HEALTH MONITORING OF FEEDBACK CONTROLLED MECHATRONIC SYSTEMS

Thesis submitted in fulfilment of the requirement for the degree of Doctor of Philosophy

By

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ABSTRACT

Health monitoring is essential in guaranteeing the safe, efficient, and correct operation of complex engineering systems. This PhD thesis presents a simulation of a non-linear, experimental-based model of a coupled tank apparatus CE105 under LabVIEW environment. The consideration of a traditional simple tank system is extended via the inclusion of non-linear elements. The simulation is used to accelerate the timescales of the monitoring and controller signals for nominal and faulty behaviour for several operating scenarios. In this study, a detailed simulation with several sources of fault was produced and run with the variety of operating scenarios to study the nominal and faulty behaviour of such mechatronic system.

It is concluded that the liquid level will not be affected by fault nature and intensity in the presence of PID controller that covers hidden faults until its signal reaches a certain threshold. Hence, the end of useful life can be predicted by tracking the PID signal at any stage of the operating scenario.

Technology advances have impacted upon monitoring, diagnostics and prognostics activities for increasingly sophisticated industrial systems and their operations. In particular, for integrated mechatronic systems, the facility provided by dynamic simulation models in presence of deteriorating faults has been investigated. For informed data-driven prognostic extrapolations, the long-term, time-varying operational profile of the mechatronic system requires recording and analysis. The contribution reported in this study relates to the simulation and experimentally validated, of a CE105 coupled-tank liquid level control system and three individual-thank liquid level system. A Sign Chart Algorithm (SCA) was developed and utilised as a novel controller-based health monitored (CBHM) system. Moreover, from the SCA and the PID signal trend, the remaining useful life of the system has been estimated. Results are reported and discussed for leakage or blockage and pump performance deterioration faults.

Keywords

Controller-based health monitoring; Liquid level system; Model-based simulation; Nonlinear system; Prognostic and health management; Remaining useful life estimation; Sign chart algorithm; System health monitoring.

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LIST OF ABBREVIATIONS

CBHM	Controller-Based Health Monitoring System
CBM	Condition Based Maintenance
CM	Corrective Maintenance
DC	Direct Electric Current
EOL	End of Life
FCA	Failure Criticality Analysis
FLC	Fuzzy Logic Control
GUI	Graphical User Interface
HM	Health Monitoring
HUMS	Health and Usage Monitoring System
I–P	Installation–Potential failure
LLTS	Liquid Level Tank System
LTI	Lead Time Interval
NI	National Instruments
PC	Personal Computer
P–F	Potential failure–Functional failure
PHM	Prognostic and Health Management
PI	Proportional Integral
PID	Proportional – Integral- Derivative controller
PLC	Programmable Logic Control
PM	Preventive Maintenance
POF	Probability of Failure
PWM	Pulse Width Modulation
RUL	Remaining Useful Life
RUL PDF	Remaining Useful Life Probability Density Function

SCA	Sign Chart Algorithm
SIMO	Single Input Multi-Output
SISO	Single Input Single-Output
SPC	Statistical Process Control
TTS	Three Individual-Tank System
VCC	Voltage, Common Collector

LIST OF NOMENCLATURES

a	Constant equal to the orifice cross-sectional area multiplied by the discharge coefficient through an orifice.
A	PID signal trend parameter
A_t	A cross-sectional area of the uniform cross-sectional container, mm^2
B	PID signal trend parameter
C	PID signal trend parameter
D	PID signal trend parameter
E	PID signal trend parameter
F	PID signal trend parameter
$F1$	PID signal trend parameter
$F2$	PID signal trend parameter
g	The acceleration due to gravity $m.s^{-2}$
h	Steady state liquid level *mm*
$\dot{h}$	The rate of change of the liquid level (*h*) concerning time $m.s^{-1}$
K	Discharge coefficient $m^2.s^{-1}$
K_c	The proportional gain of the PID controller
$\dot{m}$	Liquid mass flowrate passes through the discharge valve $kg.s^{-1}$
P	Hydrostatic pressure $N.m^{-2}$
P_i *and* P_o	Pressure difference before and after the outlet restriction respectively $N.m^{-2}$
$Q_{Blockage}$	Blockage as a percentage of the nominated flowrate
q_i	Liquid inflow rate, $l.min^{-1}$
Q_i	Inlet liquid flow rate, $m^3.s^{-1}$
Q_{lam}	Laminar outflow rate through the drain valve $\mathrm{m}^3.s^{-1}$

Q_{Leak}	Leakage as a percentage of the nominated outflow rate $\mathrm{m}^3.s^{-1}$
Q_o	Liquid outflow rate $\mathrm{m}^3.s^{-1}$
Q_p	The pump outflow rate $l.min^{-1}$
Q_{tur}	Turbulent flowrate through the drain valve $\mathrm{m}^3.s^{-1}$
R	Flow resistance through the outlet restriction.
R^2	Correlation coefficient to describe how well a trend equation describes the data in Microsoft Excel
T	Time in *seconds*
T_d	Derivative time of PID controller, min
T_i	Integral time of PID controller, min
$V1_{PID}$	Linear term of the PID signal trend
$V2_{PID}$	The exponential term of the PID signal trend
v_i and v_o	Liquid velocity at point (i and o) respectivily $m.s^{-1}$
V_{PID}	PID signal $volt$
x	Independent variable of a trend function
y	The dependent variable of a trend function
Z_i and Z_o	The vertical position of point i and o respectively m
η_p	Pumping efficiency %
$\propto$	Scale parameter, $\propto= 1$ for laminar flow through the outlet restriction, and $\propto= 2$ for turbulent flow
ρ	Liquid density $kg.m^{-3}$

Chapter One

Introduction

1.1 Background and motivation

System health monitoring is state of the art in many kinds of industrial processes. In-service system failure can be assumed as a nightmare of industrial activities. In the early monitoring system, people have often used their ears or screwdrivers for example, as a pick-up sensor of noise and vibration, while the machine was in operation. Typical modern condition-based monitoring systems consist of different kinds of sensors and data acquiring systems, integrated with computer software programmes, which analyse the relevant signals to assess the system health.

Due to the increasing complexity of the modern systems under control and the interest to achieve optimal performance, the development and monitoring of control system have significantly grown in the past decades. Mechatronic systems can be defined as the synergistic integration of sensors, actuators, signal conditioning, power electronics, decision and control algorithms, and computer hardware and software to manage complexity, uncertainty, and communication in engineered systems. The vast majority of mechatronic systems are controlled by two types of well-known controller, Proportional – Integral-Derivative (PID) controller and Programmable Logic Controller (PLC).

An effective and robust on-line monitoring and predictive maintenance technology are used to detect impending faults in machines and allow maintenance activities to be scheduled. To maintain systems operating at optimal levels, detection of faults in their critical components (e.g. valves and pumps) is essential. Any fault if it is not detected in time, will often progress to more severe failure affecting the other equipment of the system.

Liquid level systems have a wide range of sensors and electrically or manually operated control valves and pumps. Rotary and diaphragm pumps components are commonly used in such systems. They are exposed to tension-compression or repeated bending stresses developing cracks in their internal components that eventually lead to elements failure. Diaphragm fatigue and bearing degradation are well-known problems in many industrial applications. It will be essential to enhance the reliability and lifetime of equipment to run liquid level systems at optimal levels in industrial activities. This issue encourages engineers and scientists to develop different approaches of condition-based monitoring and fault detection technologies for an early alert of incipient mechanical and/ or electrical faults occurrence. Reliable and robust monitoring systems can lead to plan maintenance activities according to the system health condition before component failure, thereby minimising inherent damage to related components. Scheduled maintenance activities can cover all preventive maintenance, including routine checks, periodic maintenance and periodic testing. Hence, if a health condition-based monitoring programme is successfully implemented, it will allow the system to operate up to its full capacity without having to halt the machine at fixed periods for inspection while it shows a healthy performance even with the presence of hidden faults.

1.2 Controller-based monitoring (CBM) system

Prognostics and health management (PHM) is a new engineering approach, which enables real-time health estimation of a system during its operating scenario. Moreover, it is possible to predict the system future state based on up-to-date information by incorporating different fields such as sensing technologies, failure physics, control and machine learning, modern mathematical and statistical approaches and data acquisition. PHM enables engineers to use data and health state information to improve their knowledge of the system and provides a technique to maintain the system working in its healthy condition. Regardless, PHM has initiated at the aerospace industry; it is now expanded to be used in many applications including manufacturing and industrial activities, automotive, railway, energy power generation, and heavy industry (Kim, An et al. 2017). At first, PHM was started to reduce helicopters accident rate by the Civil Aviation Authority of the United Kingdom in the 1980s and has been developed in 1990s based on health and usage monitoring system (HUMS) that measures health conditions and performance of the helicopter. HUMS achieved excellent results to reduce accident rate by more than a half by being set on in-service helicopters (John Burt 2011). In recent years, prognostics and health management has revolutionised the perception of product reliability and has resulted in a wide range of applications. Commercial and military markets request even greater reliability from mechatronic systems where fault could lead to catastrophic failures. As a result, there is an increasing demand for a significant change in reliability towards systems health assessment, fault diagnostics, and prognostics (the real-time prediction of reliability and estimating the remaining useful life) of mechatronic systems. Also, there is a particular need to address continuous faults and intermittent failures which are common degraders of system reliability.

The goal of PHM is to minimise the possibility of time loss due to faulty operation, routine inspection, degradation of systems and maintenance. Industrial activities apply PHM to manufacturing processes and equipment management as a key part of proactive maintenance thrust that began several years ago. This approach was a natural improvement of preventive maintenance to performance or condition-based maintenance. Cost and benefit advantages are quite significant – savings in maintenance and spare parts costs, elimination of in-service stoppages, and final product quality and reliability improvements. PHM has been applied to aerospace and military systems for more than three decades.

One of the main objectives of health monitoring is continuously observing the behaviour of a mechatronic system and estimate how health it is to accomplish the future required scenario. Condition-based maintenance is based on using real-time prognostics and health management data to arrange and optimise maintenance activities. It could be worth to track the control signal of feedback controlled mechatronic systems to estimate the whole system health condition, which can be called controller-based monitoring (CBM) approaches. By observing the health condition of a system, maintenance activities can be precisely scheduled in advance, which leads to maximising the remaining useful life of this equipment. Using CBM, maintenance personnel can decide when the right time to perform a specific maintenance activity. Ideally, CBM will allow the maintenance personnel to do only the right activity at the right time, minimising spare parts quantity and cost, system downtime and time spent on maintenance. The controller signal of a closed loop controlled mechatronic system can be continuously monitored to assess the equipment health condition and predict when this system will reach its end of life in the presence of faults.

1.3 System under study

Liquid level tank system (LLTS) has a wide range of industrial application with different kinds of liquids, tanks size and shape, control approach, transducers and auxiliary components. A test rig CE105 was chosen to be used for this research purposes. The first stage is to build its model from the experimental data and then construct a comprehensive simulation under LabVIEW environment containing two types of proposed fault sources. The process of creating models from experimental data is called system identification. System identification involves building a mathematical model of a dynamic real-time system based on a set of measured input and output data (raw data). It is a process of acquiring, formatting, processing and identifying mathematical models based on raw data from the real-world system. It is beneficial to start developing a system model, as a first step, to control the system precisely. The primary objective task of modelling is to obtain a useful and reliable tool that can be used for the requirements of analysis and control system development.

In this PhD research, the system identification of real-time liquid level system is made using real-time data. From the calibration equations of the components of CE105 test rig, a detailed simulation was built and used as a virtual system to monitor its behaviour instead of the real system under different operating and faults scenarios.

The result from CE105 coupled tank system was confirmed on a new three individual tank system.

1.4 Health condition-based monitoring systems

Health condition-based maintenance needs to have continuous monitoring of system data to provide an accurate assessment of the system health, or status, a component/ system and performing maintenance based on its observed health. It involves using real-time monitoring and data acquiring and processing. Another capability that may form part of CBM system is an ability to provide an estimation of the remaining useful life (RUL) of the system or component under-monitored. This type of functionality is known as prognostics. Meanwhile, diagnostics uses to assess the current condition of a monitored system. Health condition-based maintenance approach promises a range of improvements over existing approaches. This improvement will lead to a significant reduction in overall maintenance costs, and hence, it becomes one of the primary drivers for developing such approach. Corrective maintenance approach has a relatively low maintenance cost because it leaves the system in service regardless of its health condition, i.e. the presence of fault until this fault becomes a failure. But this has high-performance costs associated with the high cost of operational failures. In contrast, preventative maintenance approach generally has a low operating cost, associated with the reduction in the probability of in-service failures. But, using a conservative estimation of a system failure probability increases the maintenance costs, associated with the removal of components before they have practically reached the end of their useful lives. It seems that the most cost-efficient approach is to undertake maintenance only when there is objective evidence of near failure, i.e. condition-based maintenance. The development of CBM approach has been enabled by the development of sensor technologies, data collection, storage and processing capabilities, and continuous improvements in algorithms and data analysis techniques. CBM systems are founded upon the ability to conclude equipment health condition using data acquired from the monitored systems. Ideally, a complete CBM system will be achieved by integrating both diagnostic and prognostic capabilities. The distinguishing factor between diagnostic and prognostic capabilities is the nature of the analysis. Diagnostics involves posterior event analysis (i.e. identifying the occurrence of an event which has already occurred), while prognostics is concerned with prior event analysis (i.e. predicting the future behaviour of the system under monitoring) (Jardine, Lin et al. 2006).

1.5 Aim and objectives

The main aims of this thesis are to develop continuous health monitoring approach and prognostics capabilities to predict when the monitored system will reach its end of useful life to be used for important equipment within the industrial domain. This thesis aims to exploit system data which is acquired as a result of experimental tests of a PID controlled liquid level system. Employing this collected data from a test rig as a real feedback mechatronic system is the primary theme in achieving these aims. However, for continuous monitoring of the real system, the acquired data from different transducers of it becomes enormous, which in turn needs to prepare massive storage media and it may take a long time to be analysed. Moreover, it is not an easy task to send such amount of data via available communication networks, internet for example, abroad to a remote monitoring and analysis centre. Offshore wind and tidal stream turbines are two examples of such systems. This research aims to develop a new health monitoring approach, which returns simple and small in size but efficient to describe in-service system health.

The first objective of this thesis is to build a detailed simulation under LabVIEW environment (virtual system) in collaborated with nonlinear system mathematical analysis. The developed health monitoring solutions have demonstrated capability and applicability to this virtual system at this stage.

The second objective is to develop a comprehensive prognostic and health monitoring system for closed-loop controlled system, in particular, a PID control liquid level system. This continuous monitoring system is based on tracking the PID signal, and it has to return simple signal but clear and contains sufficient details to observe the in-service system health. The development of such controller-based health monitoring (CBHM) system for industrial applications has the potential to deliver significant advantages including reduction of the maintenance costs, reduce in-service failure and increased plant uptime. One of the most important benefits of the CBHM system is to observe the system health remotely via the internet by uploading only the CBHM signal because it has a small size, to the system analyser. Stored data on in-site storage media from the whole system’s transducers still need to be used in order to track the history of each signal during previous operating scenarios.

The third objective of this thesis is to demonstrate how efficient the CBHM is going to detect and monitor the developed fault by adding different fault sources and intensity to the virtual system. Hence, it can be run for a broad scope of operating and fault scenarios; this is another objective of this thesis.

The final objective is to estimate the remaining useful life of the system at each step of the operating scenario based on the CBHM signal.

1.6 Contributions of this research

Equipment is usually used until failure occurrence and then having corrective maintenance. However, run-to-failure maintenance philosophy becomes a less-possible option if not impossible as systems complexity rapidly increased. System's critical components become more expensive than they were. These factors have a direct influence on the total final production costs. Thus, this programme of research investigates the qualities of using a new health controller-based approach as a reliable, stable and practical continuous monitoring technique. This approach can be used for different sort of feedback controlled mechatronic systems. This thesis claims that this new approach offers the following original contributions:

1. Early warning of slow progressed deterioration hidden faults.
2. According to the CBHM system, preventive maintenance can be scheduled to increase the efficiency of the mechatronic system by minimising unwanted stoppages.
3. Estimation of location and type of faults and their severity in real-time throughout continuous tracking the controller signal.
4. A new system-health monitoring algorithm.
5. The historical record of operating scenarios and any fault occurred in the past and how it was developed with the time.
6. Estimation of the PID control signal trend due to different faults occurrence.
7. Evaluation of the system end of life (EOL) and its remaining useful life (RUL).

1.7 Thesis outline

This PhD thesis includes seven chapters. These chapters and the research methodology are as shown in Figure 1.1. Chapter 2 summarises the literature studies that included an overview of different approaches to system health monitoring and maintenance. In Chapter 3, a non-linear liquid level system is mathematically analysed, and CE105 coupled tank system is discussed in details. Experimental calibration equations of the system components are evaluated to build a detailed virtual system. Chapter 4 presents in details proposed fault sources of CE105 and implement them in a comprehensive simulation under LabVIEW environment. A novel Sign chart algorithm (SCA) is presented as a controlled-based health monitoring approach to diagnosing the monitored system. Estimating the control signal as a result of faults, predicting when the system will reach its end of life and evaluating the remaining useful life are presented in Chapter 5. The aim of Chapter 6 is demonstrating a new three individual-tank system designed and producing, laboratory experiments and the system simulation under LabVIEW. Chapter 7 provides concluding remarks and recommendations for future research.

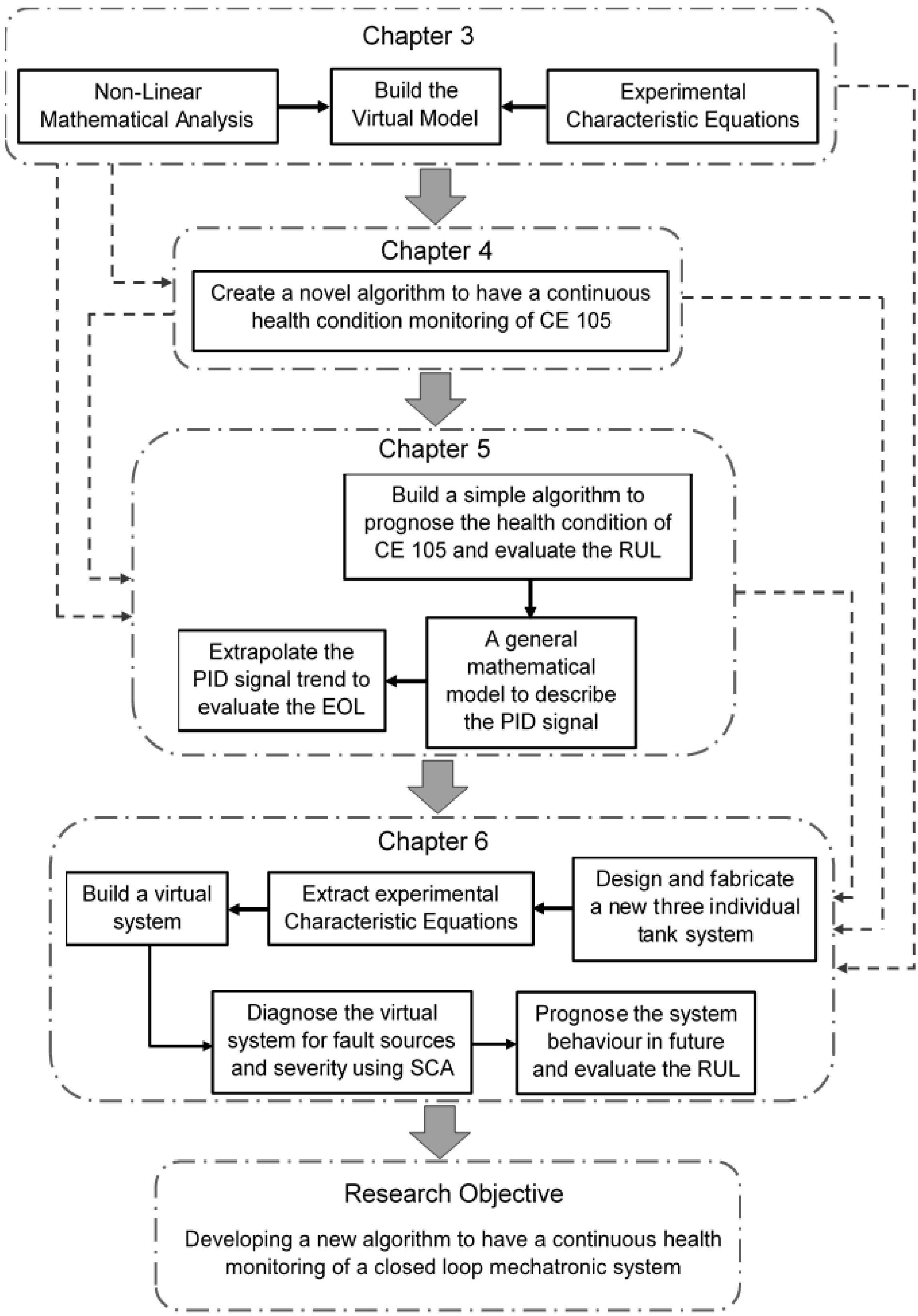


Figure 1.1 Flow chart shows the outline of the thesis

Chapter Two

System Health Monitoring

2.1 Introduction

This chapter presents a review of the background of system health monitoring, fault diagnostic and prognostic algorithms. The layout of this chapter is as follows.

Section 2.2 reviews the background of the traditional maintenance philosophies and the reason behind the preference to choose any of them to use in a specific industrial application. Final product cost can be divided into two main parts; operational and maintenance costs. This section emphasises the need to utilise health condition-based monitoring to have an efficient maintenance approach and reducing the total cost of products as a result. The relationship between maintenance cost and operating cost is presented in Section 2.3 for both of the traditional philosophies and the condition-based maintenance. Health condition-based monitoring of a typical system failure goes through several stages from hidden a fault up to failure. During them, the system shows warning signal depending on how severe the fault is going to be. This section presents these stages and the effect of having a strict estimation and its impact on the suitable time to start maintenance activities. System fault diagnostic algorithms of high technology equipment are presented in Section 2.4. Meanwhile, prognostic as the second portion of system health management is explained in Section 2.5. It presents that having an efficient prognostic approach can provide advanced notification of the next required maintenance activities. Section 2.6 defines the system health monitoring and its motivations parameters. Moreover, it presents the system health monitoring approaches and tools. Section 2.7 presents several definitions of prognostic and health management and the activities that it consists. In Section 2.8 fault diagnostic methods of mechatronic systems and data processing procedures are reviewed. A literature review is separately presented for each of experience-based, model-based and data-based prognostic approach in Section 2.9. Conclusions of this chapter are summarised at the end of it in Section 2.10.

2.2 Maintenance philosophies

There were two traditional well-established maintenance philosophies, Corrective Maintenance (CM) and Preventative Maintenance (PM), applied to maintenance activities for critical parts, subsystem and systems. Maintenance management for industrial systems aims to reduce the overall maintenance cost and to improve the availability of the systems. The first philosophy is corrective maintenance approach, which involves running a system until it fails to achieve its task. Only then it is repaired and returned to a healthy condition. This approach is deemed appropriate for elements that are costly to repair or replace. The corrective maintenance approach could be suitable in such cases, with a normal condition that the element failures will not:

- Damage to human safety.
- Lead to subsequent massive damage.
- Ultimately becomes expensive.

The second philosophy is preventative (or schedule-based) maintenance approach that utilises statistical methods. For example, the tracked or estimated mean time between failures of a given component will inform the future scheduling of the system maintenance events. Measuring the number of flight hours to have routine maintenance, inspection and repair of an aircraft engines; accordingly, is an example of the preventive maintenance approach.

In choosing either preventative or corrective maintenance, any organisation will consider the financial implications. Briefly, some other aspects to be considered are as follows. The utilisation of worst-case failure statistics to schedule preventive maintenance usually will not give an accurate estimation relating to the probability of the system failure at any point in time. A more conservative approach leads to parts frequently being replaced long before the end of their useful life. As stated, a corrective maintenance approach will maximise the useful working life of elements within a system but may ultimately lead to more extensive damage to other elements or the entire system. On the broader picture, a significant increase in repair costs combined with more extended downtime and a loss of income may prevail. The actual condition of a system, ideally known or assessed just before the failure occurrence, does not need to be taken in mind when scheduling the maintenance activity. Nowadays, there is competition between industrial companies around the world to minimise equipment size and increase their efficiency, which makes the system and equipment more complicated and expensive. Moreover, this will increase the reliance upon, and interest in system reliability and availability (Vachtsevanos 2006).

