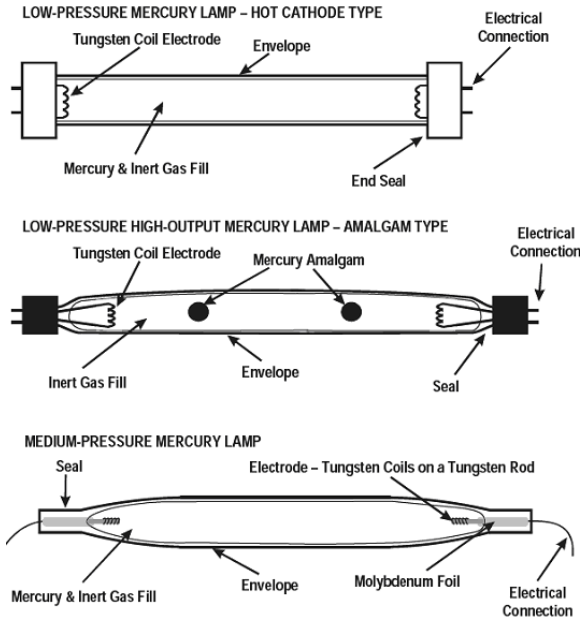

Figure B-11: Construction of UV lamp (USEPA, 2006)

The light emitted by LP and LP-HI lamps (Figure B-12a) is essentially monochromatic at the wavelength of 253.7 nm in the UV range near the maximum effective wavelength (260 nm). These lamps also emit small amounts of light at other wavelength due to higher energy electron transition in the mercury.

MP-HI lamps emits a wider range of UV wavelengths, as shown in the Figure B-12b, in the range of UV light from 200 to 400 nm (USEPA, 2006).

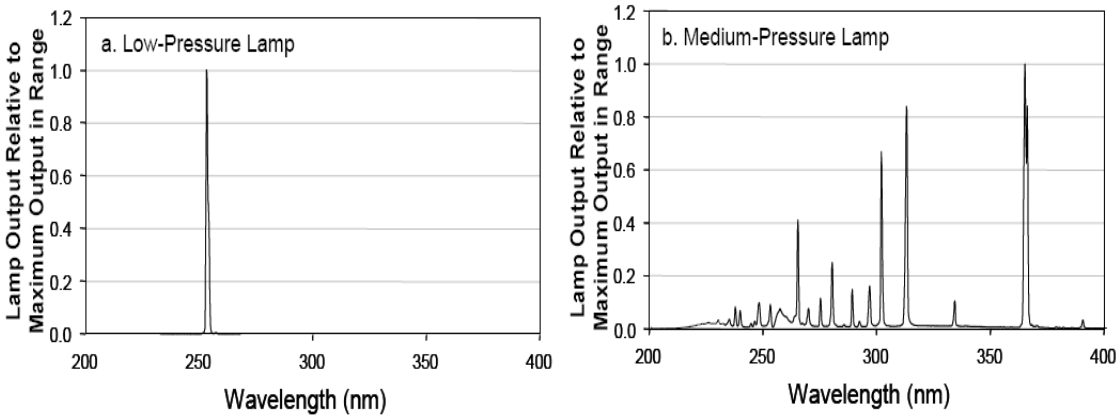

Figure B-12: UV output of LP and MP Mercury vapour lamps (USEPA, 2006)

B.7.3 Lamp Sleeves

Lamp sleeves are used to house UV lamps in order to protect them from breaking and allow them working at optimal operating temperature. Lamp sleeves are tubes of quartz with sufficient length to house the lamp and associated electrical connections. Typical diameter of sleeve for LP and LP-HI varies from 2.5 to 5.0 cm and for MP-HI lamps is between 3.5 and 10.0 cm. The position of UV lamp along the length of the sleeve, depending on the configuration of UV reactor, can vary. The lamp sleeves absorb some of UV light, as shown in the Figure B-13, and may affect the dose delivery.