Unscheduled maintenance due to unexpected equipment failure can add significant extra costs, including any failure that may be caused by an in-service equipment failure. The time needed to accomplish unscheduled maintenance activities could be extended due to a shortage of necessary parts, equipment, and staff. Moreover, there is an extra time has to be added to repair secondary failures. In the United States, the degradation of revenue as a result of the reduction or halting electricity production during this extended repair time is estimated at approximately $1.25 million per day of plant downtime for an average nuclear power plant (Coble, Ramuhalli et al. 2015). There are economic dependencies between wind turbines for example and their components. Once a maintenance team is sent to the wind farm, it may be more cost-effective to take the opportunity to maintain multiple turbines. During a turbine downtime for maintenance, it is more economical to simultaneously maintain multiple components which show relatively high risks to fail in near future than just the damaged one.

The operation and maintenance costs represent a significant portion of the total life-cycle costs of wind power generation systems, and so as other industrial systems (Hau 2013). For that, modern complex industries seek to reduce the overall products cost by:

- Reducing the maintenance cost.
- Maximising the useful life of machines and systems.
- Minimising the risk of massive failure.

Modern maintenance methods for mechatronic systems can be classified into corrective maintenance, preventive maintenance and Condition-Based Maintenance (CBM) (Jardine and Tsang 2013). By utilising health condition monitoring data collected from critical components of a system under monitoring, CBM strategy can be used to reduce its operation and maintenance costs. Condition monitoring data, such as vibration, acoustic emission, oil analysis, power voltage, electrical current data, liquid level and oil temperature are some examples of data can be collected depends on the system function and structure, from wind turbine components (Liu, Tang et al. 2010), (Hameed, Ahn et al. 2010).

Accordingly, this led to thinking of a new maintenance philosophy. Industries may have a significant improvement in both efficiency and productivity by utilising appropriate condition-based monitoring and maintenance techniques. Maintenance cost analyses have shown that a corrective maintenance activity, usually costs more than the same maintenance activities when a condition monitoring accompanied by it. Additionally, there is an extra cost has to be added for every single day shutdown depending on the type of establishment activity as shown in Table 2.1. The objective of condition-based maintenance (CBM) approach is to optimise the availability of expensive systems, moreover minimising the total cost of maintenance activity and logistics requirements. So that, the maintenance activities are performed only when there is an indication of deteriorated behaviour. (Tian and Jin 2011) claimed that they developed an optimal condition-based maintenance solution to address the issues mentioned above. A simulation method is designed to evaluate the cost, as an important factor, of the CBM policy. CBM is an advanced maintenance approach that is based on the real-time performance and/or parameter of the system health monitoring approach (Jin and Mechehoul 2010). To have efficient condition-based maintenance, some relevant data, such as temperature, pressure, electrical current, voltage, vibration level and oil temperature and quality needs to be collected and monitored

Table 2-1 Economic losses from a one-day shutdown (VTT 2015)

Establishment Activity	**Cost of every day shutdown in *Euro***
Nuclear Power Plant	300,000
Paper and Pulp Plant	200,000
Chemical Factory	100,000
Power Plant (Coal)	100,000
Oil Refinery	50,000
Cargo Ship	10,000

A system running, and maintenance costs have a significant impact on the final product cost. Therefore, for the wind turbine power generation plant so as any other mechatronic system, reliability and maintenance management have increasingly drawn interests for reducing the operation and maintenance costs (Martínez, Sanz et al. 2009). CBM programmes aim to reduce maintenance costs in the following ways:

- Reducing any scheduled activities of preventative maintenance to a minimum number.
- Minimising the unnecessary replacement of elements and hence reducing the cost of spare parts.
- Preventing a possibility of massive failure of the system.

The guarantee of decreasing maintenance costs and on the other hand extending the useful system life will lead away from the traditional either preventative or corrective maintenance philosophy, in the direction of more condition-based approach.

2.3 Condition-based monitoring

Competition between different industrial activities such as chemical industry, oil refinery, power plant and energy market to operate their plants as cheap as possible in collaboration with minimising maintenance costs. In order to provide an accurate health assessment of a component, or subsystem/system, there is a requirement to have continuous monitoring of the system variables within the condition-based monitoring system. Maintenance activity is then based on such system health observation and estimation, utilising real-time monitoring and associated data processing. In a related approach, the remaining useful life of the monitored system has to be estimated; this is the hearth of an approach called prognostics and health management (PHM). Overall maintenance cost reduction is the main driving factor in the development of condition-based maintenance methods. Fault diagnostic activities study the current health condition of a monitored system in order to detect and identify which faults in particular, have been discovered. Figure 2.1 provides a representation of the costs associated with the preventive, condition-based and corrective approaches. Generally, preventative maintenance will reduce the in-operation system failures, and the operational costs will be reduced.

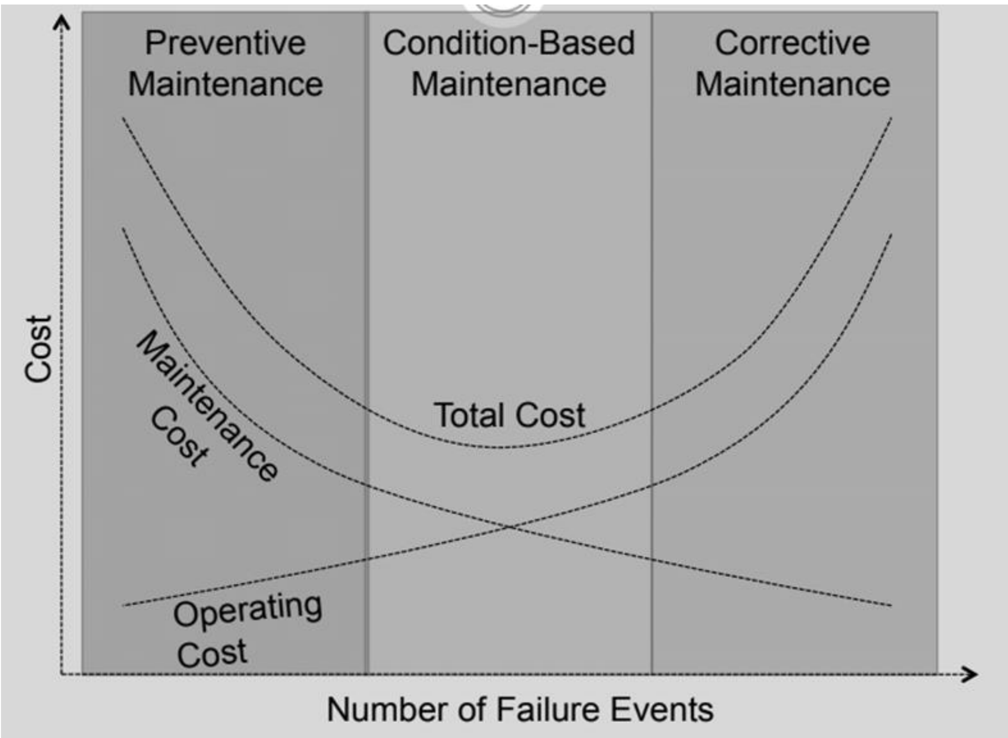


Figure 2.1 The relationship between activity costs and different maintenance approaches (Coble 2011)

Because the modern systems have a significant of components and subsystems, the existing CBM methods deal with the system components separately. Hence, maintenance decisions are made on individual components, rather than the whole system (Sørensen 2009).

However, replacing some components before they have achieved the end of their useful lives will raise the maintenance costs if a strict estimation procedure has been followed, as can be seen in Figure 2.2. (Rezvanizaniani, Liu et al. 2014) presented a review of prognostic and health management techniques to provide cost-effective solutions for health assessment of batteries.

Extreme corrective maintenance will entail relatively low maintenance costs by maximising the equipment life until it fails to accomplish its task; repairing a sudden failure during the operation period is typically expensive particularly when costly unscheduled downtime is included. The desire to achieve a more optimal cost - maintenance activity ratio requires a willingness to do maintenance when any evidence of developing faults appear, while the system still shows a healthy operational condition that leads to have condition-based maintenance methods. Figure 2.2 presents a typical machine-condition deterioration with the time. It shows that a machine, during its life from the first sign of its condition changing until the fault becomes a failure, passes through different stages. Some of these stations take months while the other may take only a few minutes. For that, machine condition monitoring is essential for any organisation because it provides valuable information to:

- Optimise the machine performance,
- Reduce the repairing time and prepare the required facilities which in turn leads to decreasing the overall maintenance costs.

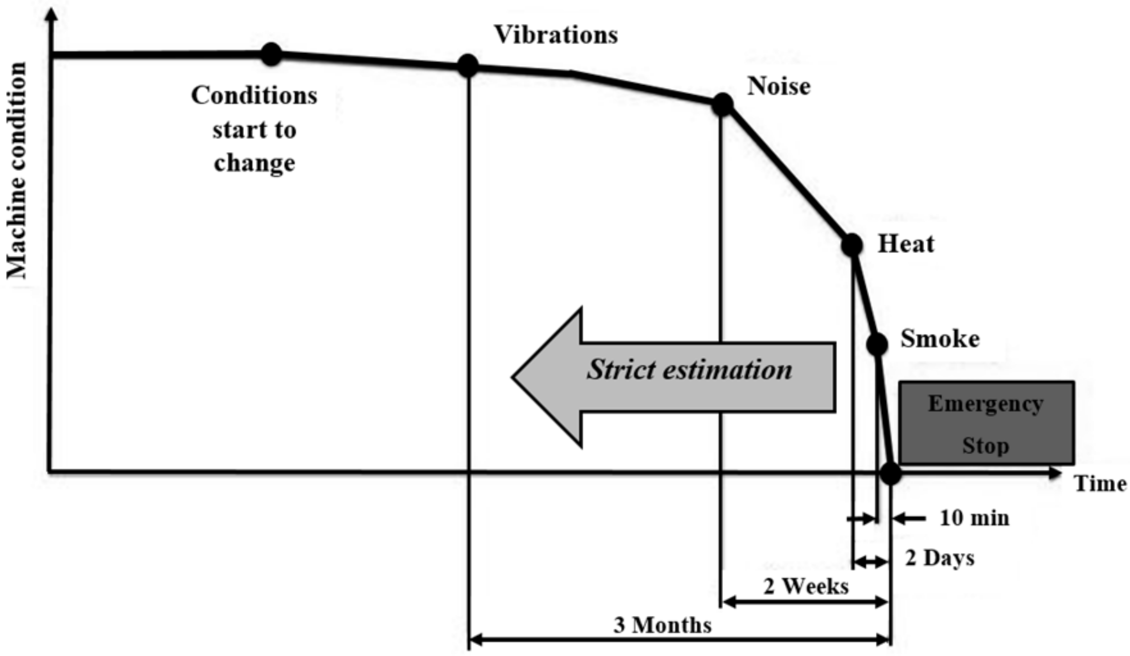


Figure 2.2 typical machine failure example and the warning signs (NI 2017)

Maintenance costs for remote locations systems, such as offshore wind turbine and tidal stream turbines, are typically high. (Bahaj 2011) noted, from his study of marine current turbines for electricity production, that to achieve an applicable economic power extraction, it is crucial to minimise uncertainty routine investigation and predictive maintenance of such equipment. For such systems, route-based monitoring or using portable diagnostics systems are not applicable. Instead, online condition-based tracking is applied from a central location (NI 2017). From another sector of electrical energy production, wind turbine, it was suggested that using an online health condition monitoring and fault detection could decrease overall maintenance costs and improve the availability of energy extraction technology (Tian and Jin 2011), (Yang, Tavner et al. 2010) and (Hameed, Ahn et al. 2010). There are several hostile or severe working environments, for such environments, monitoring of systems health condition and fault diagnosis hardware and software architectures should at this stage seek to be general and adaptable (Grosvenor, Prickett et al. 2014). Sensors, data acquiring and analysing algorithms, online communication facilities need to be developed to achieve this task. The improvement of sensors technologies in collaboration with data collection, transformation, storage and processing ability develops CBM approaches. Concurrently on-going research in the field is leading to improved and extend algorithms and techniques to analyse the collected data as a part of enhancing the condition-based monitoring. Condition-based maintenance approach was established upon the capability of understanding the health condition of equipment based on the received data from the monitored system. It is assumed that an integrated CBM system needs to include the facility of both diagnostics and prognostics.

These complementary activities are introduced in the following sections. Briefly, they can be distinguished as follows: Diagnostics contains prior event analysis, which means identifying the events that have already occurred in the past to establish a library or catalogue of information. Efficient diagnosis involves the detection, isolation and subsequent definition of the most likely faulty behaviour that has been captured. Prognostics is concerned with posterior occurrence analysis. Accordingly, the expected continuous deterioration of the monitored system in the future can be extrapolated forward in time, based upon recognition of the current health of the system and the operational profile. When the worst deterioration level is predefined and applied as a threshold that the system is predicted to fail at it, the Remaining Useful Life (RUL) can be estimated.

2.4 Diagnostics

During the last five decades, the efficiency of fault diagnostic algorithms has been applied and examined in different industrial applications. Aircraft equipment was the pioneer of applying some earliest generation of these algorithms. Robustness and reliability of a system faults diagnosis are the basis of any condition-based maintenance. As a system running during its life, some physical properties or quantities have changed with the time according to some faults or ageing for example. Monitoring the deterioration of these properties is the primary purpose of designing fault diagnostic algorithms (Vachtsevanos 2006). A perfect diagnostic system needs to have an ability to identify the unhealthy system, subsystem or element.

Usually, system fault diagnostic algorithms of the modern high technology equipment being complicated and accordingly need massive data – storage media. Nowadays, with high-power computers, stimulating the CBM to enhance these algorithms being available. It is possible in numerous developing application to identify the appearance of an ill-behaviour before the system failure. Accordingly, the maintenance staff has a valuable time to prevent catastrophic failure and to minimise the overall system downtime. Moreover, such abilities have driven the engineer efforts to improve the capacities beyond fault diagnostic activity, which is called prognostic.

(Vachtsevanos 2006) stated an acceptable definition among many others of "fault diagnostics" as; the term fault means, without a suitable maintenance activity, the system cannot achieve its task efficiently forever. Hence, the fault diagnosis is related to detecting an ill - behaviour as soon as it starts; isolating the concerned fault signal from noise and any other fault possibilities and then identify the fault type and its strength before the system ceased to operate or goes to fail.

2.5 Prognostics

The term prognostics covers a narrow scope of systems health management in compare with diagnostics. It provides information about the future health of the monitored system. Depending on the current system health condition and the historical operation profile, the prediction of the remaining useful life of the system before one or more faults occur is an obvious and widely used of prognostics. The remaining useful life refers to the time left before the system ceased to operate (Jardine, Lin et al. 2006). Figure 2.3 illustrates the timeline of a failure progression of a typical system component. It is assumed that at the start of the system life, the system is working correctly. Because of ageing and long-term of working, some incipient fault is expected to be developed in some critical component of the system. The severity of this fault is progressively increased with the time until the element fails to achieve its desired task or reached its end of life. Further damage to some equipment may lead to catastrophic damage to other components, subsystems or expose operators – life to a dangerous condition if the system is permitted to continue working in its ill – condition. It would be more desirable to predict whether the system capable of achieving the required future operating scenario without having a catastrophic failure or not. This estimation is a crucial task in nuclear power plants for example, before the next inspection interval (Jardine, Lin et al. 2006). Typically, diagnostics application occurs at the time when a component started developing a fault or beyond this until the system exposed to a comprehensive failure.

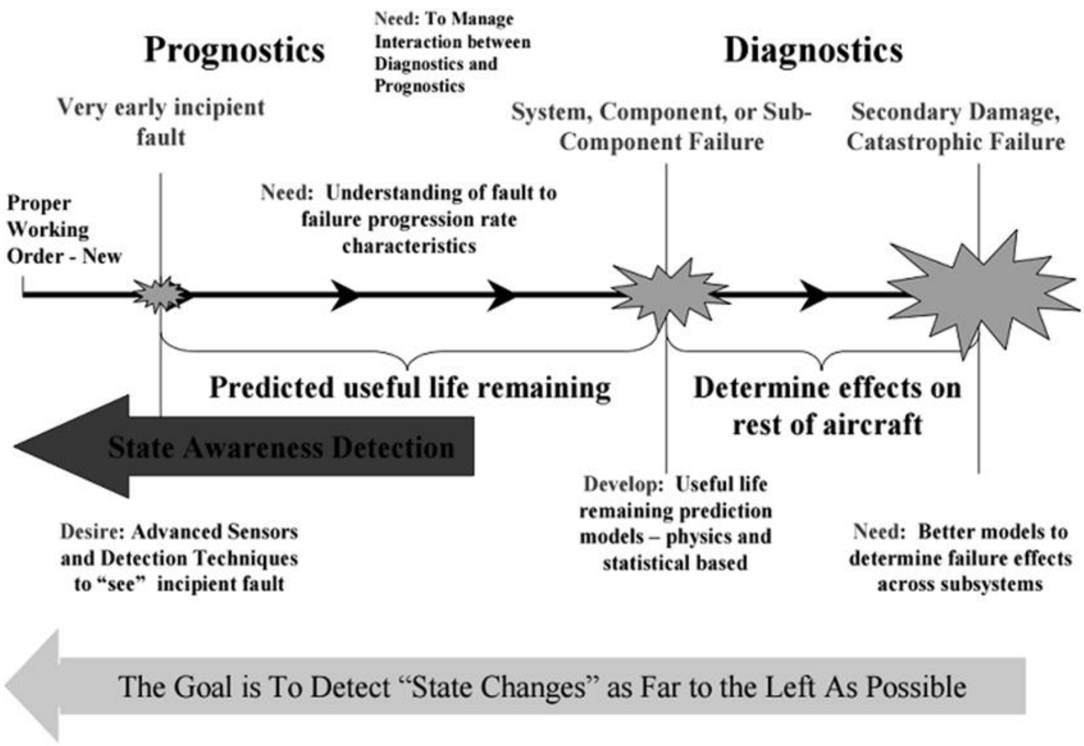


Figure 2.3 Fault Progression timeline (Hess, Calvello et al. 2006)

However, if a system developed a fault, which can be detected at an early stage, maintenance activity can be postponed until the fault progression reaches a more severe condition, but before failure occurs. The interval between the detection of a fault, condition and the occurrence of failure defines as prognostics application field.

Maintenance staff need to evaluate the remaining useful life of a system under monitoring in order to estimate if the RUL is sufficient to cover the next operation scenarios before the system failure. Assuming such a system during this interval of time has to continue working as usual before the diagnosed – fault deterioration becomes a failure.

Applying an efficient prognostic approach is to provide advanced notification of upcoming maintenance. This warning is crucial to schedule the corrective maintenance activities in advance. The provision of necessary spare parts, the experienced maintenance personnel and all logistic requirements will be essential for reaping the benefits of applying effective condition-based monitoring and maximise the saving of time and cost. During the provision period, the system works continuously until a predefined time to have a planned maintenance work. In contrast to the traditional maintenance approach where the system failure occurs without prior alarm, which leads to a massive delay in preparing the required spare parts, organising the professional team to return the system to its working condition. Interrupting the operating scenario of a system usually leads to further delay recovering it.

(Goode, Moore et al. 2000) utilised a Statistical Process Control (SPC) to divide the whole system life into two main intervals. They stated that the first interval starts directly after the system has been installed and run for the first time until a potential failure occurs, i.e., Installation–Potential failure (I–P), during this interval the machine shows a proper healthy condition.

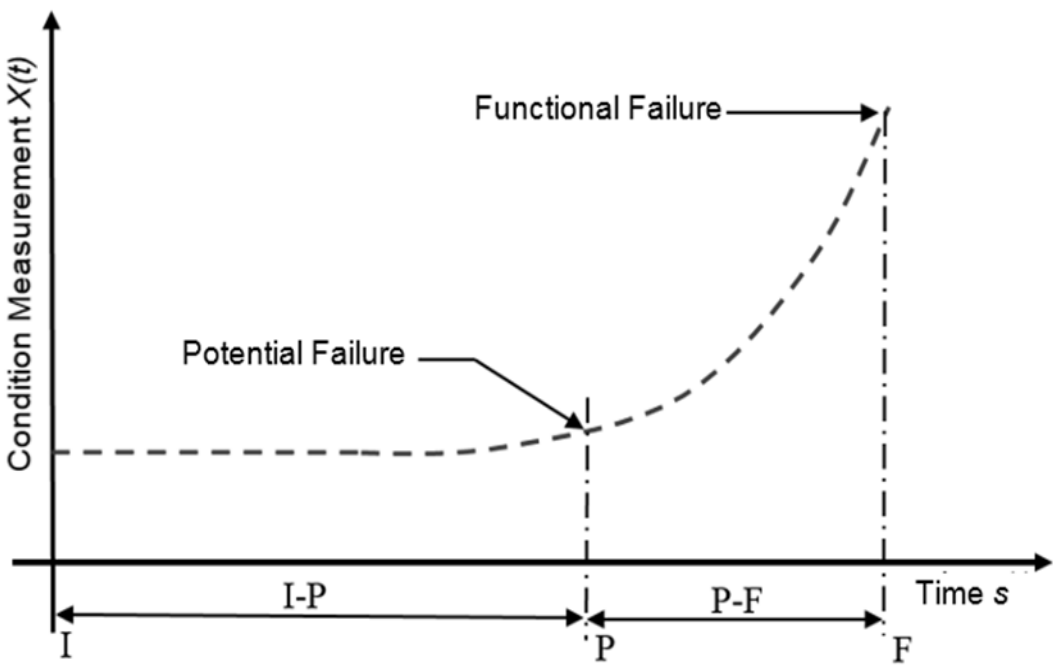


Figure 2.4 Machine life model (Goode, Moore et al. 2000)

While, the second interval as can be seen in Figure 2.4, Potential failure–Functional failure (P–F), during this period, the system is continuously running but with some problems. (Clements 2011) presented the effect of the deviation of the fault model and the reliability of the failure threshold that based on them, the system end of life will be predicted, as can be seen in Figure 2.5.

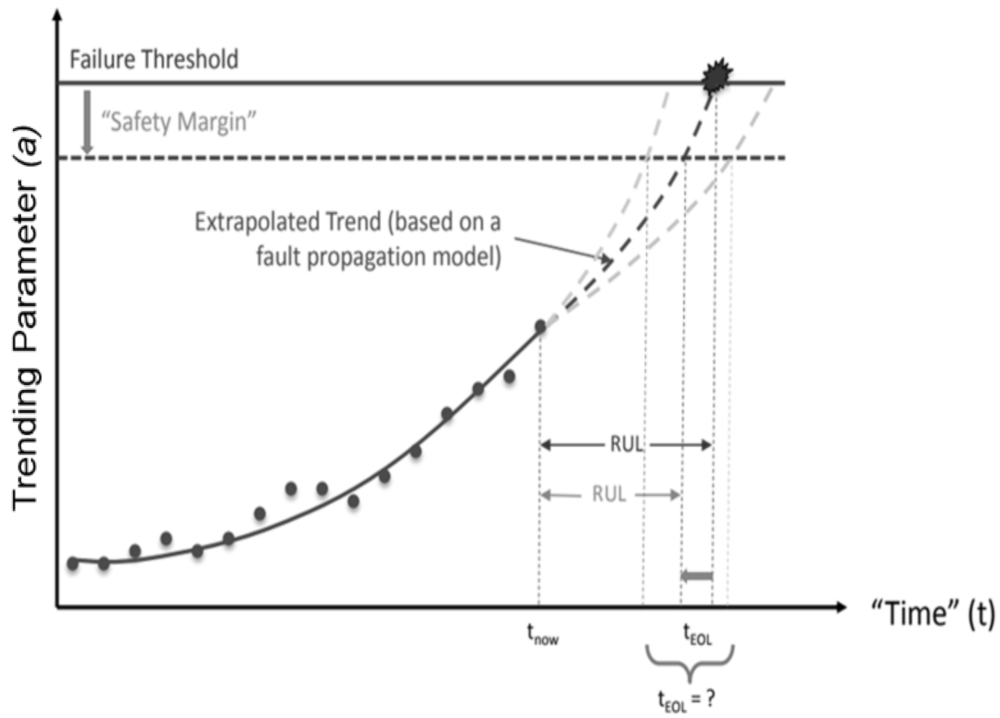


Figure 2.5 Potential failure–Functional failure (P–F) period (Clements 2011)

Practically, to monitor critical equipment, a regular examination is often utilised. A delay time analysis approach was developed by Christer and Waller in 1984 and published in (Christer and Waller 1984) and (Christer and Waller 1984) for modelling the benefit of applying this policy. A period of time between the point at which a fault is considerable and that at which the fault increases to become a failure is called a delay time (Goode, Moore et al. 2000).