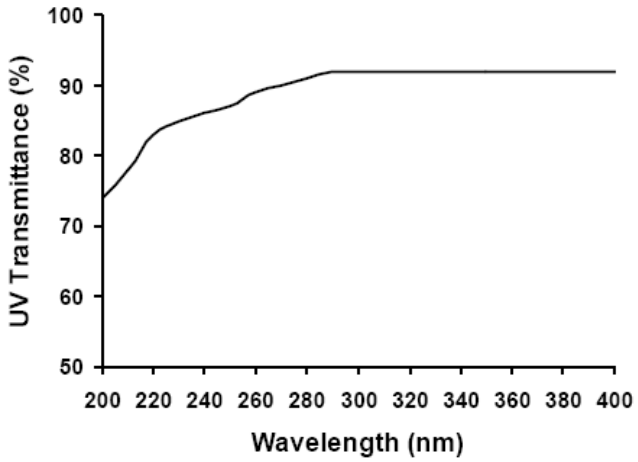

Figure B-13: UVT of 1 mm thick tube of quartz at zero degree incident angle (USEPA, 2006)

Lamp sleeves can also be fouled internally and externally that in both cases, the UVT of the lamp sleeve decreases. The internal fouling can be attributed to the disposition of material from components within the lamp or sleeve and can be controlled by appropriate selection of material (USEPA, 2006). Fouling on the external surface of the lamp sleeve is caused by combination of thermal effects and photochemical processes ((Derrick and Blatchley, 2005). Automatic or manual cleaning can take care of external fouling.

B.7.4 Cleaning system

Different approaches for cleaning the external surface of lamp sleeves have been developed and adopted by UV reactor manufacturers. The developed approaches include off-line chemical cleaning (OCC), on-line mechanical cleaning (OMC) and on-line mechanical-chemical cleaning (OMCC) methods. In OCC method, the reactor is shut down, drained and flushed with a cleaning solution. The frequency of cleaning in this method varies from once in a month to yearly basis depending on the water quality (USEPA, 2006).

In other two methods, wipers are used and move along the length of the lamp sleeve. Stainless steel brush collars or Teflon rings are used in OMC method whereas in OMCC, a collar filled with cleaning solution is used for cleaning purpose. In both methods draining of UV reactor is unnecessary and the reactor can remain on-line while cleaning process is being carried out (USEPA, 2006).

B.7.5 UV Sensors

UV sensors measure the UV intensity at a point within the UV reactor and it can potentially be used with measured flow rate and UVT to indicate the delivered dose. The measurement responds to changes in lamp output, lamp and sleeve aging, and lamp sleeve fouling. It may also respond to the UVT of the water depending on the position of sensors. Sensors need to be validated for their performance (USEPA, 2006).

B.7.6 UVT Analysers

UVT is an important parameter for calculating UV dose in the reactor. There are two types of on-line UVT analysers available commercially. One calculates the UVT by measuring the UV intensity at various distances from a lamp (Figure B-14). This type of analyser is external to the UV reactor and receives a sample of water flowing through a cavity containing and LP lamp with three UV sensors located at different distance from the lamp. The difference in sensor readings is used for UVT determination (USEPA, 2006).

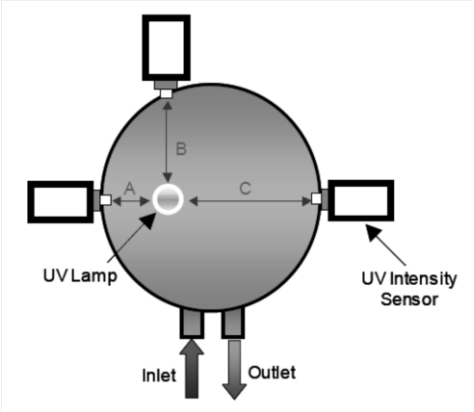

Figure B-14: Example of UVT analyser design (Source Internet)

The other type of UVT analyser is a flow-through spectrophotometer that uses a monochromatic UV light source at 253.7 nm to calculate and display UVT (USEPA, 2006).