The costs of the in-service system failure become much higher than the costs of repairing the failed elements. Unplanned shutdown due to an in-service failure occurrence of cooling water-pump within a nuclear power plant or large industrial factories for example, will add extra costs as shown in Table 2.1. Additionally, it takes longer time to recover it than the planned one. Moreover, this failure may lead to catastrophic damage to the plant and environment. If a major fault on a commercial aeroplane with passengers waiting at the gate, the cost can also surge beyond the ordinary repair costs. Such failure may lead to an unplanned shutdown, which in turn may cause massive damage to some other parts.

To achieve the desired benefit of prognostics, maintenance personnel needs to have a reliable estimation of how long the system will remain in safe operation, i.e. evaluating the remaining useful life of the system, until a predicted failure occurs. The development of efficient prognostic algorithms facing a challenge to generate an accurate prediction of remaining useful life. Prognostics involves a high degree of uncertainty by its inherent because it deals with predicting the future, as can be seen in Figure 2.5. By comparing the tasks of prognostics and diagnostics, it is considered that the former is harder than the latter, as the progress of the system fault conditions is subject to random processes that have not been occurred (Engel, Gilmartin et al. 2000).

2.6 System health monitoring

System health monitoring can be defined as a group of activities performed on a system to assess how fit to accomplish its required task. Monitoring may be limited to the observation of current system-states in addition maintenance and repair actions prompted by these observations. Alternatively, monitoring of current system states is being integrated with the prediction of future operating scenarios and predictive of future failure possibility.

Such integrated health monitoring system is motivated by the requirements of industrial activities and operators of complex systems to optimise equipment performance and to reduce the overall product costs and unscheduled downtime. Prognosis is not an easy task because it deals with predicting the future equipment health condition. Numerous modelling techniques have been reviewed in the literature and implemented in practice.

2.6.1 Maintenance strategies and motivations for health monitoring

The oldest and most common maintenance and repair strategy is "fix it when it fails." The appeal of this approach is that no data analysis or maintenance planning is required. The problems with this approach include the occurrence of unscheduled downtime at times that usually be inconvenient, perhaps preventing the accomplishment of required production tasks. Unscheduled downtime costs much more than scheduled and has more serious consequences in applications such as nuclear power plants and aircraft engines.

Motivation is provided to perform maintenance and repair before the problem occurrence by these problems. The simplest approach is to perform maintenance and repair at the pre-planned time, defined regarding elapsed or operating hours. This approach can provide relatively high equipment reliability, but it tends to be costly because of unwanted downtime for inspections and unnecessary maintenance activities. A further problem with time-based approaches is that failures are assumed to occur at specific time intervals.

The only way to minimise maintenance cost and the probability of failure is to implement continuous assessment of equipment health and continuous prediction of future failures. This procedure can be based on the system current-health with the presence of any hidden faults, operating condition and maintenance history. This approach motivates the prognostics to minimise maintenance costs and associated operational disruptions, while also reducing the risk of costly unscheduled downtime or in-service failure.

2.6.2 Health monitoring approaches

Researchers have been focused on health monitoring and its related functions and implementation during the last a few years. Through these years they have significantly developed regarding controlling philosophy, implementation, and enabling advances in technology, modelling techniques, and emerging or re-defined requirements. A brief taxonomy of the various philosophies is given in Figure 2.6.

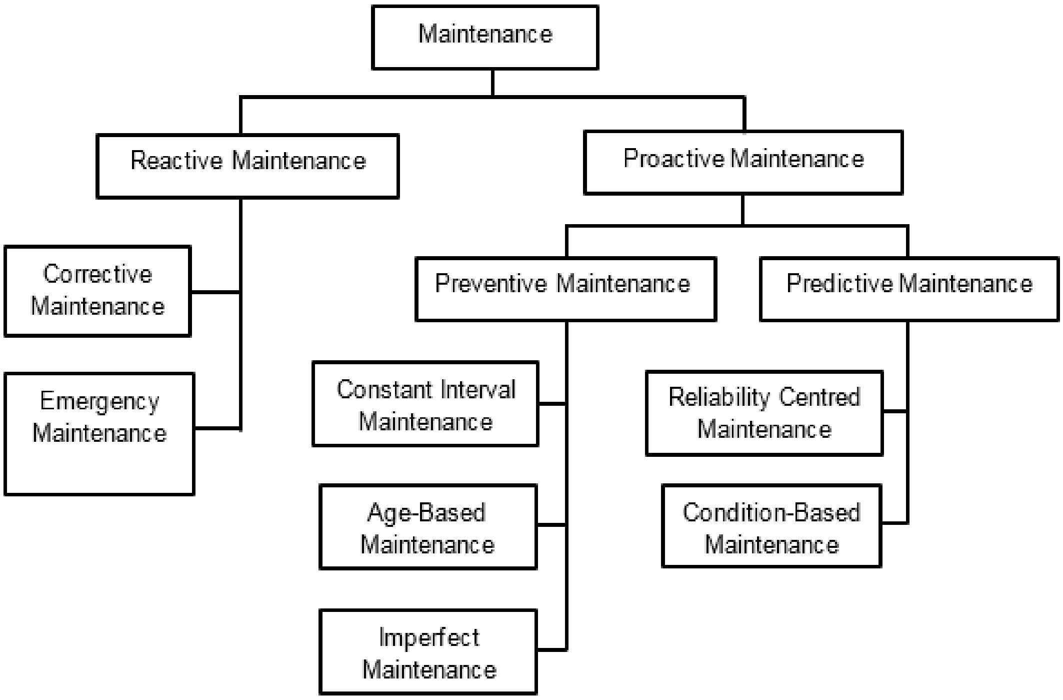


Figure 2.6 Taxonomy of maintenance philosophies (Kothamasu, Huang et al. 2006)

2.6.3 Health monitoring tools and techniques

Preserving the system health is a complex task, which requires a comprehensive analysis of the system condition, principles involved, and their applicability and implementation strategies. Table 2.2 presents methods, analysis and modelling tools, and techniques to provide data for modelling and analysis. However, it is clear that most applications are a combination of the listed methods and techniques and the list is far from being exhaustive. For example, and because of their generalised applicability, parameter estimation techniques such as regression, maximum likelihood and expectation maximisation can be used in all of the listed categories. There is also a close association between reliability-based maintenance and statistical maintenance techniques.

Table 2-2 Maintenance tools and techniques

Methods	Tools	Measurement techniques
Reliability-based maintenance	• Parameter estimation techniques. • Numerical analysis techniques • Markov chains	• Vibration analysis • Thermography • Acoustic emission • Wear/debris monitoring • Lubricant analysis • Process measurements
Model based failure detection and identification	• State space parameter estimation • Artificial neural networks • Knowledge-based systems • Fuzzy inference systems • Neuro-fuzzy systems	
Signal-based failure detection and identification	• Fourier analysis • Wavelet analysis • Wigner-Ville analysis • Diagnostic parameter analysis	
Statistical failure detection and identification/ maintenance	• Bayesian estimation/ reasoning techniques • Markov chains • Hidden Markov models • Proportional hazards models	

- **Reliability-based maintenance**

A popular maintenance approach of complex systems is going through estimating the reliability of the system. Traditionally, reliability is estimated from the time-to-failure distributions of the system. The most reasonable drawback of such approach is that multiple failure mechanisms often interact with each other in unpredictable ways and this affects the degradation rate of the system, causing it to deviate considerably from the predicted failure distribution.

- **A model-based approach to failure detection and identification**

Model-based approaches to failure detection and identification are based on analytical redundancy or functional redundancy, meaning different signals are compared and evaluated to identify presented faults in the system or its components. This comparison between the measured signal and the estimated values is generated by the system's mathematical-model. A general structure of model-based approaches is as presented in Figure 2.7.

Residual generation is essential in a model-based approach. However, the involved techniques in model-based diagnosis differ in the production and definition of residual. For example, in some cases, it is a disagreement of the system output estimation and the error in the parameter of the system's estimated model itself. It is crucial that the generated residual be dependent only on faults in the system rather than on its operating condition. Several techniques have been presented in the literature for this residual generation are a modification or improvement of the following three principles.

- Observer-based approaches (Beard 1971) and (Patton and Chen 1997).
- Parameter estimation technique (Kitamura 1980).
- Parity space approach (Chow and Willsky 1984).

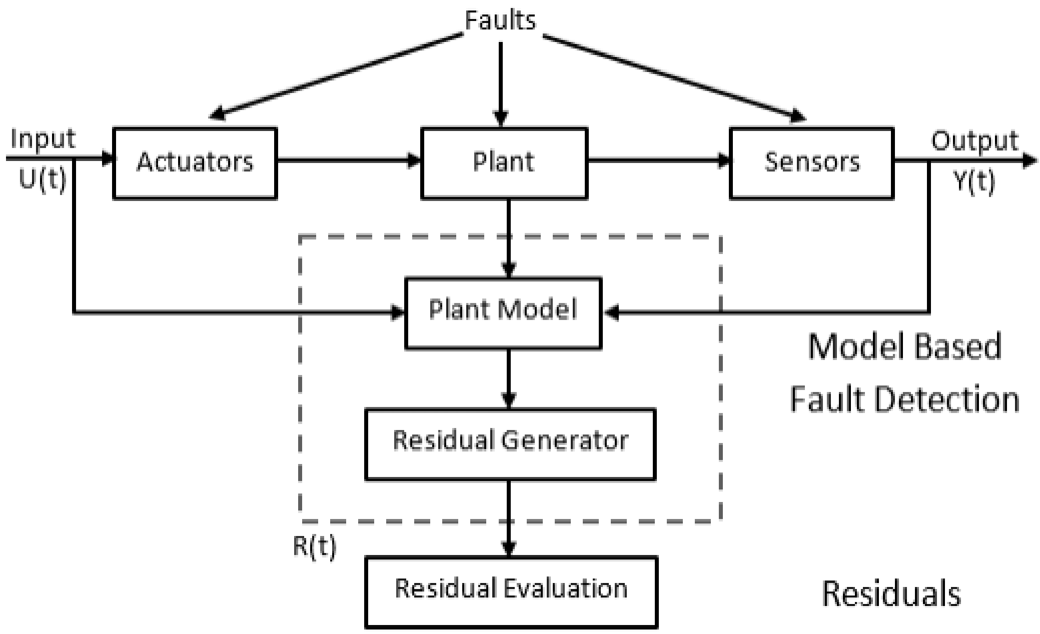


Figure 2.6 General flow chart of model-based approaches (Simani, Fantuzzi et al. 2013)

- **Signal-based failure detection and identification**

Signal-based failure detection and identification approaches focus on detecting the changes or variations in a signal and subsequently identifying the difference. In the literature, the change detection in a system has been extensively explored, and there are few effective techniques that have integrated various ideas from parametric modelling principles with signal-based principles such as spectral analysis. Some of these techniques are formulated around model-based approaches, i.e., generation of deviation from nominal signals and diagnosis of the residuals. Some of the detection algorithms are modelled in the form of hypothesis testing involving a change in the mean (known or unknown) such as the generalised likelihood ratio test and the Page-Hinkley stopping rule.

- **Statistical failure detection and identification/ maintenance**

A wide range of applications uses Bayesian statistics and Bayesian parameter estimation for failure detection and identification. Some other interesting algorithms are presented in (Berec 1998), (Won and Modarres 1998), (Wu, Chen et al. 2001), (Leung and Romagnoli 2000) and (Ray, Townsend et al. 2001). Moreover, another important aspect is to identify the detection intervals, optimisation of cost and replacement decision-making. Markov chains seem to be widely used for optimising maintenance strategies, and some algorithms are reviewed in (Wang and Sheu 2003), (Al-Hassan, Swailes et al. 2002) and (Zhang and Zhao 1999). Another interesting application of using hidden Markov models is given by Bunks et al. (Bunks, McCarthy et al. 2000). Proportional hazards modelling has also been used for reliability estimation and estimation of effects on failure rate ever since they were used by Feigl and Zelen (Feigl and Zelen 1965). (Kobbacy, Fawzi et al. 1997) and (Hollander and Peña 1995) were both reported some interesting theoretical approaches and applications related using PHM.

2.7 Prognostics and health management

Researchers have studied prognostics and health management systems for different engineering applications to increase system reliability, availability, safety and to reduce the maintenance cost of engineering equipment. The term PHM has been used to describe a system that developed to execute a condition-based maintenance philosophy. With the time, the term prognostics has a broad definition than only fault prediction. A comprehensive review, related to PHM of rotatory machinery is presented by (Lee, Wu et al. 2014). Nowadays, it is referred to some extra activities such as (Hess, Calvello et al. 2006):

- Fault or failure detection.
- Fault or failure isolation from other signals if there is any.
- Diagnostic enhancement.
- Material condition assessment.
- Monitoring performance.
- Prognostics.

(Saxena 2010) presented a definition of PHM as an estimation of remaining useful life of a component or subsystem.

Typically, in remedial maintenance work, damaged parts need to be replaced. Hence, organisations prepare a long list of spare parts to be ready when required for maintenance activities to save the ordering time. With an efficient health monitoring system that sends an alert of upcoming fault, the maintenance activity can be scheduled in advance. Any necessary resources can be prepared, and experienced maintenance staff needs to be ready at a specific time in the future, and only the required spare parts can be ordered. Accordingly, by integrated the PHM system into the organisation logistics system, the massive amount of pre-prepared spare parts becomes unnecessary. This system will order only the required components in suitable time according to the received fault alert. With this ability, the organisation may reap the benefits of efficient condition-based maintenance and receive maximum costs savings.

(V, Medjaher et al. 2017) summarised the typical prognostics and health management steps as shown in Figure 2.8.

It is claimed that while the benefits of utilising prognostics are obvious and in accompany with the growth of the related scientific research in recent years, this technology has not become commonly used for some reasons, uncertainty for example. The uncertainty is a fundamental drawback of developing the real predictive prognostics. Improving the certainty is the feature of prognostic technology in future. From researchers experience within nuclear power plants sector, (Coble, Ramuhalli et al. 2015) presented prognostics and maintenance approaches for nuclear power plants components.

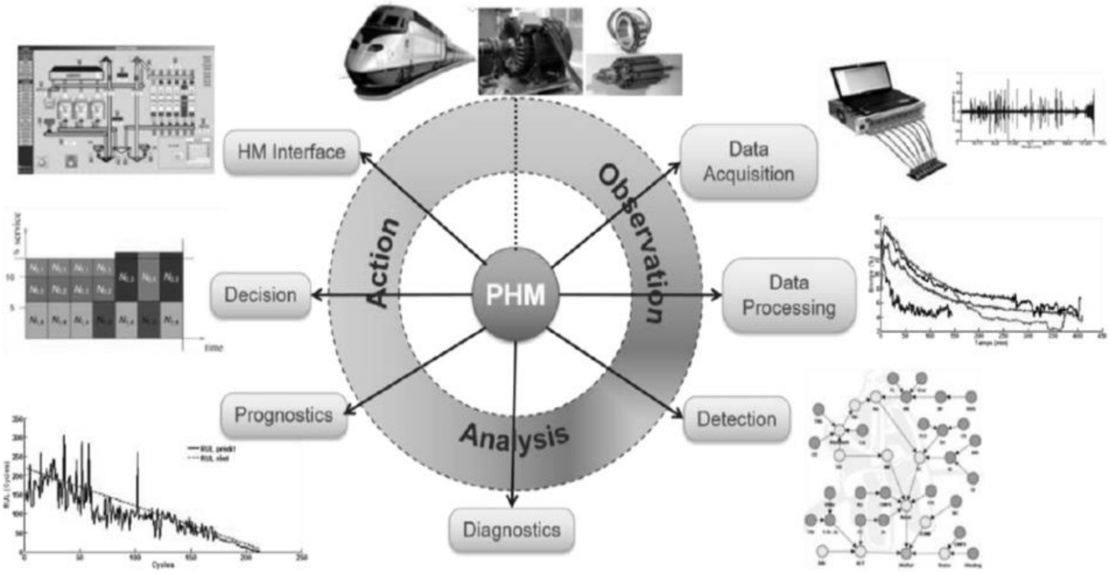


Figure 2.7 Prognostic and health management steps (V, Medjaher et al. 2017)

2.8 Fault diagnostics

Different kinds of techniques for failure detection, isolation and identification have been developed and investigated by researchers and engineers during the last several decades across a wide range of applications. A complete survey of the strategies and techniques utilised as a part of fault diagnostics will not be discussed in this PhD thesis. As represented by (Vachtsevanos 2006) the variety of application fields in fault diagnostics is matched only by a majority of enabling technologies which have appeared throughout the years, in order to diagnose a system fault events. (Venkatasubramanian, Rengaswamy et al. 2003), (Venkatasubramanian, Rengaswamy et al. 2003), (Venkatasubramanian, Rengaswamy et al. 2003) and (Jardine, Lin et al. 2006) provided excellent series of review publications of introduction and reference source to the different techniques approaches used in fault diagnostics. Moreover, they presented various applications to which these approaches have been utilised. (Kandukuri, Klausen et al. 2016) presented diagnostics and prognostics methodologies under reliability centred maintenance and CBM for two critical components; planetary gearboxes and low-speed bearings of wind turbines as their case study. Authors analysed different condition monitoring (CM) data for bearing and gearbox diagnostics, and they concluded that vibration signal is better in detecting gearbox faults and acoustic emission is suitable for bearing fault detection.

2.8.1 Failure criticality analysis (FCA) studies

The first step of a PHM system development is to analyse the criticality of failures. The objective of FCA studies is to label each failure to its reasons or roots cause (Vachtsevanos 2006). Moreover, and as a part of the FCA objective, it needs to investigate the possibility of any other problems in contact with the current fault. The failure severity models, their occurrence frequency, the system behaviour under different fault conditions are some investigations of FCA studies. Inputs from various sources such as system designers, field speciality experts, experienced maintenance personnel, and equipment specialists are some typical requirements of the FCA development study. (Vachtsevanos 2006) presented an adequate overview of the FCA studies.

2.8.2 Feature extraction feature extraction

Data pre-processing covers data cleaning and data analysis steps. Cleaning raw data from errors/noise increases the chance of getting error-free data for further investigations, as shown in Figure 2.9. The second step of data pre-processing is data analysis, which, involves feature extraction, feature evaluation, and selection processes. Cleaned sensory time series should undergo a feature extraction process to extract only the important and useful features that reflect system health condition being monitored. Extracted features should indicate the fault progression of the system. The feature extraction techniques are categorised in the literature into three categories; time-domain based, frequency-based and time-frequency based techniques (Jardine, Lin et al. 2006). The time-domain based feature extraction techniques (e.g. root mean square) are used to analyse the comprehensive characteristics of data and to extract the features in the time domain. The frequency-domain based feature extraction techniques (e.g. Fourier transform) transform the data into the frequency domain and are used to detect and identify faults which are not possible with time-domain based methods.

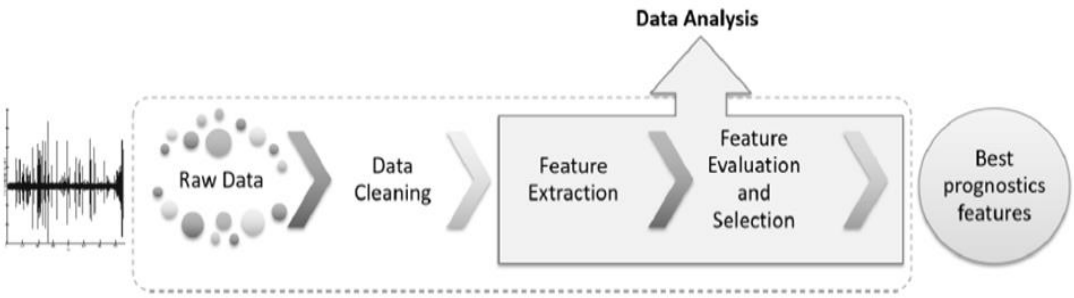


Figure 2.8 Data pre-processing procedure (V, Medjaher et al. 2017)

The time-frequency domain-based techniques (e.g. Fourier transform) analyse the data in both time and frequency domains. Feature evaluation and selection process is the second crucial step of data analysis after extraction. A feature estimation can be defined as a feature goodness quantification process in feature selection. Different techniques are used to quantify the feature goodness (i.e. the trend of degradation) such as monotonicity, prognostability and trendability. Monotonicity characterises a parameter of general nature of increasing or decreasing. Prognosability measures the spread of the parameter's failure value for a population of systems. Finally, trendability indicates whether the parameters for a population of systems have the same underlying trend, and hence can be described by the same parametric function. (Coble and Hines 2009). The best features, which have clear degradation trend, are further selected in a feature selection process after evaluation (Kimotho and Sextro 2014). More information on data feature extraction techniques is presented in several publications such as (Sharma and Parey 2016); (Zhu, Nostrand et al. 2014). This stage as a part of PHM algorithm is designed to identify the trend of the data, which can be utilised to assess the present fault situation of a monitored system. It is assumed that the creation of the data feature trend is normally application-dependent and it is supposed to be the most important stages in any PHM system. Generating data features that can be utilised to assess the current fault conditions of a monitored system is one of the primary purposes of designing a PHM system. For helicopter gearbox monitoring example, the extraction feature from the vibration acquired data might be utilised to recognise some critical magnitude. This value is regarding the value of a vibration signal of the critical magnitude of the gear – mesh frequency in the gearbox.

2.8.3 Fault diagnosis methods

(An, Kim et al. 2015) reviewed a data-driven and physics-based prognostics algorithm regarding model definition, parameter estimation, robustness in noise and bias handling in condition monitoring data, to provide practical prognostics options for beginners so that they can select appropriate methods for their fields of application. According (Vachtsevanos 2006) the methodology of fault diagnosis can be classified into one of the sorts of approaches, model-based and data-based.

- **Model-based methodologies**

Model-based fault diagnostic approaches utilise a mathematical model of the system under monitoring. By using such a model, evaluations the outputs of the system or the process model are produced which are then, in turn, compared with the real system response to create a residual signal. Based upon a contrast between the model response and the real system output, possible fault conditions are recognised based on the magnitudes and properties of the generated residual signals. The generated residual signal is the difference between the process output signal and the model output signal for the same input, as can be seen in Figure 2.10, which represents the essential ideas of a typical model-based algorithm for fault diagnostics purposes.

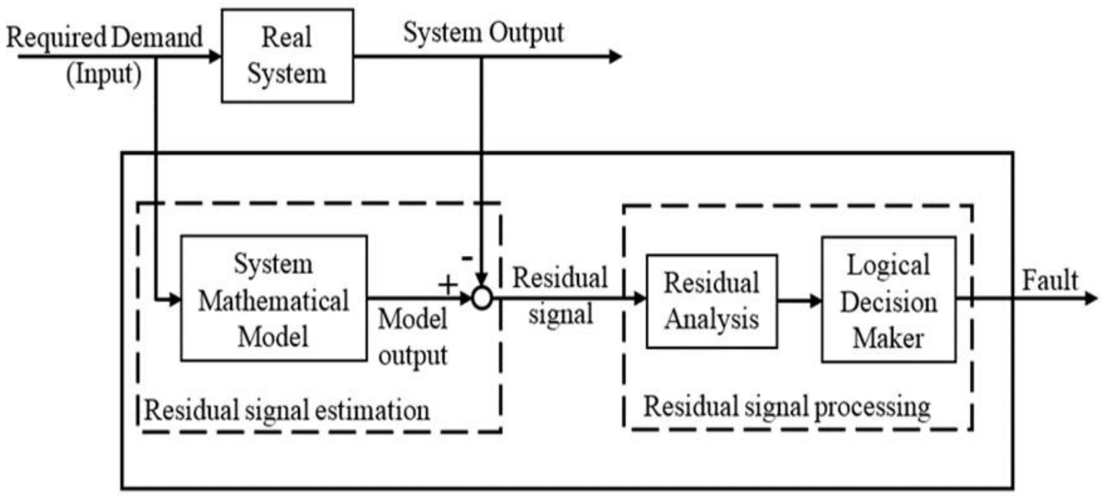


Figure 2.9 Model-Based Diagnostic algorithm

As shown in Figure 2.10, a correlation between the real system and the process model are utilised to create a residual signal. This procedure is commonly known as residual estimation. The magnitude of the residual signal should be equal to around zero during the operation of a healthy system. This value indicates that the model, which shows fault-free response precisely describes the healthy behaviour of the monitored system. In the circumstance where the estimation of the residual signal goes away from zero, suitable signal-processing and analysing is connected to the estimated residual signal. The processed residual signal is then passed to a decision logic process, which is utilised to describe the behaviour of the residual signal onto a particular – fault condition. This procedure is usually depicted as remaining processing. While Figure 2.8 outlines the general principle of model-based fault diagnostics, traditional model-based fault diagnostic strategies can be further classified. (Isermann and Balle 1997) arranged particular methodologies into three sorts: parameter identification - based strategies; equality condition-based techniques and observer-based approaches. Each of these methodologies will briefly describe.

i. ***Parameter identification – based strategies*** utilise a dynamic model of the monitored system in which the model parameters value can be estimated by using the input/ output information, employing suitable system identification procedures. The identified parameters values may change after at the time, and these deviations are used to recognise the presence of a fault condition.
ii. ***State and output monitor – based method*** utilises a system model of healthy behaviour. For this situation, some state estimation algorithms such as Kalman filter are used to estimate the system variables as results of the system inputs. The estimation of state factors is then used to rebuild the outputs of the system and to compare them with the corresponding outputs of the pragmatic system to generate a residual, which in turn can be utilised to specify the faults.
iii. ***Consistency equation- based approaches*** analyse the behaviour of a monitored system with a process model which depicts typical healthy behaviour. Checking the consistency of the mathematical model of the system under observation, using the measurements of the actual

system, is an essential principle. A fault is announced when its value reaches a predefined threshold. This strategy is as similar to the state and output monitor – based approaches (Patton and Chen 1994).

The main aspect of a model-based strategy to fault diagnostics is the necessity for an accurate and robust mathematical model of the monitored system. These models are usually derived using ordinary differential equations regarding the physical properties of different elements of the system and the interactive relationships between these members. The Dynamic physical model of a monitored system is used as Laplace transformation model or converted into the state-space model, before applying the previously described approach. The main advantage of using a model-based fault diagnostic approaches is the ability to detect unexpected faults (Vachtsevanos 2006) because the utilised models are generally based on the physical theories of failure. In contrast, data-driven approaches are typically built on the historical scenarios of each fault condition which they are designed to recognise. However, for nowadays real world systems, it may not be practicable to apply mathematical modelling because many modern mechatronic systems are quite complicated or even impossible to derive accurate mathematical models of such the whole system.

- **Data-driven methodologies**

The universal fundamental of data-driven approach, which applied to deal with fault diagnostics is to use pattern recognition techniques to figure the measured data or highlight it to equipment fault within the fault space (Jardine, Lin et al. 2006). A wide range of procedures has been connected to fault diagnostic issues. (Jardine, Lin et al. 2006) classified data-driven methodologies into two types; statistical approaches and artificial intelligence – based approaches. Under these main categories, a different scope of procedures has been applied to a wide assortment of fault diagnostic issues. A brief overview of different approaches and application will be presented in the following sections.

i. ***Statistical Approaches.*** A traditional statistical process control (SPC) approaches, which was originally developed for the quality control theory purpose, is widely utilised in fault diagnostics. The principle of SPC is to measure deviations of current signal behaviour from predefined limits of the healthy normal condition. If a current signal falls out of the predefined control limits, this may be an indication of some fault condition. (Gallagher, Wise et al. 1997) presented an example of development multivariate SPC tools for monitoring and fault detection applied in a semiconductor etch chamber.

(Fugate, Sohn et al. 2001) attempted to use statistical process control methods to vibration-based damage detection. They demonstrated that this statistical process control was applied to acquired data from vibration test of a concrete bridge column while the column was progressively damaged. Moreover, they stated a statistically significant number of error terms outside the control limits indicated a system transit from a healthy state to a damaged state.

ii. ***Classification Approach.*** Both statistical methods and artificial intelligent-based methods have been utilised for data classification approaches, which are commonly applied techniques in data-driven fault diagnostics. The utilisation of these techniques depends on the availability of a fault style library or database of historical failure examples. These relate to extracted features from observed systems to particular fault conditions. Modelling the relationship between fault features, or fault indicator measurements and fault classes is the purpose of applying classification based approaches (Vachtsevanos 2006). Such methodologies do not have the capability of model-based approaches which in turn utilise models, built upon the physics of failure, which can detect even unforeseen fault conditions. Despite the absence of the availability of a sophisticated mathematical model of the monitored system, data-driven classification approaches can be built.

2.8.4 Novelty detection

Novelty detection aims to identify the behaviours of collected data that are not consistent with normal expectations. Categorizing the received data that is deferred in some regard to the data that are available during the training period is the task of novelty detection algorithm. (Markou and Singh 2003) defined the novelty detection as the algorithm that uses to identify the new or unknown data or even signal that a machine learning system is not warned during the system preparation period. (Pimentel, Clifton et al. 2014) provided a comprehensive updated and structured investigation of novelty detection review paper that has appeared in the machine learning literature. An equipment behaviour in association with fault conditions can be predicted depending on the availability of historical failure example, which leads to developing fault diagnostic capability, historical data-based approaches in particular. In pragmatic systems, there is a lack of data related to historical failure, particularly the data that covers all the imaginable behaviour that might be detected in the presence of a fault condition. On the other hand, there is plentiful of data describing the behaviour of a healthy system. The fundamental principle of novelty detection algorithms is to build a system model based on the acquired data of a healthy behaviour of the system during operation. Collected data from the future operation of the monitored pragmatic system will be compared with that of the pre-built fault-free model, measuring the deviation between them regarding a specified threshold, abnormal or novel events are identified which may indicate some fault conditions. The ability to detect novel occurrences from data classification system is important. It is not a simple task to teach a machine learning system on all possible circumstances that the system may face in its service life. It might be essential for such system to distinguish among all known and unknown information during the application. It has been realised practically speaking through different studies that the novelty detection is a big challenge. Therefore, there exist some models of novelty detection that have been demonstrated good performance on different scope of data. It is evident; there is no particular best approach for novelty detection and the achieved success depends on the type of technique utilised as well as statistical properties of data dealt with. Novelty detection approach is assumed to be a sort of classifier. For some application requirements, the classifier needs to act as a detector rather than a classifier (Markou and Singh 2003), because the requirement is to distinguish whether an input data is a piece of the information that the classifier was prepared on or it is a new unknown data. (Chandola, Banerjee et al. 2009) reviewed a structured and broad overview of extensive research on novelty detection techniques spanning multiple research areas and application domains.

2.9 Fault prognostic:

To enable the benefits of an active condition-based monitoring approach, it needs to have real predictive prognostic capabilities. Mainly, there are two sorts in system prognostics. Apparently, the commonly used prognostics is to predict the remaining useful life, i.e., how much time is left before the system exposed a failure due to one or more faults. This ability is built to prepare information to maintenance staff about the system that has developed some fault giving them an adequate lead–time so that the required personnel, equipment, spare parts any other logistic requirements can be prepared and organised in advance. This preparation will lead to minimising the process downtime and maintenance costs.

The truly predictive prognostics is the generation of long-term forecasts, depicting the signal progression or fault indication, for requirements of evaluating the remaining useful life (RUL) of an ill-behaved system or equipment (Orchard and Vachtsevanos 2009).

For a deteriorated system, it is a significant challenge to develop prognostic abilities because of the inherent significant amount of uncertainty in connecting with the prediction of the system behaviour. Therefore, when selecting appropriate procedures for the advancement of prognostics abilities, there are two issues to consider:

- ***Uncertainty representation*** means the ability to demonstrate different sorts of uncertainty deriving from various sources.
- ***Uncertainty management*** is relevant to the approaches and instruments needed to continually compress the uncertainty limits while a fault is progressively developed (Vachtsevanos 2006).

2.9.1 The remaining useful life

Remaining useful life (RUL), or also in some literature called remaining service life, refers to the remaining time before the monitored system or some of its critical equipment stop performing the required task, or the future operation scenarios. To have an accurate translation of the RUL, it is crucial to find a proper definition of failure. Data on the failure mechanism must be ready in combination with the data on the failure progression to do prognosis. A trending model of some particular condition variables is usually utilised to track the fault progression. Mainly, the failure mechanism can be described in two ways:

- The first way assumes that the failure is a function of the condition variables only, which reflect the real fault level, in combination with predefined boundary condition. The failure is commonly defined according to this case as: It is assumed that the failure occurs if the fault level reaches a pre-defined limit (failure threshold).
- The second one is, by utilising the available historical data, a model of the failure mechanism has been created. Accordingly, the failure has different definitions. For example, a failure can be defined as an event at which the system is running at an unsatisfactory performance, or it can be a functional failure when the system fails to achieve its required demand, or it can be just a breakdown when the system stops running.

The prognostic approach can be categories into three main classes (Jardine, Lin et al. 2006):

- Statistical procedures
- Artificial intelligent approaches
- Model-based approaches.

Remaining useful life probability density function (RUL PDF) is the fundamental concept within prognostic. A prognostic algorithm creates the RUL PDF as an output, depicting the distribution in time of possible system failure times, as shown in Figure 2.11. Considering it, at time *A,* a prediction is made followed by an estimation of the RUL PDF. When the RUL PDF has been estimated, the following step is to schedule the required corrective maintenance activities. The destination time to have the maintenance action is built upon both:

- Avoiding in-service system failure.
- Maximising the system useful life.

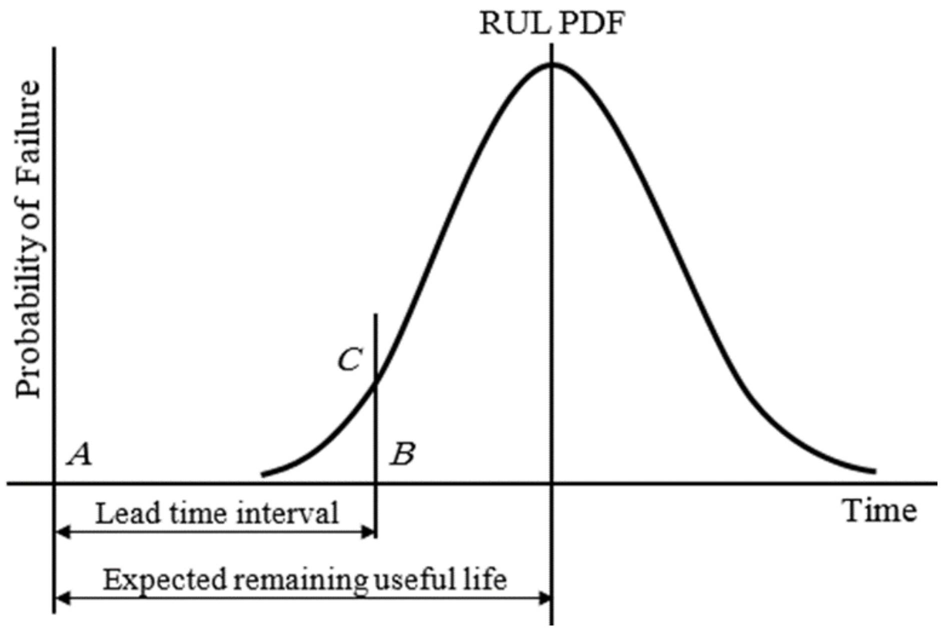


Figure 2.10 The remaining useful life probability density function (Clements 2011)

The maximum permissible Probability of Failure (POF) will be a considered key in the development of a necessities determination for a prognostic algorithm. The likelihood of failure value marks the maximum adequate danger level of a system failure, beyond this threshold; the system is unable to operate for an extended time because the risk of failure has increased considerably. From the maximum allowable probability of failure and the assessment of RUL PDF, the just in time point *B*, as an important term can be identified. This term can be defined as the latest point in the equipment lifetime which before it, the corrective maintenance must be activated in order to prevent the system from working beyond its maximum value of the permissible probability of failure, point *C*. Alternatively, in another word, before the system developing a catastrophic failure. There are some factors would usually be considered in the real industrial systems to select the maximum value of permissible probability of failure. Such factors contain safety, criticality and economic considerations. In order to have a plan for the next operation scenario, the system current condition needs to be considered. If the RUL of a system cannot cover the next operation scenario or accomplish the required task, then the corrective maintenance activity becomes crucial to avoid an in-service failure. In some individual systems and for particular operation scenarios where safety is a primary consideration, it needs to avoid an in-service failure as much as possible because the latter may lead to a catastrophic failure or put the system, operators and environment in dangerous situations, for example, nuclear power plant. Accordingly, for the maximum allowable value of the probability of failure, a conservative value might be chosen. In contrast, for some expensive system or equipment, operators may accept a higher maximum allowable POF value to maximise the system service life by weighing the economic factor than avoiding the in-service failure, diamond headed cutting tool is an example of such sort of equipment. Figure 2.11 illustrates an assumption maximum permissible POF of 5 per cent for demonstration. There is another key measure can be evaluated when the just in time point *B* has been recognised. This key is the Lead Time Interval (LTI), which is defined as a period of time between the point that the prediction is created point *A* and the just in time point, point *B*.

In order to avoid operating the system beyond the maximum permissible POF, maintenance activities have to be done before the lead time interval LTI elapses. Because of the LTI gives a real-time estimation of the remaining life before the system works beyond the maximum permissible POF. While, the remaining useful life in combining with LTI values can be utilised to automate the maintenance decision system, both for the former are essential for the maintenance team to schedule the required activities to avoid the in-service system failure.

Moreover, spare parts and instrument can be pre-ordered via the automatic logistics system when a predicting failure is oncoming; this could be achieved by estimating the RUL and LTI. The desired benefit out of this strategy is to have a small list of spare-parts and equipment on site and to reduce the shipping costs.

2.9.2 Prognostic techniques

There is a wide assortment of techniques have been utilised to predict the RUL of a monitored system that is applied to different applications. As illustrated in Figure 2.8, prognostic approaches can be classified into three categories (Vachtsevanos 2006):

1. Experience-based approach.
2. Data-driven approach.
3. Model-based approach.

As can be seen in Figure 2.12, the experience – based prognostics approach has a wide range of system applicability. As it shows an increase in the cost and accuracy when moving forward the model-based prognostics approach, there is a similar reduction in the applicability of the different approaches. Increasing the complexity and/ or the cost of different approaches causes a reduction in the applicability scope. By modifying solutions to specific prognostic implications, improving the capability may be achieved.

There is a narrow scope of prediction of this approach if we can say that, because it is assumed that the system follows the same historical failure time-distribution model and hence to avoid in-service failure, a preventive maintenance activity is scheduled.

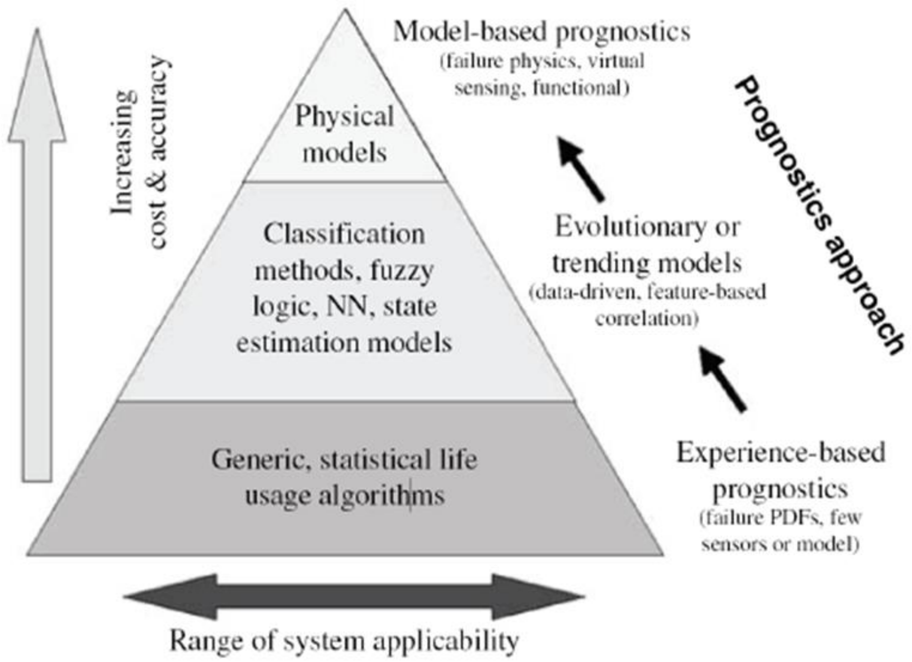


Figure 2.11 Technical approaches to prognostics (Byington, Roemer et al. 2002)

1. **Experience-based prognostic approaches**

This technique is assumed to be one of the most straightforward prognostic approaches because it depends only on the statistical collected information from the historical failure rate of the system or equipment. Later, this data will be employed to create a life service model, i.e. the distribution of failure rate over working time. Accordingly, scheduling the preventative maintenance activities can be improved by utilising this methodology based on the mean time between failures. While this approach cannot be presented as a real prognostic technique, there is a narrow scope of prediction, if we can say that, in this approach. Because it is assumed that the system will follow the same historical failure time distribution model regardless of its current condition and hence, to avoid in-service failure, preventive maintenance activities are pre-scheduled accordingly. Nevertheless, this approach has a broad scope of applications in low cost and less critical systems. Moreover, this approach can be used in some applications where there is a lack of data from sensors, on it the system condition can be concluded.

2. Model-based prognostic approaches

Theory of failure models of systems under observation that derived from first physical principles is used in the most capable prognostic approaches. Until now, the main application scope of these approaches has to consist the model of crack initiation and propagation as a fault model in structure members (Ray and Tangirala 1996). The main advantages of using physics of failure models for model-based methodology purposes is the capability to integrate a physical model of an observed system and the capability to prognoses the degradation of the system under different operation conditions. There are some limitations on using model-based prognostic approaches due to the ability to improve highly reliable models of complex systems or processes. In many applications, it is acceptable to propose a particular dynamic model to describe the development of a degradation system if a physical model that built from the first principles is complex or unavailable. For some simple systems, liquid level process as an example, even it is understandable and easy to derive its physical model from the first principles, it is a significant challenge to build the system model consisting all actuators and sensors characteristics. Due to ageing and long-term of usage, the characteristic equation has changed with time, and hence, it is not fidelity to use the same characteristic formulae provided by the manufactural. Nevertheless, built a model based on current members' condition and behaviour might be worth. Because of the collected data from the system under observation is utilised to create such prognostic models, this sort of prognostics approaches are described as hybrid approaches.

3. Data-based prognostic approaches

For the purposes of prognostic and in many situations, it is impossible to derive robust and accurate models because of the complexity of systems under observation. Instead of this, historical acquired data that describe the system behaviour in the presence of some incipient faults are available. Accordingly, it might be worth to predict the RUL by using data-driven methods which describe how collected signals of a system developed with the time. There are two sorts of strategies that data-driven prognostic approaches are typically followed.

- The first strategy consists of two stages, utilising a suitable dimensionality reduction, feature extraction, or pattern matching techniques to figure the system signals onto one-dimension index either damage, degradation, or health.

Because this first step is concerned with the analysis of posterior events, it is assumed a part of fault diagnostic steps. When the current level of deterioration is identified and in the presence of a predefined threshold of fault limit, the extrapolation will be done. While modelling the relationship between the monitored signals and the remaining useful life of the system as a generated output of the model, be the second strategy. A brief overview of data-based techniques that have been employed in prognostic problems is presented in the following section. Meanwhile, more comprehensive reviews of data based prognostic approaches have been presented in (Si, Wang et al. 2011), (Dragomir, Gouriveau et al. 2009), (Heng, Zhang et al. 2009) and (Tsui, Chen et al. 2015). Moreover, (Kan, Tan et al. 2015) presented data-driven prognostics approach for non-linear and non-stationary machine processes. They studied prognostics techniques that can deal effectively with non-linearity and non-stationarity systems and concluded with further improvements in prognostics.

- ***Time series approaches*** This data-driven methodology depends upon projection techniques, which means extending the present level of deterioration into the future and hence it is assumed to be the least complicated data-driven method. This approach is a time series prediction method. Exponential smoothing techniques, which has been presented in (Byington, Roemer et al. 2002) and autoregressive models that have been discussed in (Saha, Goebel et al. 2009), (Wu, Hu et al. 2007), are used to deal with this approach for prediction purposes.

- ***Artificial neural networks*** this approach might be the most popular data-driven techniques that applied for the prognostic requirement. This technique mimics the relationships between the input and the output variable according to a model structure built on the neural structure of the brain. The network weights and biases, which characterise the interconnections between the neurons, are adjusted during a training procedure to expand the appropriate between the input and output data on which the models are prepared.

Other methodologies beyond time series and artificial neural network based methods, scope of different systems have been applied to prognostic applications. (Goebel, Saha et al. 2008) Compared to three data-driven techniques: artificial neural networks; Gaussian process regression; and a consistent vector machine approach for prognostics. Other data-based methodologies that have been utilised for prognostic problems include hidden Markov models (Zhang, Xu et al. 2005), and Neuro-Fuzzy networks (Wang, Golnaraghi et al. 2004).

(V, Medjaher et al. 2017) summarised, in a table, some papers that can be used to understand the general concepts of condition monitoring systems. They presented in this table, important problems, the domain, the approach classification and remarks pointed out in the review papers synthesised from the publications. Moreover, this table contains beside the author names and the year of their publication, main issues and remarks studied by review papers in the literature.

(Guillén, Gómez et al. 2013) presented the main topics of PHM integration framework regarding diagnostics and monitoring approaches by synthesising PHM review papers in several application fields. Then, they discussed the functionality of PHM, maintenance types, prognostics approaches and proposed the integration of PHM with e-maintenance for proactive decision making.

2.10 Summary and knowledge gaps identification

Maintenance has a significant impact on the final product costs and the availability of industrial systems. Prognostic and health management of a whole system and predicting when it will reach its end of life is not an easy task and inherently has a high level of uncertainty. A typical prognostic and health management go through some essential steps as shown in Figure 2.6. Regarding safety, there are some critical systems in direct touch with human and environment safety such as; automotive, train, nuclear station, chemical and aerospace industries need to deal with. These need smart predictive maintenance systems with very high reliability due to the possibility of catastrophic failure consequences. Based on this, intelligent and reliable PHM technology development is urgently needed to deal effectively with maintenance optimisation activities of critical-complex systems efficiently. Subsequently, developing the PHM system should consider resources and system degradation, environmental effects, failure behaviours, failure interactions and related uncertainties (Qiao and Weiss 2016).

A summary of the identified knowledge gaps is now given below. To reduce production costs and unrequired stoppage and increase the system useful life, an efficient prognostic and health monitoring approach needs to deal with the following:

1. The amount of acquired data from modern systems, depending on the number of sensors and their signal types, becomes enormous. There is a significant challenge to analyse such a massive amount of data in-site or transfer to a remote instantaneous monitoring and data analysis centre via internet for example even with modern technology.
2. It is believed that system failure occurs suddenly. In reality, there is slowly progression of faults deteriorate with the time. In the closed-loop control system, the controller allows the system shows a healthy behaviour regardless of the presence of faults while the control signal is less than a specific threshold.
3. All real systems show nonlinear behaviour.

To deal with this reality and to provide a contribution covering the health monitoring deficit, it is essential to develop:

I. A continuous health monitoring approach with the following specifications:
   - Continuous and instantaneous health assessment of the in-service system.
   - Undependable on historical knowledge and previous faults-occurrence to be a general approach and applicable for any feedback controlled mechatronic systems.
   - Provide simple but clear enough output signal to assign any change in the required demand and/ or the presence of any hidden fault.
   - The output signal needs to be small in size for the online monitoring and data transfer requirements.
   - This approach output signal does not need massive storage media because of its small size, and hence, it can be saved accumulatively to track the system health throughout a long time in the past.
   - The output signal capable of being implemented with the control system to have an integrated control and health monitoring system.
   - This monitoring approach capable of diagnosing the system faults and assigning the sort of fault, intensity and the fault location.

II. Continuous evaluation of the system remaining useful life at any stage of the operating scenarios in the presence of faults by observing the control signal continuously via the health monitoring algorithm before the system reaches its end of useful life.