B.7.7 Temperature Sensors

Flowing water through UV reactor can absorb the heat generated form UV lamps and

prevent the reactor from overheating. Nevertheless, temperature can rise when the reactor is partially filled with water or flow of water is stopped. Therefore, UV reactors are equipped with temperature sensors to shut off the operation when temperature is above recommended operating range (USEPA, 2006).

B.8. UV Dose-Monitoring Strategy

The dose-monitoring strategy determines the operating parameters that can be used to confirm delivery of UV dose. It affects how a UV reactor is validated, how instrumentation and controls are designed and finally how the reactor is operated. UV manufacturer design their system to operate under either of the following approaches:

3. The UV intensity setpoint approach
4. The calculated dose approach

Table B-1 summarises the key characteristics of these two monitoring approaches and indicates the monitoring parameters for each approach.

Table B-1: Dose-monitoring approaches

Dose-monitoring Strategy	Parameter Used as the Operational Setpoint	Parameters Monitored During Operations to Confirm Dose Delivery
UV Intensity Setpoint Approach	UV Intensity	Flow rate Lamp status UV intensity
Calculated Dose Approach	Calculated or Validated dose	Flow rate Lamp status UV intensity UVT

B.8.1 UV Intensity Setpoint Approach

In this approach, one or more "setpoints" will be established during the validation testing of UV reactor. During operation of UV disinfection system, UV intensity will be measured by UV sensors and it has to be equal or greater than the setpoint(s) to ensure the delivery of validated dose. It is important to know that true measurements must be expected when UV reactor is working under validated operating conditions (operation within validated range of flow rates and lamp status). One key characteristics of this approach is that UVT is not a monitoring parameter during operation and instead, UV intensity readings should accounts for changes in UVT. The position of UV sensors is

very important and should be as close as possible to ideal location. This will ensure that UV intensity is proportional to the UV dose, irrespective of changes in UVT and lamp output. This means that if the sensor is too close to the lamp, changes in the lamp output will have impact on the measured UV intensity. Alternatively, if it is too far from the lamp, then changes in UVT of the water will have the disproportionate impact on UV intensity readings (USEPA, 2006).

There are two operating strategies for the UV Intensity Setpoint Approach known as single-setpoint and variable-setpoint operations, which are described and compared in Table B-2.

Table B-2: Comparisons of single-setpoint to variabl-setpoint operations (USEPA, 2006)

Operating Strategy	Description	Advantages	Disadvantages
Single-setpoint	One UV intensity setpoint is used for all flow rates that were validated	Simplest to operate and control	When flow rate is variable, not energy efficient under most conditions because reactor is overdosing at low flow rates
Variable-setpoint	The UV intensity setpoint is determined using a lookup table or equation for a range of flow rates	Lamp output can be reduced at low flow conditions to reduce energy costs	More validation data are needed. More complex operation compared to single-setpoint approach. Necessitates more advanced UV reactor monitoring and control.

B.8.2 Calculated Dose Approach

In this approach, a dose monitoring equation is used to estimate the UV dose according to the measured parameters, such as flow rate, UV intensity and UVT, during reactor operations. UV manufacturer may use numerical models to develop a theoretical dose-monitoring equation. Although this equation can be considered as starting point, but EPA strongly recommends using an empirical monitoring equation developed during validation testing. Validation tests are conducted over a wide range of flow rates, UVT values and lamp power combinations and then the empirical equation will be generated (USEPA, 2006).

B.8.3 Advantages and Disadvantages

The principal operating advantages of the UV Intensity Setpoint Approach is that it is not required to measure UVT of the water to show dose delivery. The other advantage, especially in case of single-setpoint, is its simplicity to control with one operational setpoint and one maximum flow rate. EPA believes that this approach is suitable for small systems (USEPA, 2006).

The advantage of Calculated Dose Approach over UV Intensity Setpoint Approach is its flexibility to reduce the operating costs by manipulating lamp power in case of higher UVT. It also provides flexibility in positioning the UV sensor. Other advantage is that the operation is more intuitive because the calculated dose can be compared to the required dose for target microorganisms (USEPA, 2006).