Chapter 3 presents CE105 liquid level system as a test rig for this PhD research purposes. It reviews the system components and transducers, which for them the characteristic equations were experimentally prepared to build the virtual system and compare its behaviour with that of the real system.

Chapter Three

Liquid Level Tank System

3.1 Introduction

Considering the gaps that presented in Chapter 2 of this thesis, a liquid level system model was built. As a typical nonlinear liquid level system, CE105 was mathematically analysed. Moreover, an experimental model that will be used for the purpose of this research was built according to the characteristic equation of each mechanical and transduces to verify the consistency between the pragmatic and its virtual system.

This chapter presents a review of the background and the theory behind the mathematical analysis of the liquid level system, which is used as a case study in this chapter. Later, the experimental characteristic equations of the liquid level system will be used to build its virtual system. This PhD research is based on model-based diagnostic, prognostic and health monitoring approach; the virtual system is used for the development of controller-based health monitoring and prognostic algorithms that present in Chapter 4 and Chapter 5. The layout of this chapter is as follows.

Section 3.2 reviews the background and the discharge water flow condition and its impact on the system linearity. Section 3.3 presents mathematical analysis principles of a liquid level system. While in Section 3.4, the mathematical model is expanded and discussed based on Bernoulli's Equation and Lavoisier law of mass conservation to describe liquid outflow rate through the system discharge restriction. Section 3.5 describes CE105 coupled tank system, which used in this PhD research as a test rig. It presents some important system parameters combined with the system components. Experimental test approach and the primary results and their discussions are presented in Section 3.6. This section presents a mismatch between experimental results and that of the mathematical model because of the reasons that presented in detail in this section. Section 3.7 describes the characteristics of the system discharge valve after taking the required arrangement to deal with its pre-discussed behaviour in Section 3.6. Section 3.8 reviews the experimental procedure to estimate the characteristic equation of each transducer and system components in order to use them in Section 3.9 to build a detailed simulation of the CE105 under LabVIEW environment. Section 3.10 presents the response consistency of

CE105 couple tank system and its simulation. This simulation will be used later as a virtual system for Chapter 4 and Chapter 5 purposes.

3.2 Liquid level system

Liquid Level Tank Systems (LLTS) are used in an extensive variety of industrial process applications, such as within water treatment industries, power plants, papermaking and petrochemical industries. Such systems often require liquid to be pumped, stored in tanks, and then allowed to flow to other tanks.

The fundamental objective of the controller utilised within the liquid level system is to maintain the liquid level at its required height in a tank. Moreover, to be able to accept new set values in order to regulate the liquid level in the presence of liquid discharge from the tank. In many LLTS applications, the outflow rate needs to be constant during the processor to be changed to a new value by either modifying the controlled liquid level or manipulating the discharge valve opening. Controlling a liquid height in a tank and consequently, the liquid free outflow rate is of crucial importance for mixing reactant process, for example (Essahafi 2014).

The control of liquid level systems has attracted the attention of many researchers around the world during the last few decades. (Mahapatro 2014) argued that the control of an LLTS be classified as one of the most challenging benchmark control problems because of its non-linear and non-minimum phase characteristics. The challenge is to keep the liquid level at its demand or change it to a new value by manipulating the pump voltage regardless of the outflow condition (Postlethwaite 1996). Here, it is assumed that the liquid is non-viscous and incompressible which means there is no change in density of the liquid during the process. Before designing a controller, it is essential to understand the system behaviour under different operating scenarios. An LLTS is commonly controlled by using a conventional Proportional- Integral- Derivative (PID) controller as a widely recognisable type of feedback controller. Currently, a PID controller is one of the most common control algorithms utilising to control processes. It is used in domestic and industrial applications, for example, heating and cooling systems, liquid level monitoring, flow and pressure control application. Such a feedback controller minimises the difference between the required demand and the related plant measured variable through regulating the process-controlled inputs. Furthermore, every single element of a PID controller refers to a particular action taken on the error (Kumar and Dhiman 2011).

(Hussein and Mishra 2014) investigated interconnected CE105 coupled tank system by using a proportional-Integral PI controller for the purpose of monitoring and control the liquid level system. They used the LabVIEW programme to implement a control algorithm to control the liquid level regarding the difference between the tank inlet and outlet flow rate. Their control algorithm was based on sending driving voltages to the pump in the range between 0 to 10 *volts* depending on the system measure variable, i.e., the liquid level. They concluded that the CE105 has been successfully controlled using PI controller through LabVIEW software with a proportional gain equal 4 for each tank and $(5 * 10^{-5})$ and $(1 * 10^{-4})$ as an integral gain for tank 1 and tank 2 respectively.

In considering the dynamic behaviour, and associated simulations, of liquid level control systems the outflow characteristics are usually considered as a primary nonlinear feature. However, (Ogata 1997) stated that an LLTS could be assumed linear if the free outflow can be considered laminar;

$$Q_{lam} = K.h \tag{3-1}$$

Where Q is a steady state liquid free outflow rate, $(\mathrm{m}^3.s^{-1})$, *K* is a coefficient $(m^2.s^{-1})$, and *h* is a steady state liquid head, (*m*). In contrast, when the flow through the discharge valve is turbulent, the steady state outflow rate is:

$$Q_{tur} = K\sqrt{h} \tag{3-2}$$

Often this characteristic can be linearised when the change in the system variables are kept small. For non-linear simulations, the square root characteristic is widely used to model the flow through hydraulic orifices as the discharge valve can be analogous to an orifice. This recruitment may cause numerical problems because the derivative of the flow concerning the pressure drop tends to infinity when the pressure drops approaches zero. Moreover, for small values of the pressure drop, it is more reasonable to assume that the flow depends linearly on the pressure drop (Borutzky, Barnard et al. 2002). Similarly, (Ogata 1997) stated that a system could be considered linear if the outflow is laminar. Even if the flow is turbulent, the system can be linearised when the change in the variables are kept small. (Himanshu Gupta April 2012) stated that to achieve the desired output, it is essential to control the process variables in any process. Moreover, they stated that because of all real systems behave as nonlinear systems; conventional controllers are not always capable of providing satisfactory results. Accordingly, they suggested a design of a Fuzzy Logic Controller (FLC) to control the liquid level of a coupled tank system.

For the current research, the aim is to include such primary non-linearity along with any non-linear effects.

3.3 Mathematical analysis of liquid level system

In order to study the time response of a control system, its dynamic differential equation needs to be solved. A schematic diagram of the considered system is shown in Figure 3.1. The basic assignment of that controller is to maintain the liquid level at its desired value and be able to accept new setting values. This purpose is accomplished for instance, by manipulating the inflow rate of the liquid by changing the electric power which supplied to the pump. Here, it is assumed that the liquid is a non-viscous and incompressible fluid, which means its density and viscosity are supposed to be constant during the process. The hydraulic capacitance of liquid is a term used to describe the potential energy stored as a liquid. the height of liquid in a container as shown in Figure 3.1, i.e. a so-called pressure head, is one form of such stored energy.

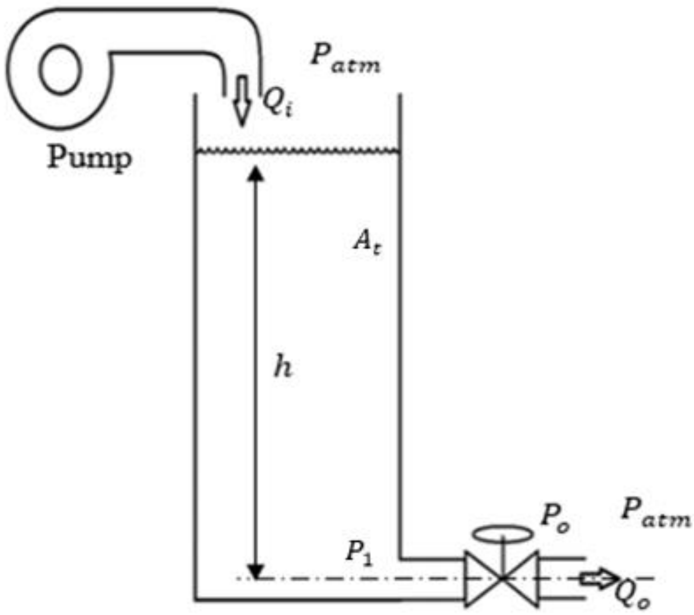


Figure 3.1 Schematic Diagram of a Single Tank System

3.3.1 Lavoisier Law of mass conservation

In general, the mass of liquid in the tank at any time is:

$$mass = \rho . h . A_t \tag{3-3}$$

The accumulated liquid in the tank is equal to the difference between the liquid masses entering and leaving the tank with respect to time.

$$\rho(Q_i - Q_o) = \rho . \dot{h} . A_t = \dot{m} \tag{3-4}$$

Where;

$Q_i =$ Inlet liquid flow rate, $(m^3 . s^{-1})$

$Q_o =$ The outlet liquid flow rate through the discharge valve, $(m^3 . s^{-1})$

$\rho =$ Density of the Liquid, $(kg . m^{-3})$

$\dot{h} =$ The rate of change of the liquid level (h) with respect to time, $(m . s^{-1})$

$A_t =$ A cross sectional area of the uniform cross-sectional container, (m^2)

$h =$ The liquid height in the tank, (m)

While there is no change in the liquid density during this process, the level becomes:

$$\dot{h} = \frac{Q_i - Q_o}{A_t} \tag{3-5}$$

The liquid flow through the discharge valve is due to pressure difference between points $(i \ and \ o)$ which they are P_i and P_o respectively as seen in Figure 3.1. The pressures are given by:

$$P_i = \frac{m.g}{A_t} = \frac{\rho.h.A_t.g}{A_t} \tag{3-6}$$

$$P_i = \rho.h.g \tag{3-7}$$

Meanwhile, $P_o = 0$, because the outlet pipe is open to atmospheric pressure.

According to the Antoine Lavoisier law of conservation of mass, which states that mass in an isolated system is neither be created nor destroyed by chemical reactions or physical transformations. Thus, the amount of matter cannot change.

The mass of liquid passes through the discharge valve $(\dot{m})$ between points $(i \ and \ o)$ is constant at any time, i.e., $\dot{m}_o = \dot{m}_i$, thus,

$$\dot{m}_o = \rho.Q_o = \frac{\Delta P^{\frac{1}{\propto}}}{R} \tag{3-8}$$

$$\dot{m}_o = \frac{(P_i - P_o)^{\frac{1}{\propto}}}{R} \tag{3-9}$$

Where;

Scale parameter $\propto = 1$ for laminar flow through the outlet restriction.

And $\propto = 2$ for turbulent flow.

$R =$ Flow resistance through the outlet restriction.

$\rho =$ Density of the liquid $(kg.m^{-3})$

$g =$ The acceleration due to gravity $(m.s^{-2})$

$\dot{h}$ = The liquid free surface velocity up and down $(m.s^{-1})$

$P_i\ and\ P_o =$ The pressure difference before and after the outlet restriction respectively $(N.m^{-2})$.

Points $i\ and\ o$ are two points at the same horizontal level inside the tank before the discharge valve and after it, which open to atmospheric pressure respectively.

$$\dot{m} = \rho.Q_o = \frac{(\rho.g.h)^{\frac{1}{\propto}}}{R} \tag{3-10}$$

$$Q_o = \frac{(\rho.g.h)^{\frac{1}{\propto}}}{\rho.R} \tag{3-11}$$

By substituting Equation (3-11) into Equation (3-5);

$$\frac{dh}{dt} = \dot{h} = \frac{Q_i - \frac{(\rho.g.h)^{\frac{1}{\propto}}}{\rho.R}}{A_t} \tag{3-12}$$

For laminar flow through the outlet control valve where $\propto$ is equal 1, Equation (3-12) becomes:

$$\frac{dh}{dt} = \dot{h} = \frac{1}{A_t}\left(Q_i - \frac{g}{R}h\right) \tag{3-13}$$

However, for turbulent flow, $\propto$ is equal to 2, and Equation (3-12) becomes:

$$\frac{dh}{dt} = \dot{h} = \frac{1}{A_t}\left(Q_i - K.\sqrt{h}\right) \tag{3-14}$$

Where;

$$K = \frac{\sqrt{\rho.g}}{\rho.R} \tag{3-15}$$

Then, Equation (3-14) is a mathematical model that describes the behaviour of the liquid level system at any time. It is evident that the system model is nonlinear. For the tank level circumstance, the nonlinearity, if desired, could be smoothed or linearised around a particular operating liquid level(h). Such linearity is achieved by using the slope of the nonlinear system behaviour at a specific liquid level.

3.3.2 Bernoulli's Equation

Bernoulli's Equation applied to a liquid flow through an outlet valve is deemed to be analogous to sharp-edged small circular orifice behaviour. Such analogous consideration will not eliminate the difference in shape feature between an assumed circular orifice and the real valve opening, restriction shape. The liquid discharge velocity (v_o) through the outlet valve at the bottom of the tank is deriving from Bernoulli's Equation, Figure 3.1:

$$\frac{P_i}{\rho g}+\frac{v_i^2}{2g}+Z_i=\frac{P_o}{\rho g}+\frac{v_o^2}{2g}+Z_o \tag{3-16}$$

Where:

P_i = A gauge pressure at point (i) inside the tank $(N.m^{-2})$.

v_i = A liquid velocity at point (i), $(m.s^{-1})$

Z_i = The height of point (i) measured from a horizontal level, (m).

P_o = A gauge pressure at point (o) which equal to zero because it is open to atmospheric pressure $(N.m^{-2})$

v_o = A liquid velocity at point (o), $(m.s^{-1})$

Z_o = The height of point (o) measured from the same horizontal level of point (i), (*m*).

It is usual to assume that points (*i*) and (*o*) are at the same horizontal level, as can be seen in Figure 3.1. Then,

$$P_i=P=\rho gh \tag{3-17}$$

with $v_i \ll v_o$, $Z_i=Z_o$ and $P_o=0$

Consequently, Bernoulli's Equation becomes:

$$h=\frac{v_0^2}{2g} \tag{3-18}$$

$$v_o=\sqrt{2gh} \tag{3-19}$$

If the valve is assumed to behave as an ideal sharp-edged circular orifice, the flow through the valve will be related to a square root of the liquid level (*h*) in that tank.

The volumetric outflow rate through the discharge valve can be expressed as a function of the liquid level (*h*) in the tank by the following expression:

$$q_o = a\sqrt{2gh} \quad (3\text{-}20)$$

Then the general dynamic equation will be:

$$\frac{dh}{dt} = \frac{1}{A_t}\left(q_i - a\sqrt{2gh}\right) \quad (3\text{-}21)$$

Now adopting the units more applicable to the experimental arrangements:

h = the liquid depth in the tank measured from the liquid free surface to the centre of the outlet valve at the bottom of the tank, (mm).

A_t = the cross-sectional area of the uniform tank, (mm^2).

q_i = the inflow rate,$(l.min^{-1})$.

a = constant equals to the orifice cross-sectional area multiply by the discharge coefficient through this orifice.

This coefficient depends on many things such as the orifice cross-sectional area, the size of the orifice, the material which made from and the puffer smoothness. Meanwhile, the liquid characteristics are considered to be constant.

(Dorf and Bishop 2005) stated that the vast majority of physical systems show linear behaviour within limited ranges of their variables. However, all systems become nonlinear when the variables are increased unlimitedly. The linearity of a system is defined according to the system excitation and response. If a system satisfies the properties of superposition and homogeneity, it considered a linear system.

3.4 Description of CE105 coupled tank system

In this study, a coupled tank apparatus CE105 was selected for the study of both its nominal and faulty behaviour. This plant is developed by TecQuipment (TQ) Education and Training Ltd, 2001. The functional schematic diagram of CE105 couple tank system is shown in Figure 3.2, the system key features are illustrated in Figure 3.3, and its specifications are summarised in Table 3.1.

(TecQuipment, Hussein and Mishra 2014) stated that the CE105 test rig had become a standard system for control laboratories equipment designed specifically for teaching and practical investigation of elementary and advanced process control engineering principles. Controlling a liquid level and consequently liquid outflow rate, as they would typically occur in process control industries might be studied using a CE105 coupled tanks apparatus. It may also utilise this test rig as an introduction to the design, operation and application of a PID controller. CE105 provides an ability to investigate the effect of each element (P, I and D) of the PID controller. The basic control challenge is to regulate the liquid level in one of the system tanks by manipulating the voltage of the liquid pump.

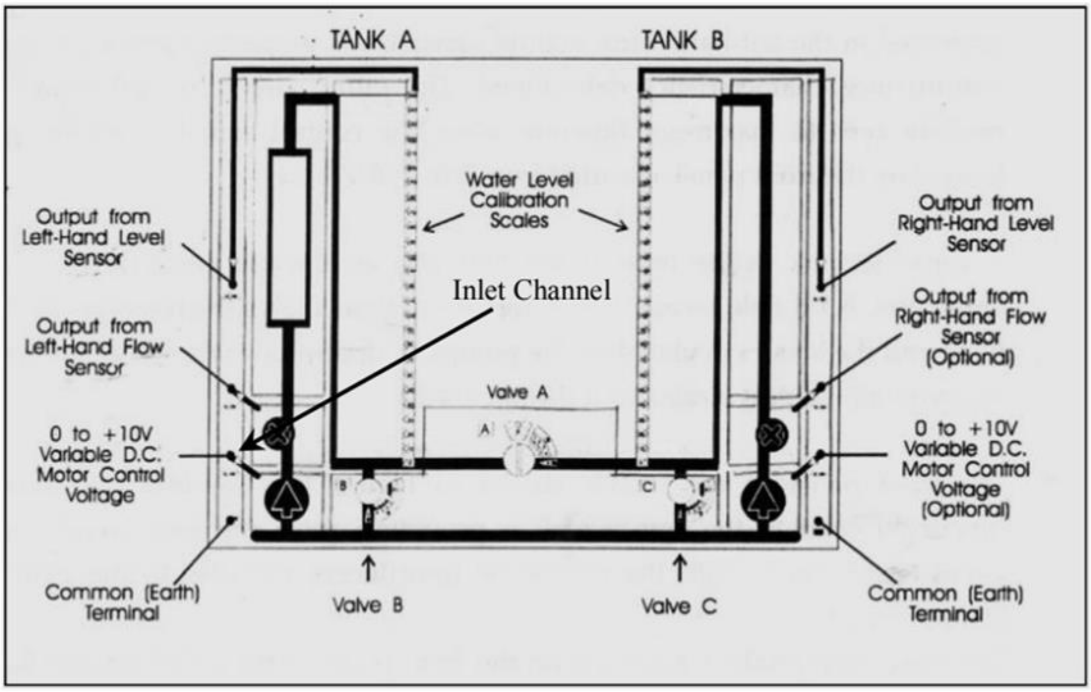


Figure 3.2 Schematic functional diagram of CE105 coupled tank system (Hussein and Mishra 2014)

Table 3-1 Specification of a coupled tank liquid level system CE105 (TecQuipment)

Tank 1	Cross-Sectional Area = 9350 mm^2
Tank 2	Cross Sectional Area = 9350 mm^2
Valve A, B, C	10 *mm* Valve adjustable area [a] (Slot) Full Cross-Sectional Area = 78.5 mm^2
Liquid Level Sensor	0 to 10 *volt* DC Output Corresponding to 0 to 250 *mm* as indicates on the front panel water level scales
Pumping Flow Rate Sensor	0 to 10 V DC Output Corresponding to 0 to 4.4 $l.min^{-1}$ as indicates on the front panel rotameter
[a] the adjustable area of the valve is divided into five main positions.	

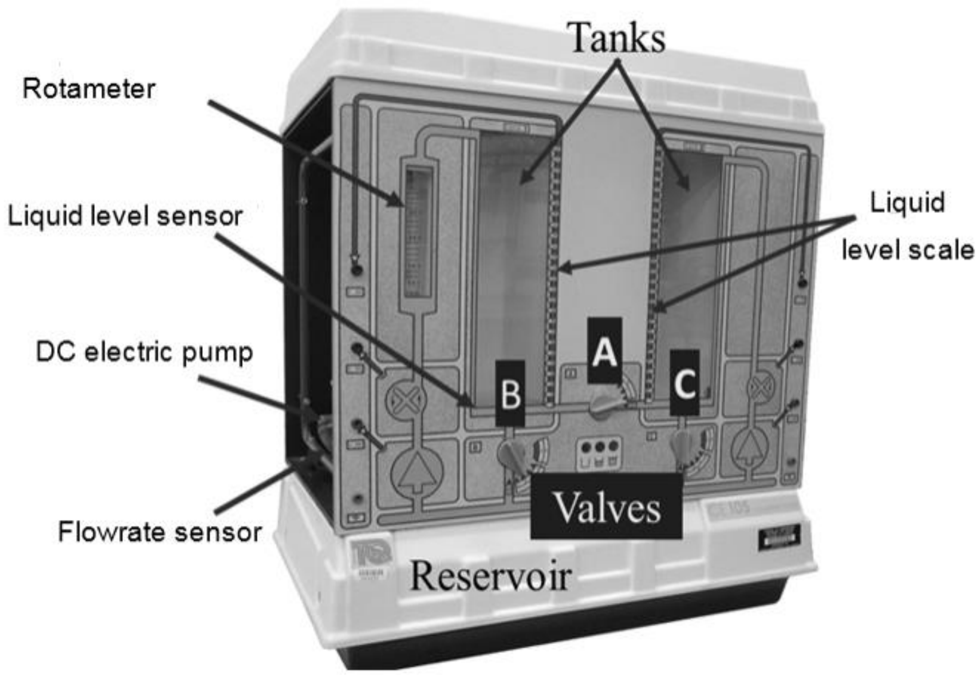


Figure 3.3 CE105 Coupled Tank System

Each tank is equipped with a pressure-sensing liquid level sensor that provides output signals proportional to the trapped air that in turn proportional to the water level in the tank. Moreover, the water level in each tank is clearly visible through transparent windows on the front panel. Also, there are two operator readable adjacent scales enable the actual levels to be determined for sensors calibration purposes. A variable speed DC motor and pump set utilises to pump the water from the system main reservoir into the left-hand tank, either under manual or automatic control. Alternatively, the right – hand tank can be filled from the left tank via valve A for the purpose of two – tank experiments. A traditional rotameter – variable area type flow meter was installed vertically on the main inlet tube to provide a direct flow rate indication in ($l.min^{-1}$) water. In addition, an in-line impeller indicates the pumping water flow rate to electronic impulse transducer is utilised to indicate the pumping water flow rate.

This system has two tanks mounted side by side. These tanks are interconnected by a flow channel, from every single tank to a common reservoir. This reservoir is situated below, through three regulator valves A, B and C. Valve A is mounted in the channel between the two tanks at the bottom of them to control the liquid flow between the two tanks, as can be seen in Figure 3.3. Meanwhile, valve B and C are mounted on the drainpipe of every single tank at level (46 *mm*) approximately, measured downward from the tank bottom. Such valves are used to control the liquid flow rate from each tank to the system reservoir. The liquid flow characteristics of the coupled tank system can be controlled and changed to a wide range of physical characteristics. This task can be achieved by changing the cross-sectional area of the valve (A, B and C), each of them can be varied over five main grades, i.e. from 0 to 4.

The connections between the internal circuits of the CE105 and a CE120 control panel which provides analogue and digital control and a computer-based controller are via circuits access mounted on the detailed front panel. This controller allows the system operator interactively to investigate a various aspect of control scenarios.

The CE120 controller contains analogue facilities such as summing amplifiers, proportional and integral amplifiers, separate access to the three terms of a PID controller, variable potentiometers, a function generator and a DC reference voltage supply. To produce the desired circuit performance, these might be connected to each other in different combination. These facilities are directly accessed and controlled by utilising an external personal computer (PC) with suitable software, LabVIEW programme for example. Therefore, it is possible to control and monitor the performance of the CE105 under the control of the software provided to perform open and closed loop experiments.

For the purpose of this research, some functions of this usual control panel were replaced with a PC interface. The LabVIEW control software was interfaced via a USB – NI 6008 DAQ data acquisition board. This test rig, as provided, has a pressure sensing liquid level sensor and a flow rate sensor.

In this element of wider evaluations and testing, the left tank is used to control the liquid level in it and monitor the condition of the system health. The collocation of the water pump, a PC set, a data acquisition board, CE120 controller and a control panel under LabVIEW environment was used to study the CE105 apparatus behaviour as an open and closed loop system, as can be seen in Figure 3.4.

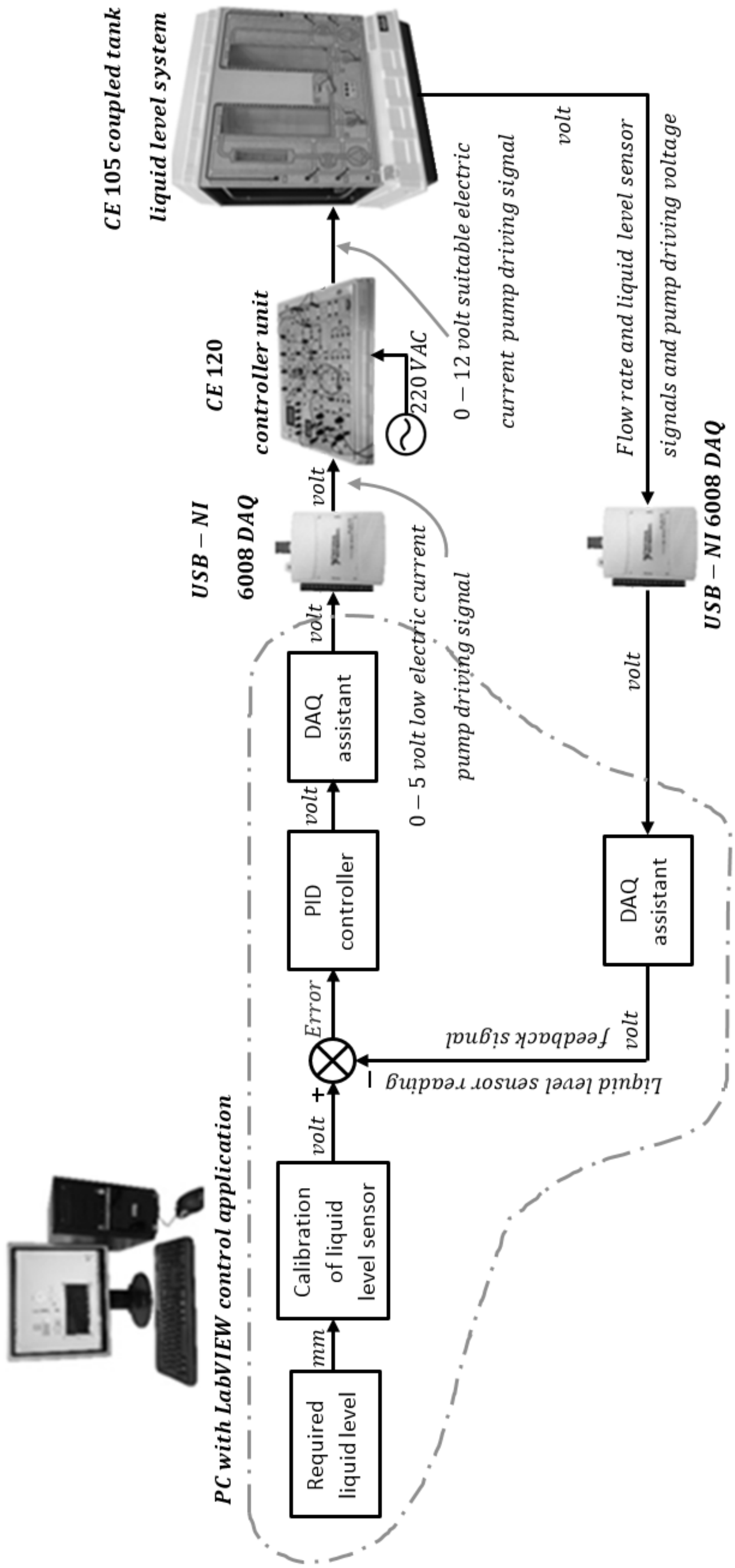


Figure 3.4 Schematic diagram of the system

3.4.1 Rotameter water flowmeter:

A traditional rotameter water flowmeter is vertically mounted on the front panel of the system, as can be seen in Figure 3.3. The flow rate indicator consists of a float freely moves inside a graduated transparent – tapered glass tube where the internal cross-sectional area gradually becomes bigger downstream, as can be seen in Figure 3.5. This indicator has divided to measure a water flow rate in $l.min^{-1}$ at room temperature. As the flow through the tapered tube increases, the float is lifted by the liquid flow based on buoyancy and the pressure difference between the upper and the lower sides of the float. This sort of flow meter needs to be carefully mounted vertically because the force of the pressure difference acts against the gravity force which in turn pulls the float downward. It is ready to have a measurement value when the float reaches the equilibrium position as the upward force exerted by the liquid flow equals the weight of the float itself. For the same liquid which has a constant density and viscosity, there is a unique float position corresponds to a specific liquid flowrate.

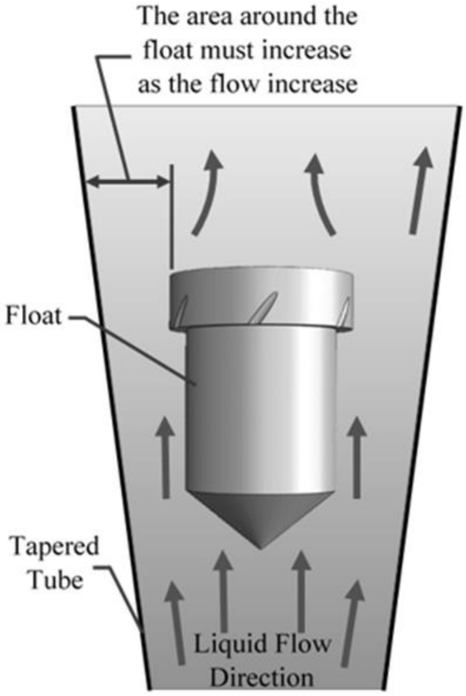


Figure 3.5 Rotameter water flowmeter

3.4.2 Pressure-sensing liquid level sensor

Every single tank has fitted, via flexible tubing, to a piezo-resistive silicon differential-pressure sensor type SenSym 139-SX01DN. This transducer is sensing the pressure difference between its two ports, *P1* and *P2*, as shown in Figure 3.6 and provides output signals in the range of 0 to 10 volt in direct proportion to the trapped air pressure between the liquid in the tank and the sensor as a function of a water pressure head.

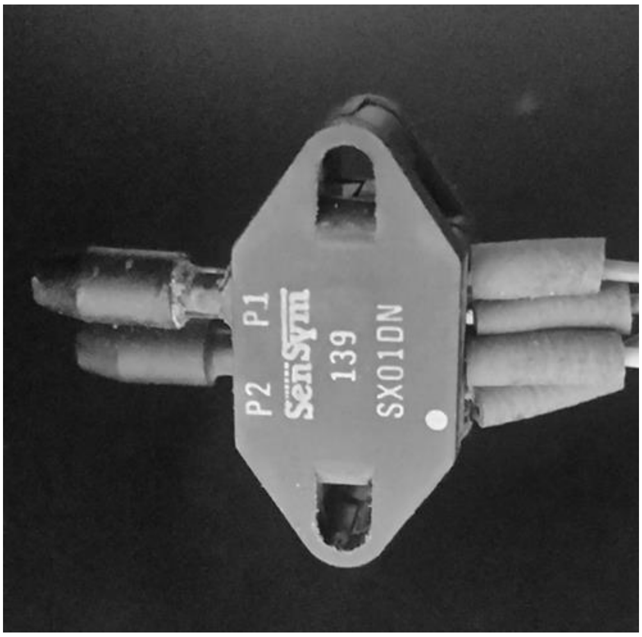


Figure 3.6 differential pressure sensor type SenSym 139-SX01DN

The pressure at any point below the free surface of a liquid in any direction has a direct proportion to the height of the liquid above this point. The pressure in a liquid, at any point, is influenced by three main factors:

1. The depth of the liquid measured from the measurement point up to the liquid free surface.
2. The pressure exerted on the liquid free surface.
3. Liquid density.

Accordingly, during the process, the pressure at a point is affected by the liquid depth rather than the container volume if the liquid density and the exerted pressure on the liquid surface are assumed to be constant. The measurements of the liquid level can be accomplished by using a pressure sensor with considering the variables mentioned above. If a liquid container is open to the atmospheric pressure, then the effect of the pressure exerted on the liquid free surface could be neglected by utilising a differential pressure sensor.

Mainly, there are two sorts of pressure sensor classified according to the type of the measurement:

1. Absolute pressure sensor:

This kind of sensors measures the pressure relative to absolute vacuum pressure. An example of this sort of absolute vacuum is the pressure of the space above the mercury surface in the mercury (Hg) barometer.

2. Differential pressure sensor:

It measures the difference between two pressures and introduces them as an input to the sensing unit. Some fluid flowmeter is an example of using a differential pressure sensor. There is a reduction in fluid pressure, as a result of increasing its velocity through a constricted cross-sectional pipe according to Venturi effect.

A gauge pressure sensor is another type of differential sensor that is built to measure the relative pressure of space to atmospheric pressure. An example of this sensor is the pressure sensing liquid level sensor that used in the coupled tanks apparatus CE105. This sensor compares between the head pressure of a liquid in a tank and the atmospheric pressure and converts the result into an analogue voltage.

Each tank of the CE105 coupled tanks system is connected to a differential pressure sensor via a calibration tube. This tube is open at its other end to the bottom of the tank. As the pressure sensor closes the other end of this tube, the pressure of the trapped air in the calibrator tube has a direct proportion to the liquid level in the tank if the ambient and medium temperature is assumed constant.

The liquid level will be determined based on the hydrostatic pressure that is produced by a column of liquid on the bottom of the calibrator tube, i.e., the tank bottom. This pressure has the same amount of that on the sensor through the trapped air in the calibrator tube. The pressure sensor has two ports, one of them is opening to the atmospheric pressure, and the other end is connected to the calibrator tube. If the density of the liquid is assumed to be constant and will not change during the process, and the change of the acceleration due to gravity is negligible. Hence, the hydrostatic pressure can be derived by a simple expression:

$$P = \rho g h \tag{3-22}$$

Where;

$P =$ The hydrostatic pressure$(N.m^{-2})$,

$\rho =$Density of the liquid$(kg.m^{-3})$,

$g =$The acceleration due to gravity $(m.s^{-2})$ and

$h =$The liquid depth in the tank (m).

Resolving the above equation for h:

$$h = \frac{P}{\rho g} \tag{3-23}$$

There are some concerns hinder high-quality system performance. One of the major such concerns is a calibration experiment related to the thermal system equilibrium (Higuchi H., Takeda S. et al. 2001). (Howell 2009) Stated that, in order to have an ideal calibration activity, it should be done at one temperature which it has to be the same as the pumped liquid, the receiving container and the surrounding environment. Moreover, the ambient temperature should not change significantly during the process. A system operator should take every opportunity to minimise the impact of the thermal equilibrium on the system behaviour whenever it possible. The experiments envisaged by using the CE105 tank system in the lab environment are unlikely to be performed under the previous conditions.

Liquid density varies with changes in its temperature. For example, the maximum density of water is 999.972 (for pure water 1000) $kg.m^{-3}$ at +4 *°C*. Meanwhile; it is 999.841 $kg.m^{-3}$ at 0°C. However, at room temperature, i.e., +22 *°C* the density of water is 997.774 $kg.m^{-3}$. All measurements for the purpose of this study were done at room temperature around +22*°C*, ±3*°C*, where water density variation is about ±0.1% (Shtargot, Mirza et al. 2013).

A wide range of industrial, commercial, and medical applications entail accuracy pressure measurements with ±1% up to ±0.1% or better, with reasonable cost, and often with very low power consumption. Because the process environment temperature is within this range, the results are valid as they verify.

3.4.3 Water pump

The CE105 apparatus, which used for this study, is provided with, SHURflo Diaphragm Pump, Model No. 208 – 110 – 41 to pump the water into the system's left-tank. This diaphragm pump, from its - nameplate, designed to pump an open water flow of (6.4 $l.min^{-1}$) at maximum voltage supplied of 10 *DC volt*. A *DC* motor - pump set is used to rise the water from the system reservoir to the left tank. This water pump is usually driven and controlled by connect it to a CE120 control panel. For the purpose of this research, the CE105 apparatus has been connected to a PC via a data acquisition DAQ NI USB – 6008 and the controller CE120. The latter control panel was implemented to provide a sufficient power to drive the system water pump. CE120 has been used as a proportional amplifier to boost the PC signal to match the pump drive voltage and to provide the required DC electric current consumed to drive the water pump at different pumping rate. A control panel unit under LabVIEW environment was developed to study the open and closed loop system response. As can be seen in Figure 3.4, a collocation of the water pump, a PC, NI USB-6008 data acquisition, CE120 controller and the control panel unit under LabVIEW environment have been used to study the open and closed loop system behaviour. This collocation enables an operator to control the water pump discharge and hence the liquid level under different scenarios via a PID controller.

3.5 Experimental tests:

3.5.1 Discharge characteristic study:

Experimental tests were done on CE105 apparatus to validate the developed mathematical model of the LLTS. Especially for the validation experiments;

- Valve A that connects the two tanks was fully closed.

- The regulator valve B was set to be partially open at position 3. This partial opening allowed free water flow from the left-hand tank to the system reservoir.
- Several open – loop experimental tests were accomplished on the CE105 to evaluate the calibration equation of each indicator, transducer and the system elements.
- While the discharge valve B was fixed at the same set position, to change the liquid level different drive voltages were applied to the DC motor – water – pump.
- When a step change drive voltage was applied, the liquid level rose until it reached a steady – state level, and then the system parameters were recorded.

The recorded parameters were the liquid level in *mm* and the corresponding liquid level sensor reading in *volt*; the pump drive voltage in *volt*; the tank inflow rate in $l.min^{-1}$ and the corresponding flow rate sensor reading in *volt*. At steady – state, the inlet and outlet flows are in balance state with the water discharge, (for any exit valve setting) being a function of the head of water above the exit restriction. Further tests allowed the relationship between the drive voltage and the outlet valve setting to be established. A voltmeter mounted on the CE120 control panel was utilised to measure the drive voltage and the voltage of any other transducer. Meanwhile, the liquid level could be measured directly by the operator in (*mm)* through the readable scale, as can be seen in Figures 3.2 and Figure 3.3.

3.5.2 Results and discussions

Figure 3.7 shows the experimental relationship between the liquid level and the outflow rate through valve B. The latter was evaluated by equating the outflow rate to the inflow rate at steady – state conditions.

According to Equation 3-11;

$$Q_o = \frac{(\rho.g.h)^{\frac{1}{\propto}}}{\rho.R} \tag{3-24}$$

Terms are as previously defined.

According to Bernoulli's Equation, (Dorf and Bishop 2005) and (Ogata 1997), the outflow rate is usually expressed as a power function of the liquid level, because of other variable are assumed to be constant during the process. Moreover, the liquid flow resistance *R* through the outlet restriction, which in turn a function of the exit cross-sectional area, is assumed constant. The power of this function is $\left(\frac{1}{\propto}\right)$, which depends on the kind of flow through the exit regulator valve. Where, $\propto$ equals 1, if the flow is laminar and accordingly, the relationship becomes linear. Meanwhile, $\propto$ equals 2, if the flow is turbulent and the relationship becomes non-linear.

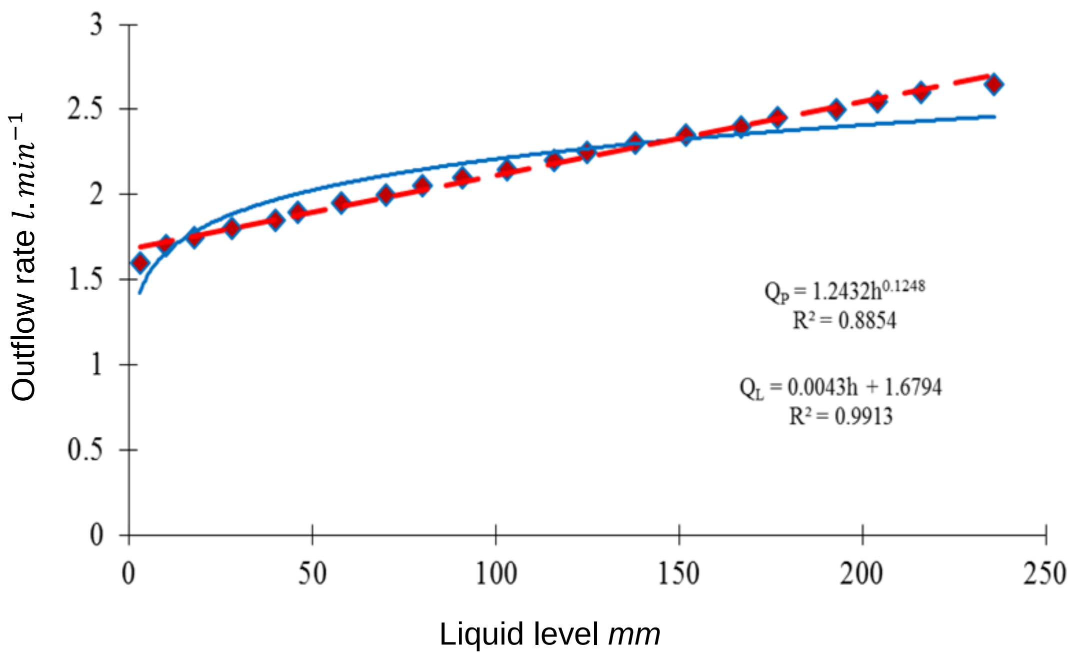


Figure 3.7 Experimental relationship between liquid level and the outflow rate through valve B when valve A is completely closed

Despite what (Dorf and Bishop 2005) stated, that all systems become not linear when the variables are increased unlimitedly. This system, for this particular case, is not fitting a real system nature because it mostly shows a linear response, as shown in Figure 3.7.

It was deemed that the following were of relevance:

- The liquid level in this experimental test varied from zero up to the maximum tank height of 250 *mm*.

- The regulator valve B could not be assumed as a perfect sharp-edged circular diameter orifice.

As shown in Figure 3.7, there are two trend lines describe the best curve fitting as a power function Q_p and as a linear function Q_L. The power function trend, which is usually used to describe the hydraulic flow through an orifice, shows a correlation coefficient (R^2 = 0.885). Meanwhile, for the linear trend the correlation coefficient shows (R^2 = 0.991), which means that the linear trend is describing the relationship stronger than the power function trend.

Accordingly, it was assumed that the water flow through valve B could not be defined as either perfect laminar nor perfect turbulent flow. Hence, a power function with power value between 1 and 0.5 be a reasonable expression to describe the relationship between the outflow rate and the liquid level, if the latter changed significantly. Moreover, this approach is convenient for Bernoulli's equation that usually presents mathematically as a square root formula for turbulent flow.

3.5.3 Time to evacuate the tank of CE105 coupled tank system

To confirm the previous results, another set of experimental tests have been accomplished on the CE105. For the same outlet valve B setting (position 3).

- The left-hand tank was filled to a specific liquid level.
- The tank was allowed to settle at its steady-state level.
- The water pump was then turned off, and the liquid was allowed to drain out of the tank.
- The time to evacuate the tank was recorded.
- The previous steps were repeated three times for the same liquid level, and then this test was repeated for other levels.

The relationship between liquid level and the time of evacuation is shown in Figure 3.8. It is recognised that the relation is linear.

From Figure 3.8 and for the best curve fitting, a linear function T_L gives a correlation coefficient R^2 = 0.997, which means the relationship between the liquid level and the time to evacuate the tank is a linear function. Despite that, the power function T_P trend gives (R^2 = 0.999) and a liquid head power of 0.9122 which can be assumed closely to be linear. Accordingly, the variation between the two trends is not reasonable.

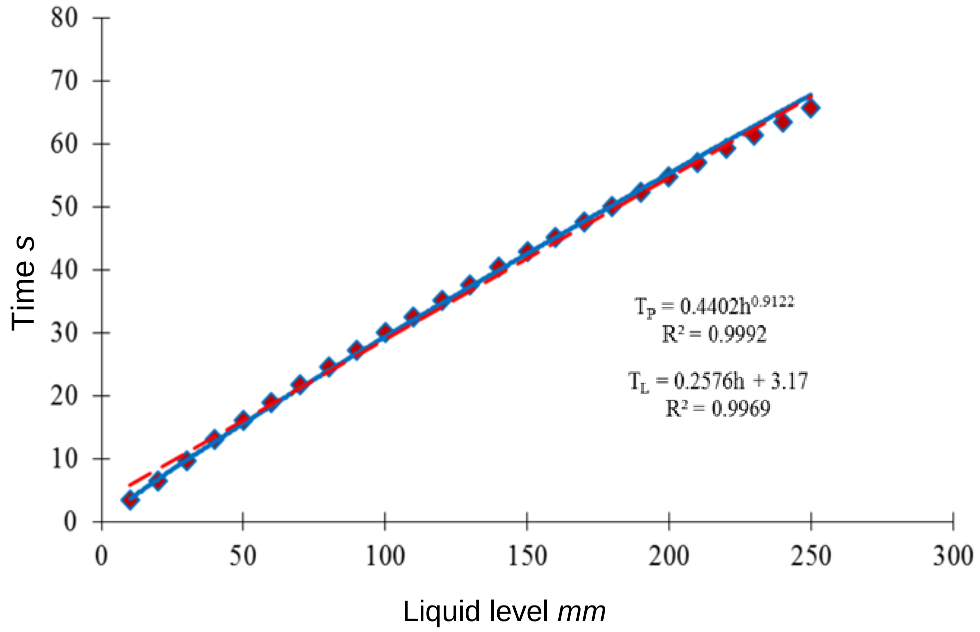


Figure 3.8 Time needed to evacuate the tank through valve B

3.5.4 Passing the drain water through valve *A*

In order to verify the behaviour of the regulator valve, valve A was chosen to study its characteristics as follows:

- Valve B was turned out to be completely closed.
- In contrast, valve A was again set at position 3.
- Valve C was set to be completely open allowing the water passes through it directly to the main reservoir and avoiding any amount of accumulated water in the right-hand tank.
- Several voltages were applied on the pump to reach a steady – state liquid level each time.
- For each, the system parameters were recorded.

1. The relation of the liquid outflow rate through valve *A* as a function of liquid level in the left-hand tank is as shown in Figure 3.9. On this figure, the best curve fitting as a power function Q_P and as a linear function Q_L can be shown. The power function with a power of a liquid level equal to 0.5211

is strongly describing the relationship rather than the linear with a correlation coefficient of R^2 = 0.983 for the former and R^2 = 0.903 for the latter. Accordingly, the system behaves like a real non-linear system following Bernoulli's Equation with a power between 1 and 0.5.

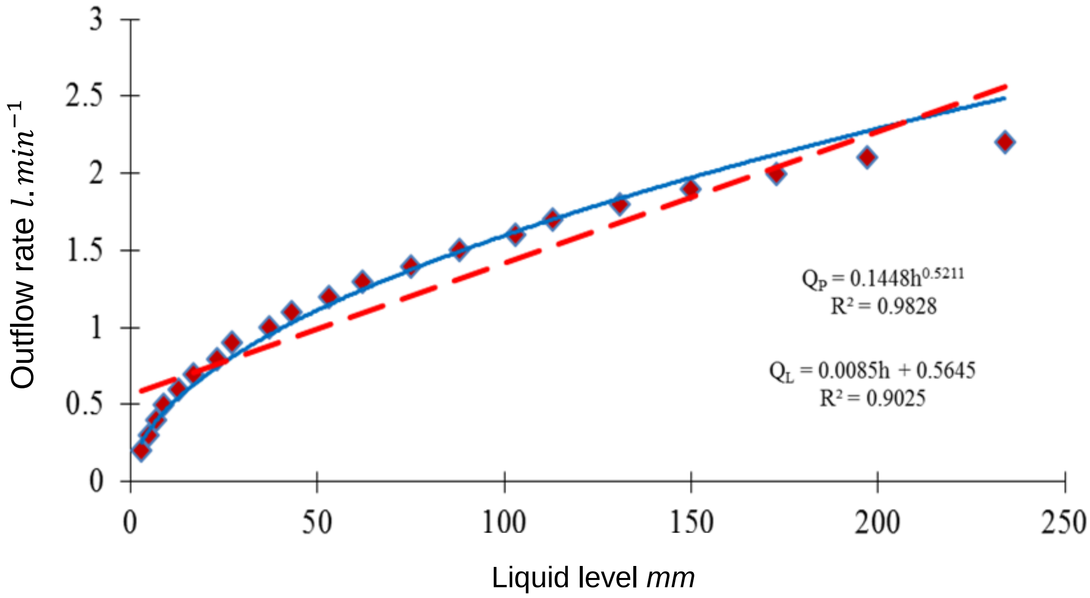


Figure 3.9 Experimental relationship of the outflow rate through valve A as a function of the liquid level when valve B is completely closed

2. To validate the results that pre-discussed in (1) above for Figure 3.9, another set of experimental tests were accomplished following the same steps that presented in Section 3.4.3. The relationship between the liquid level in the tank and the time to evacuate it is shown in Figure 3.10. From this figure, it can be recognised that the trend of the relationship is more power function T_P with a power of 0.629 and a correlation coefficient of R^2 = 0.999 than linear function T_L with R^2 = 0.978. Hence, all the next experimental tests were accomplished using the pre-discussed arrangements in Section 3.4.3.

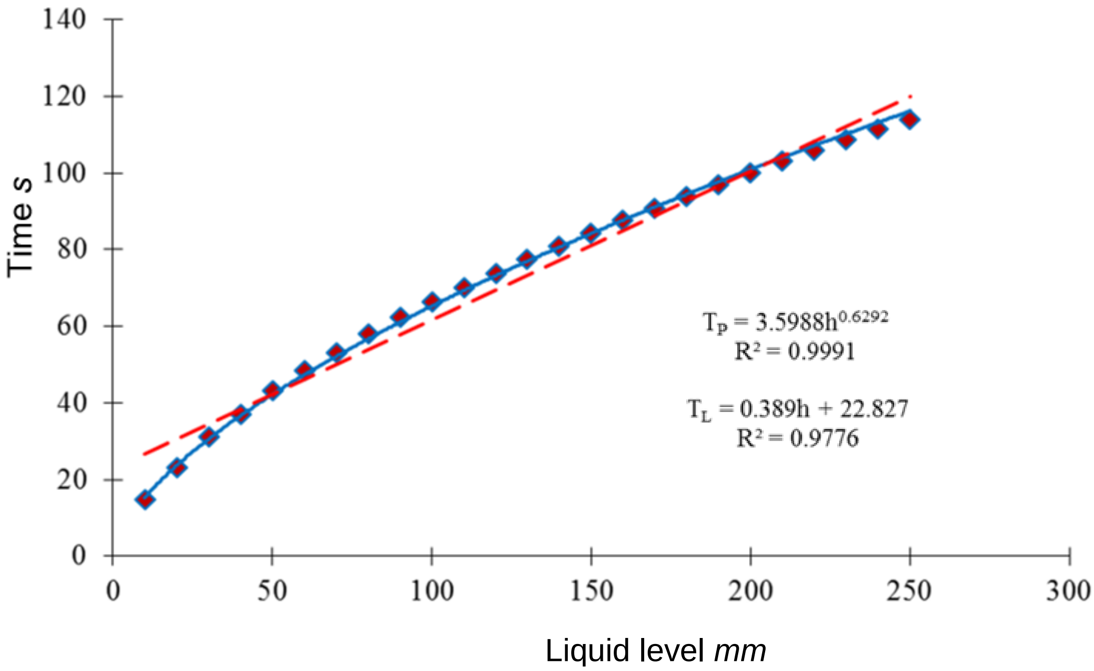


Figure 3.10 Time needed to have the left tank empty through valve A, valve B was fully closed

3.5.5 Results and discussions:

The previous results have been discussed in this section, and test experiments procedure has been concluded accordingly. By comparing the results, which present the experimental relationship of the liquid outflow rate through different valves as a function of the liquid level, as can be seen in Figure 3.7 to Figure 3.10. From Figure 3.7 and Figure 3.9 for the experimental relationship between the liquid level and the outflow rate through valve *B* and valve *A* respectively, it might easy to recognise that:

- The flow through valve *A* shows a non-linear behaviour and its trend, which is estimated by Microsoft Excel 2016, is a power function. The power of the liquid level *h* in the function is 0.5211, and it is assumed to describe the relationship as a square root equation. This result is consistency to Bernoulli's Equation.
- In contrast, Figure 3.8 shows a linear relationship between the liquid level and the outflow rate. If a power function has been chosen to describe the trend, the power of the liquid level *h* = 0.1248. This value is farther away from the stated range, i.e., 1 to 0.5 according to Equation 3-11.

- Meanwhile, if a linear trend has been chosen, then Figure 3.7 shows more linear behaviour with R^2 = 0.99. Nevertheless, Figure 3.9 shows less linearity with (R^2 = 0.9).
- As can be seen in Figure 3.8, a linear behaviour to evacuate the liquid from the tank through valve B. Meanwhile, Figure 3.10 shows a not linear trend to discharge the liquid through valve A.

These variations could be related to the following reasons:

a. The discharge restriction (valve B) is a regulator valve. Which means, to control the outflow rate through it, it needs to adjust its cross-sectional area. Arguably, the analogy between a sharp-edged circular orifice that is used in the mathematical analysis of the system and a regulator valve might not be completely satisfied.
b. There is an eccentric vertical shift between the centre of the valve B, which is assumed to be the valve discharge constriction, and the zero measured liquid level in the tank. The pressure sensing liquid level sensor is mounted at the bottom of the tank, i.e., zero level. As can be seen in Figure 3.11, this eccentric distance is about 46 *mm* measured from the tank bottom downward. It is inapplicable to track the liquid level neither by level indicator nor by the pressure sensor, through this part of the system for the following reasons:

- The water tube in this area is not transparent, and it is positioned behind the non-transparent system body.
- The sensing-point of the liquid level sensor is at the base of the tank, i.e., zero level.

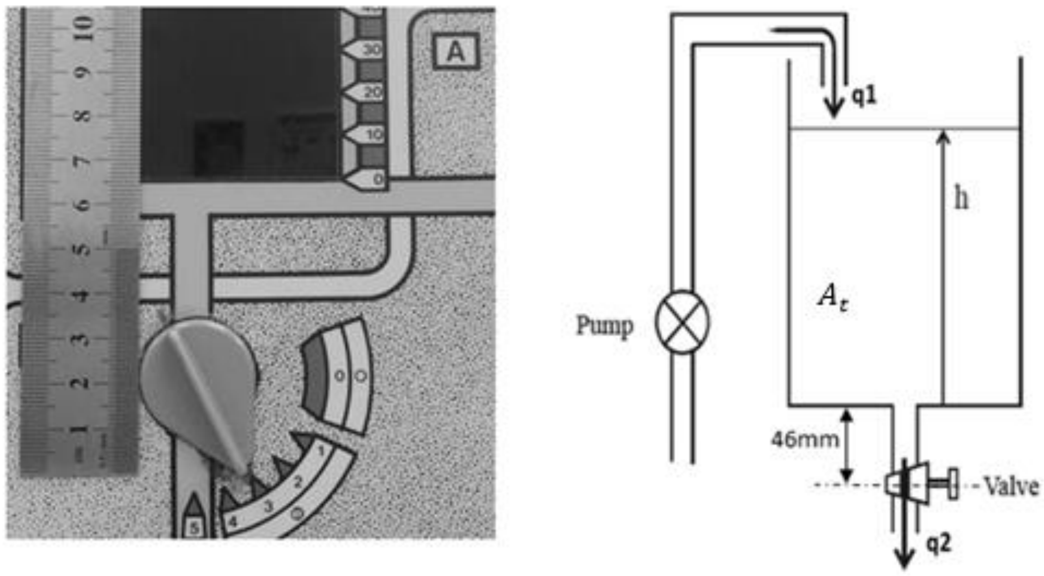


Figure 3.11 A single tank system with the outlet valve distance

Accordingly, it is impossible to overcome the shape and/ or the opening of the valve type problem that represented in (a) above because, valves (A, B and C) have been built in the existing system. The possible solution is by designing a new system using changeable sharp-edged circular orifices. To study the liquid outflow rate through the discharge restriction, it may need to use different diameter orifices in combine with the liquid level as a function of accumulative liquid in the tank.

Nevertheless, by shutting valve B completely (fully closed) and directing the liquid from the left-hand tank to the right one through the valve A which it is by design located at the zero level, the problem (b) might be overcome. Consequently, the liquid passes from the right tank to the system reservoir through the valve C. In order to prevent any accumulative liquid in the right-tank that leads to increase the liquid height in it and to eliminate any resistance caused by the discharge water restriction, valve (C) was set to be fully open.

The CE105 apparatus might reasonably be assumed a not linear system. Moreover, to eliminate the effect of the eccentric distance of valve B and for the purpose of the rest of this research, valve B was fully closed, and valve C was fully open. Valve A was set to a specific opening to give, in collaborated with the liquid level, the required discharge

3.6 Discharge valve characteristic:

According to the previous discussion, the regulator valve *A* was chosen to be the system liquid discharge valve. Arguably, a regulator valve has endless setting positions. By changing its setting, it might not be easy to have the same previous characteristic again. Hence, to study the valve behaviour at different valve settings, there were sets of tests have been done.

- Valve *B* was closed, and valve *C* was fully open.
- Valve *A* was set at position 3 for the first time.
- A DC voltage was applied gradually to drive the system water pump until it starts rising water to the tank level.
- When the water starts accumulating in the tank, it needed to wait until it reached the steady – state and then the system parameters were recorded.
- Another voltage was applied to increase the liquid level and when it reached a new steady – state level the parameters were re-recorded. This step was repeated several times until the nearly full.
- The previous steps were repeated for different valve *A* main settings 2, 3 and 4 and other three sub-positions, i.e., between 2–3, 3–4 and 4–5.

The water outflow rate as a function of the liquid level in the tank for each set of valve *A* was demonstrated in Figure 3.12.

As can be seen in this Figure 3.12, all positions of valve *A* are showing non-linear power function trend of an outflow rate versus the corresponding liquid level in the tank. Moreover, there is a consistency between the mathematical model that was previously expressed in this chapter Equation 3-11, and the experimental result as a power function. There are still some minor variations might be due to the differences between the ideal orifice shape and real regulator valve depending on its setting, i.e. the valve opening. It is clear; there is a relationship between the parameters and powers of the characteristic equations of valve *A* in different settings. Figure 3.13 shows the linear relationship between the parameters and present its trend equation. Moreover, this figure shows a second order equation to describe the relationship between the powers of the characteristic functions. Consequently, at any random set of valve *A* and if a steady – state liquid level and the corresponding outflow rate are known, then the valve set could be easily evaluated by interpolation from Figure 3.12. This set position could be employed in Figure 3.13 to evaluate the parameter and the power of the characteristic equation. This equation describes the liquid outflow through valve *A* at the existence opening. Which could provide a possible tool to predict the outlet valve setting by knowing only the steady – state liquid level and outflow rate. Consequently, the characteristic equation could be estimated for the unknown set position.

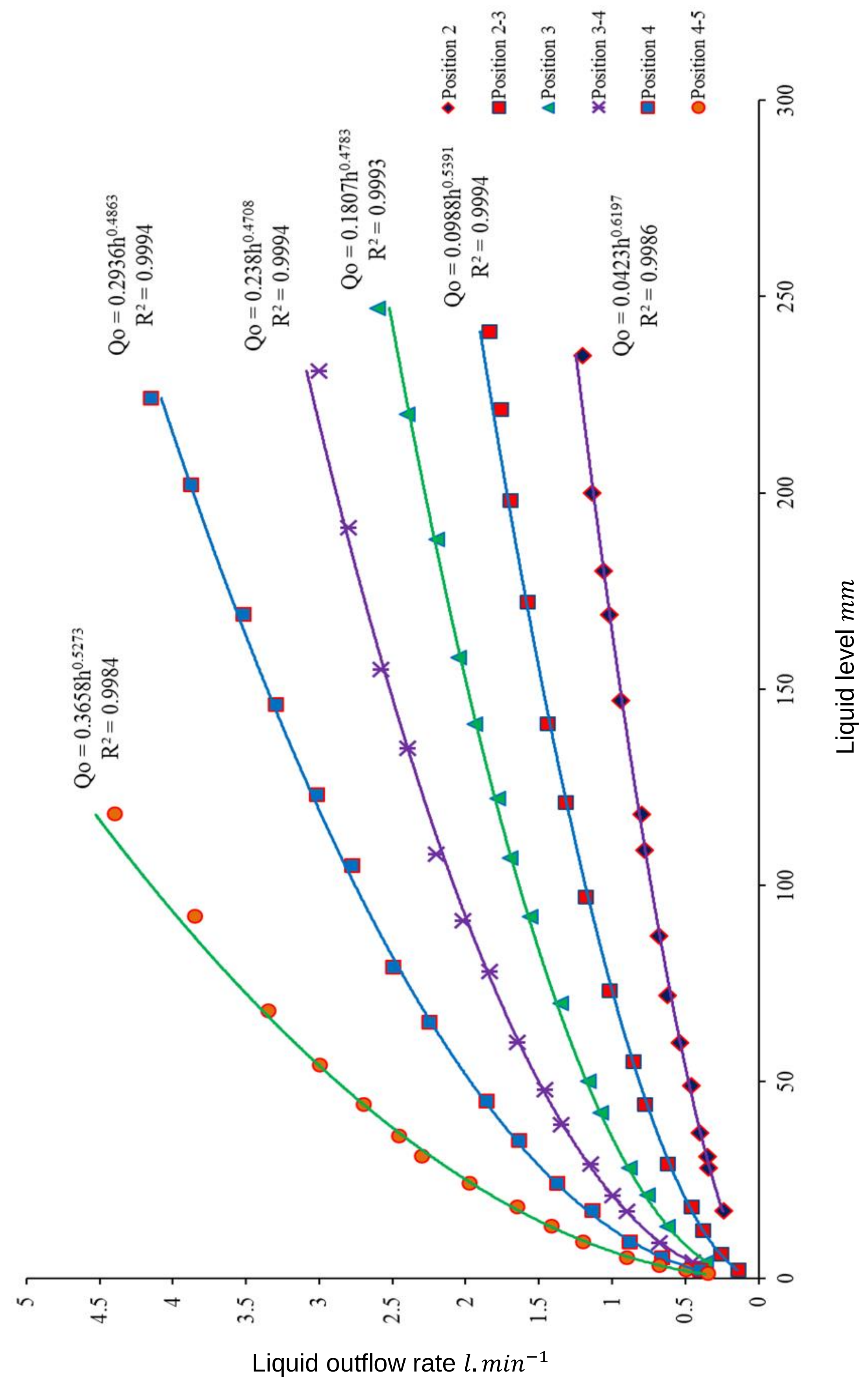


Figure 3.12 Liquid outflow rate as a function the liquid level for different valve A

To deal with the control problems of tank liquid level, it could be useful to have the following details:

- The tank input flow rate.
- The outlet flow rate.
- The tank dimensions.
- Transducers and sensors calibration equations.

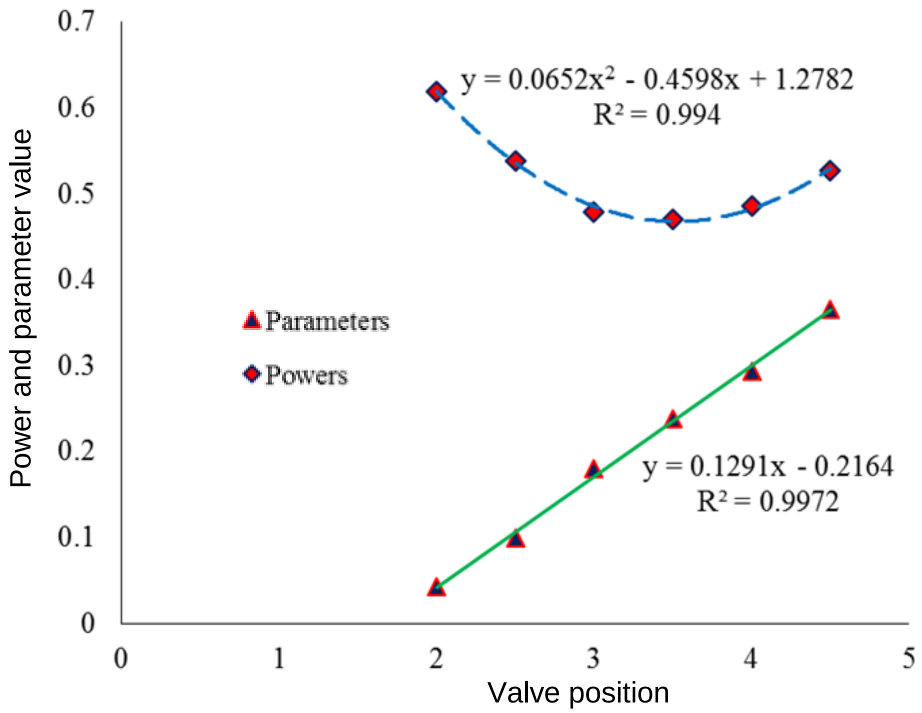


Figure 3.13 Powers and parameters of the characteristic equations of valve A positions

3.7 Calibration Equations

Figure 3.14 presents a block diagram of a liquid level system to generate a closed-loop control system model. The system transducers and other elements could expose to have their characteristics change with the time. For simulation requirements, sensors and actuators need to have their calibration equations.

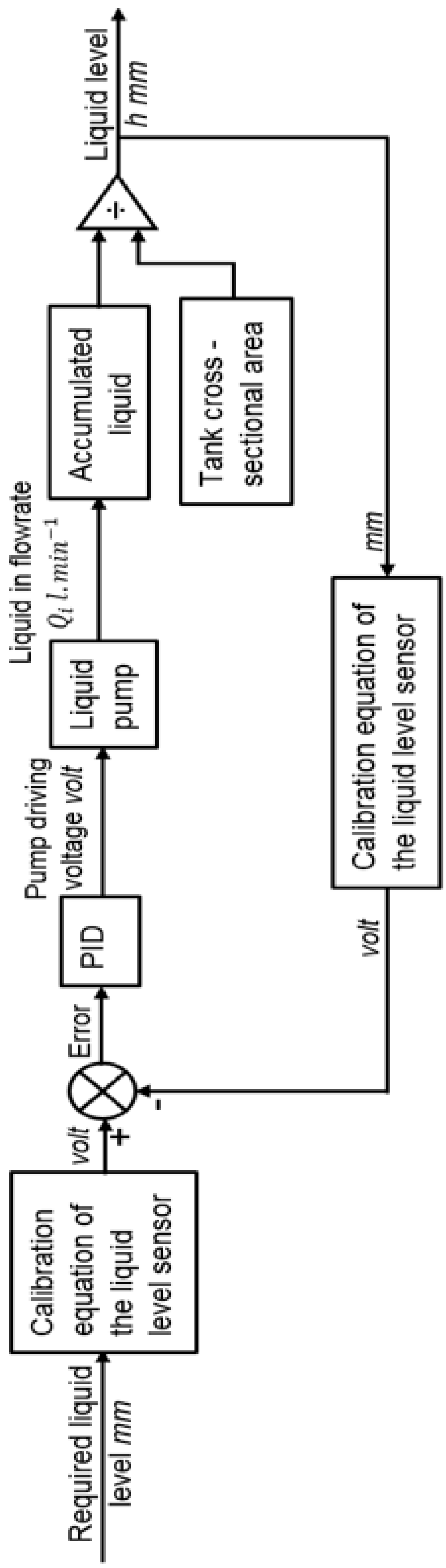


Figure 3.14 A block diagram of the liquid level system to generate the system model

In manual control systems, an operator needs to interrupt the indicator measurement and takes the appropriate action. Open loop control system is an example of such sort of systems with level measurement indicators. Usually, in closed loop systems, indicators are used to state calibration equations of each transducer in automatically controlled systems. Meanwhile, to have an electronic – controlled closed – loop system, it needs to have some electronic transducers to convert physical quantities into electronic signals. The pressure sensing liquid level sensors and a flow rate sensor have been added to drive and control the system. Even though, the indicators are utilised to state the calibration equations of each transducer. Sensors have manufactured to convert some physical quantity to an electronic signal with some precision of accuracy depending on the application this sensor will be used. Manufacturers usually provide a characteristic curve of the instrument showing the range and the relationship between the two quantities the equipment deals with. Changes in a sensor reading are usually related to some factors such as ambient and medium temperature and pressure; liquid viscosity; and some changes in dimension with the time. Calibration of a sensor is a primary process followed to preserve the sensor accuracy under the same condition that it produced for. Accordingly, the calibration of an instrument could be defined as a process followed to determine its accuracy. This process may consist of obtaining a reading from the sensor as an electronic signal and the corresponding physical quantity measured by using a standard instrument. Moreover, International Vocabulary of Metrology (VIM 3 2008) defines the calibration as shown: “An operation that, under specified conditions, in a first step, establishes a relation between the quantity values with measurement uncertainties provided by measurement standards and corresponding indications with associated measurement uncertainties and, in a second step, uses this information to establish a relation for obtaining a measurement result from an indication“

For the calibration purposes of the CE105 apparatus, valve B was set to be fully closed; valve C was set to be fully open and only valve A was set at position 3. A voltage was supplied to the DC electric water – pump to have a related liquid flow rate. When the liquid reached its steady-state level, this level in *mm*; the corresponding pressure sensor reading in *volt*; the water inflow rate to left–hand tank measurement through water flowmeter in $l.min^{-1}$; the flow rate sensor in *volt* and the pump voltage were recorded. At steady state, the amount of water comes into the tank is equal to that goes out and hence, the change of the accumulated water in the tank is equal to zero. Consequently, there is no change in the water level with the time.

3.7.1 Pressure – sensing liquid level sensor

As can be seen in Figure 3.15, the relation between the liquid level and the pressure–sensing liquid level sensor reading, is a linear proportional relationship. The calibration equation, as the best curve fitting of the liquid level sensor, is:

$$y = 0.0386\,x + 0.0131 + E_y$$

OR $$y = 0.0386x + 0.3231 \tag{3-25}$$

Where; E_y = zero error of the sensor. This error might be changed because of some reasons such as, the ambient and/or the liquid temperature, or changing of the sensor characteristics with time.

Equation (3-25) will be used later in a simulation to set the set point in *millimetres* rather than *volts*.

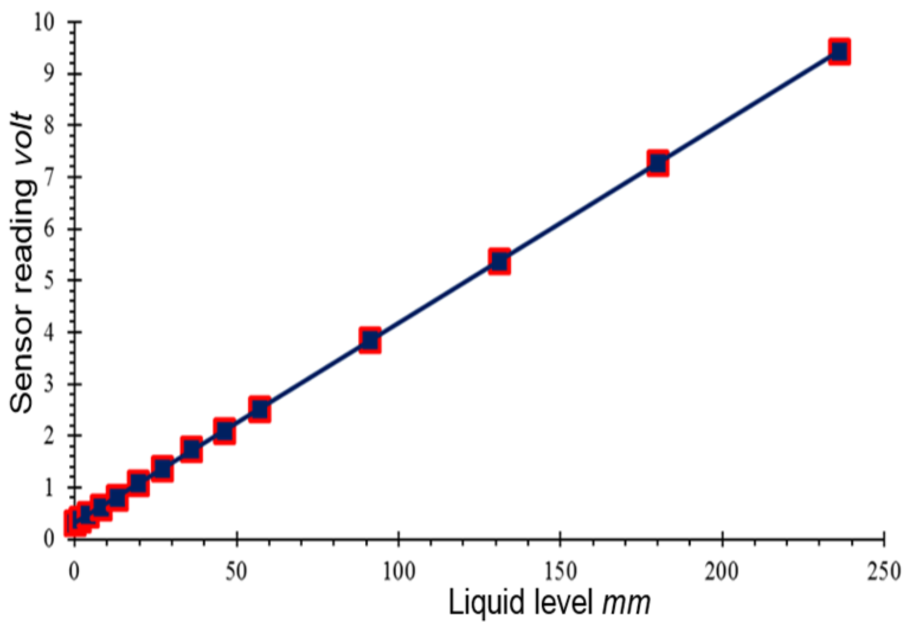


Figure 3.15 Calibration equation of the liquid level sensor mm to volt

3.7.2 Inflow rate sensor

The correlation between the readings of the inflow rate sensor in *volt* and the corresponding liquid flow rate measured on the system rotameter in $l.min^{-1}$ is displayed in Figure 3.16. From this figure, it is apparent that the sensor output voltage is proportion linearly with the amount of liquid flows through the sensor. From the best curve fitting, the calibration equation of the inflow rate sensor is:

$$y = 2.0954x + 0.2377 \tag{3.26}$$

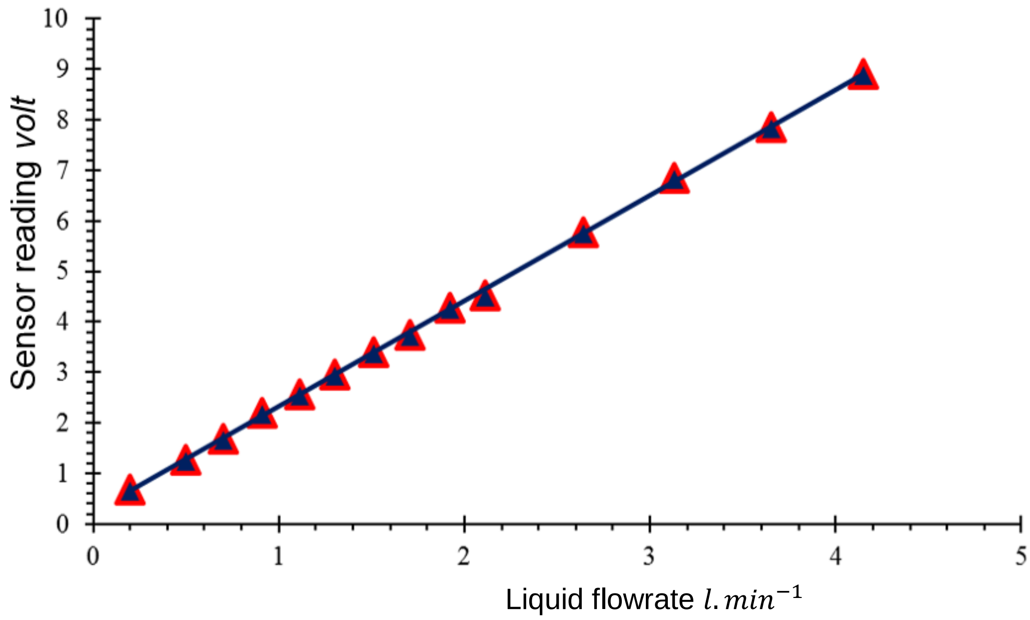


Figure 3.16 Calibration equation of the liquid flowrate sensor

3.7.3 The liquid pump calibration equation

A liquid pump characteristic is usually being presented as a curve showing the liquid flow rate in $(l.min^{-1})$ or $(l.s^{-1})$ as a function of the out – flow resistance, which is usually being presented as a liquid head in m or the out pressure in $(N.m^{-2})$. Sometimes, the inlet/ outlet differential pressure or head is used instead. Another relation might be presented to show the pump outflow rate as a function of the electric current in *amp* for the electric pump, in this case, it is assumed the voltage supplied is constant, or the power consumption in (*kW)*. The characteristic curve of a Model No. 2088-403-144 (Aqua-King), which similar to that used in the CE105 apparatus, is shown in Appendix A. An alternative model data is presented here because of the data sheet of the system water – pump is not available neither in the lab nor online or even at the manufacturing company.

For the control study, it needs to utilise a variable speed water – pump, for example. This sort of pump provides a variable outflow rate as a function of different voltages applied. But unfortunately, there is insufficient technical information about the pump "SHURflo Diaphragm Pump, model 208 – 110 – 41" even online or at the manufacturer. The dynamic differential equation of the Diaphragm pump needs to be expressed and prepare to implement in the system simulation under LabVIEW environment. The pump calibration equation could be divided into two parts, a steady – state part and a dynamic part, as follow:

a. Water - pump steady – state equation:

The water pump shows a nonlinear behaviour because there is no output flow when the drive voltage is less than 2.0 *volt*. Hence, for the purpose of simulation requirements, the active part of the steady-state behaviour of the pump was considered, as shown in Figure 3.17.

The linear steady-state calibration equation of the water pump is:

$$y = 0.515x + 0.0135 \tag{3-27}$$

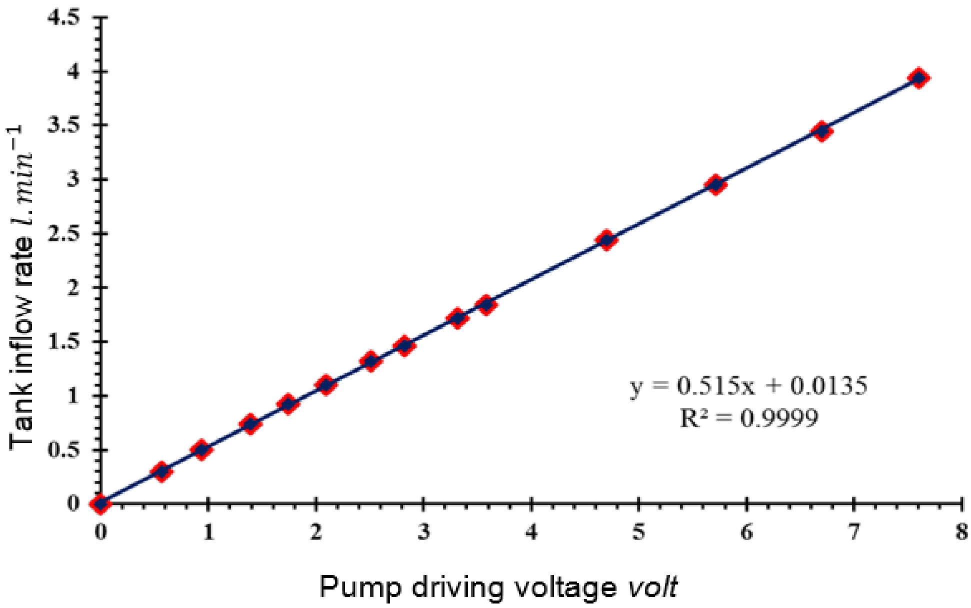


Figure 3.17 Calibration equation of the water pump at steady – state

b. The dynamic characteristics equation:

This section describes the instantaneous response of the water pump when its driving voltage was increased or decreased as a step function, as shown below. First of all, a driving voltage was supplied to the pump and waiting until it reached the corresponding steady – state. Secondly, a new voltage as a step function was supplied, and the instantaneous flow rate was recorded as a function of time taken to reach a new steady – state. This procedure was repeated several times to confirm the result for different driving voltages. Then, the pump dynamic-model was estimated by using MATLAB-System Identification Toolbox, which is utilised to create linear and nonlinear dynamic system models from the measured input-output data. Simulink results show the system water pump behaves as a second-order plant with the s-domain Laplace transfer function shown in Equation (3-28) and the response curve is as shown in Figure 3.18.

$$y = \frac{1}{1 + S + 0.29s^2} \tag{3-28}$$

The Laplace transformation of the overall calibration equation of the DC electric water-pump becomes:

$$Q_p = \frac{0.515x + 0.0135}{1 + s + 0.29s^2} \tag{3-29}$$

Where;

V_p is the pump drive voltage ($volt$),

s is called the (complex) frequency variable in (s^{-1}),

And Q_p is the pump outflow rate ($l.min^{-1}$).

This function is valid either the voltage supplied to the pump is increased or decreased as can be seen in Figure 3.19.

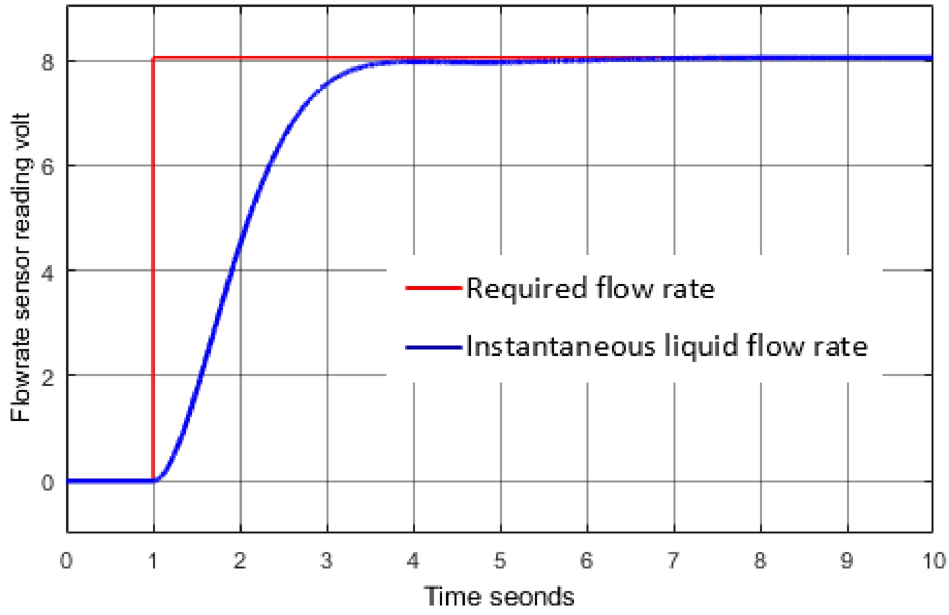


Figure 3.18 The pump dynamic response

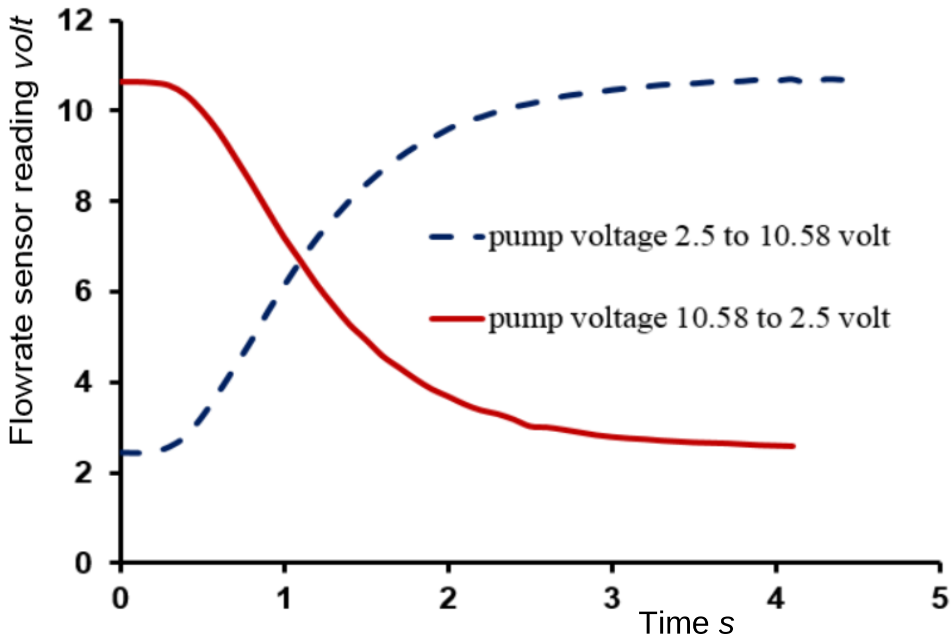


Figure 3.19 Dynamic response of the system electric-pump

3.7.4 The drain valve characteristic equation:

The characteristic equation of the water free outflow – rate through the discharge regulator restriction needs to be estimated. This valve was set to a specific opening, i.e., position 3. A set of voltages was applied to the water – pump and waited until the water in the tank reached its steady – state level corresponding to each voltage. The drain regulator valve opening was kept unchanged during this calibration process. The water-free outflow – rate as a power function of the liquid depth in the tank is as can be seen in Figure 3.20. The characteristics equation as the best curve fitting is:

$$q_o = 0.2383\, h^{0.514} + 0.003 \qquad \text{(3-30)}$$

From Figure 3.20 and the characteristics Equation 3-30, the free outflow-rate equation is a non-linear equation, where *h* is the liquid height *(mm)*.

There is a significant similarity between Equation (3-30) and Bernoulli's Equation. For the latter equation, it is assumed that the passing water through the outlet valve is incompressible, which means its characteristics (density and viscosity) will not be changed during the process.

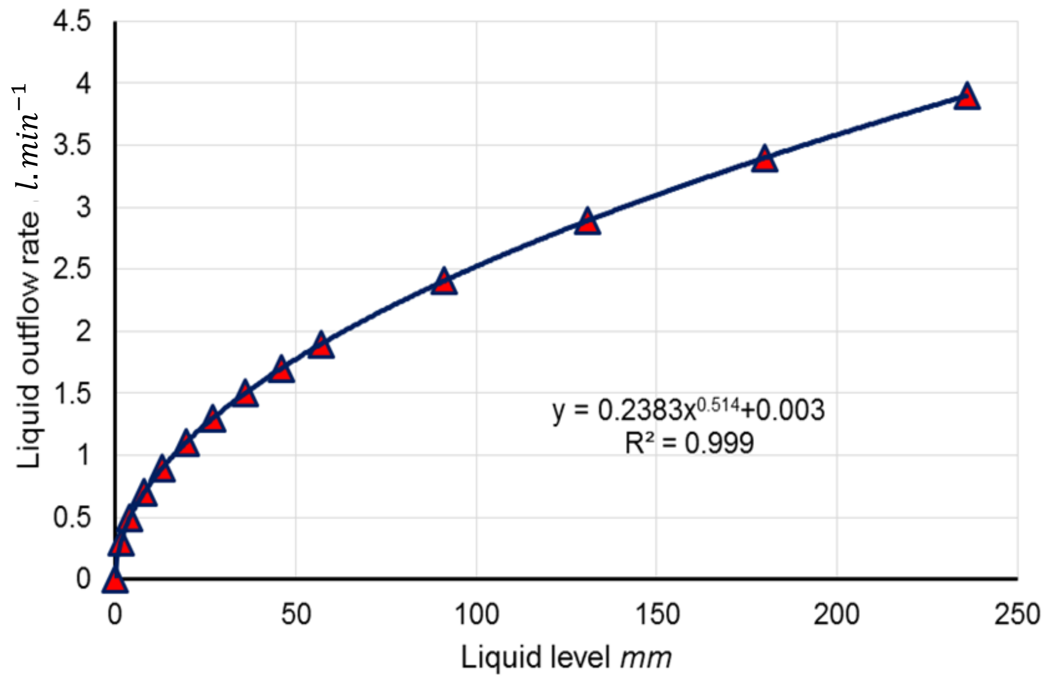


Figure 3.20 Calibration equation of the outflow rate through exit regulator

3.8 Simulation of CE105 under LabVIEW environment

Under LabVIEW environment, the pre-evaluated calibration and characteristics equations from Section 3.6 were used to build:

1. Graphical User Interface (GUI) to run the CE105 coupled tank system as can be seen in Figure 3.21. Figure 3.22 presents the block diagram of the GUI where a PID block, which will be discussed in detail in Chapter 6, was used to control the system response. The parameters of the PID controller are set to their default values by LabVIEW as shown in Table 3.2. The PID input signal is the required liquid level as a step function which, it set in *millimetres* on the GUI, and it then converted, for the purpose of the controller requirements, into a voltage according to the calibration equation of the liquid level sensor as shown in Figure 3.23. Meanwhile, the controller output is a driving voltage generated by the PID on the programme to the water pump through NI USB – 6008 DAQ and the control panel CE120 respectively, as can be seen in Figure 3.4. The feedback signal is the reading of the liquid level sensor as a voltage that sent to the PID controller on the programme via DAQ assistance board. A median filter, as shown in Figure 3.22, was added to smooth the noisy signal acquired from the pressure sensing liquid level sensor. The PID output range high was set to 10 *volts,* and the low was set to 0 *volts* according to the pump driving voltages. While, for the purpose of this research, the PID gains were set to their default values set by LabVIEW programme, as can be seen in Table 3.2 and Figure 3.21.
2. A simulation was built using the characteristic equation of the system elements as shown in Figure 3.25 and Figure 3.26 and the parameters shown in Table 3.2 with an option to choose either open or closed-loop control system. This virtual system was examined to study the consistency of its response with the behaviour of CE105 coupled-tank liquid level system. The front panel of the simulation under LabVIEW environment and its block diagram are as shown in Figure 3.24 and Figure 3.25 respectively. It is clear that the calibration equations,

Equations 3-25 to 3-27 are linear – first order equations with zero error while the other are non-linear equations.

A PID controller attempts to correct the error between a measured process variable and a desired set-point by calculating and then outputting a corrective action that can adjust the process accordingly. The PID controller calculation involves three separate parameters; the proportional, the integral and derivative values. The proportional value determines the reaction to the current error; the integral determines the reaction based on the sum of recent errors and the derivative determines the reaction to the rate at which the error has been changing (Basilio and Matos 2002).

Table 3-2 The parameters identification for the simulation model

<table>
<tr><th></th><th>The simulation parameters</th><th>Range</th><th>Note</th></tr>
<tr><td>1</td><td>Liquid level set-point</td><td>0– 225 mm</td><td>According to the tank height of the test rig CE105</td></tr>
<tr><td rowspan="4">2</td><td colspan="3">PID gains:</td></tr>
<tr><td>Proportional gain (K_c)</td><td>1.000</td><td rowspan="3">Set by LabVIEW as default values</td></tr>
<tr><td>Integral time (T_i, min)</td><td>0.010</td></tr>
<tr><td>Derivative time (T_d, min)</td><td>0.000</td></tr>
<tr><td>3</td><td>The tank cross-sectional area</td><td>9350 mm^2</td><td>According to the tank cross-sectional area of CE105 apparatus</td></tr>
<tr><td>4</td><td>PID output range high</td><td>10 volts</td><td rowspan="2">According to the pump driving voltages</td></tr>
<tr><td>5</td><td>PID output range low</td><td>0 volt</td></tr>
</table>

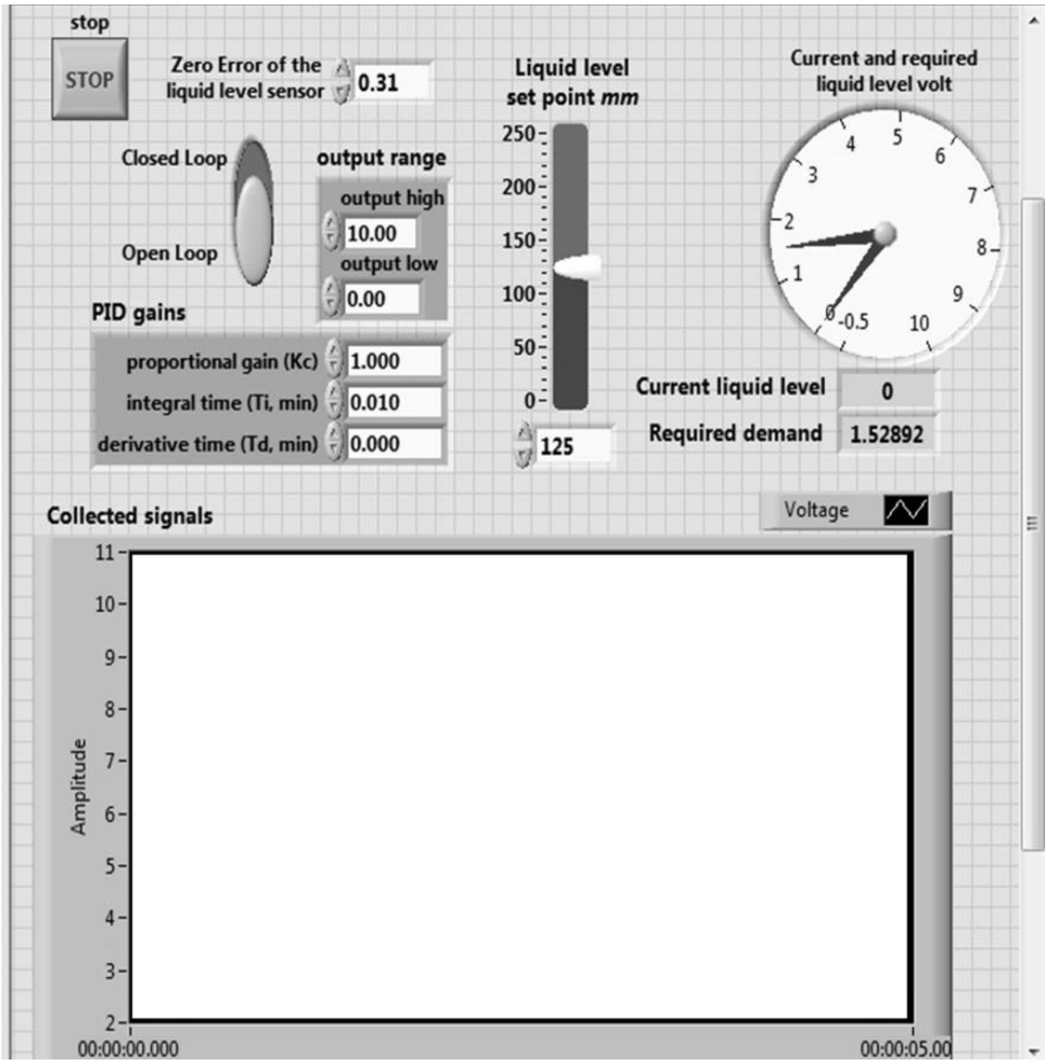


Figure 3.21 Front panel under LabVIEW programme environment to operate and data acquiring of CE105 coupled tank system

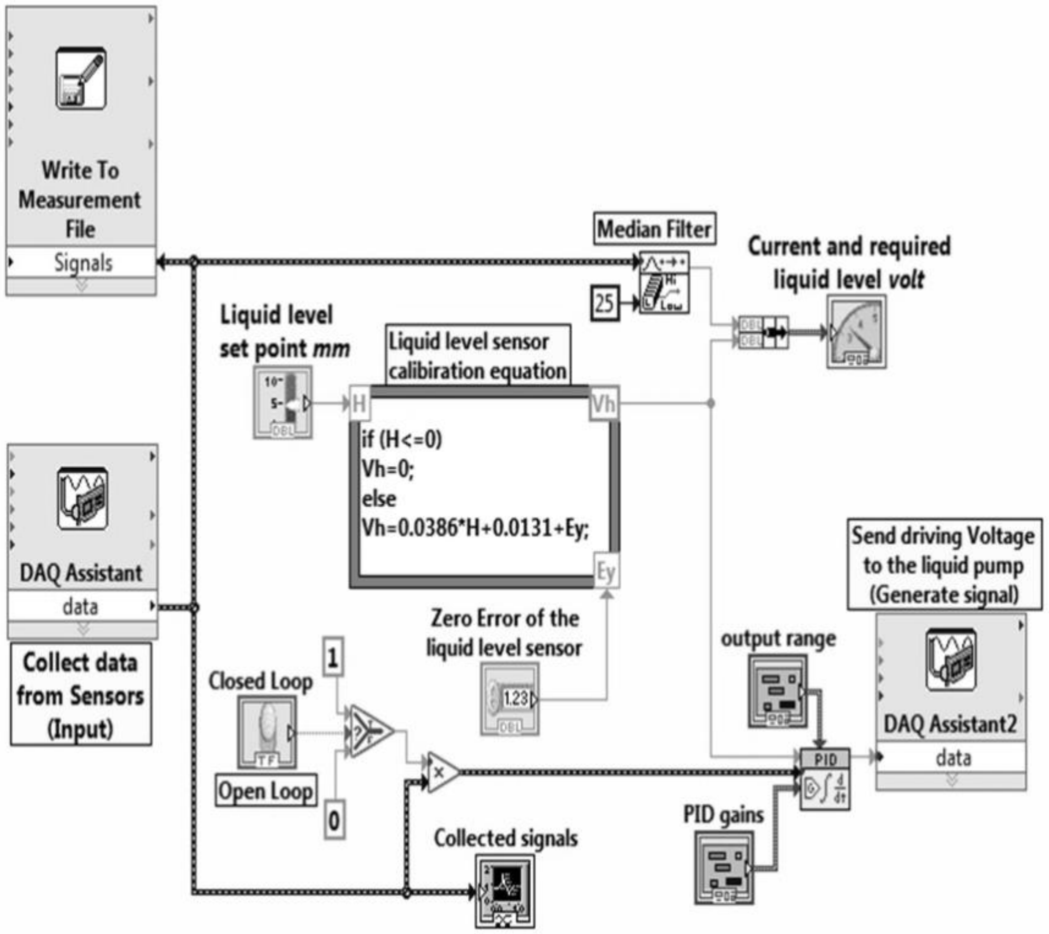


Figure 3.22 Block diagram under LabVIEW programme environment to operate and data acquiring of CE105 coupled tank system

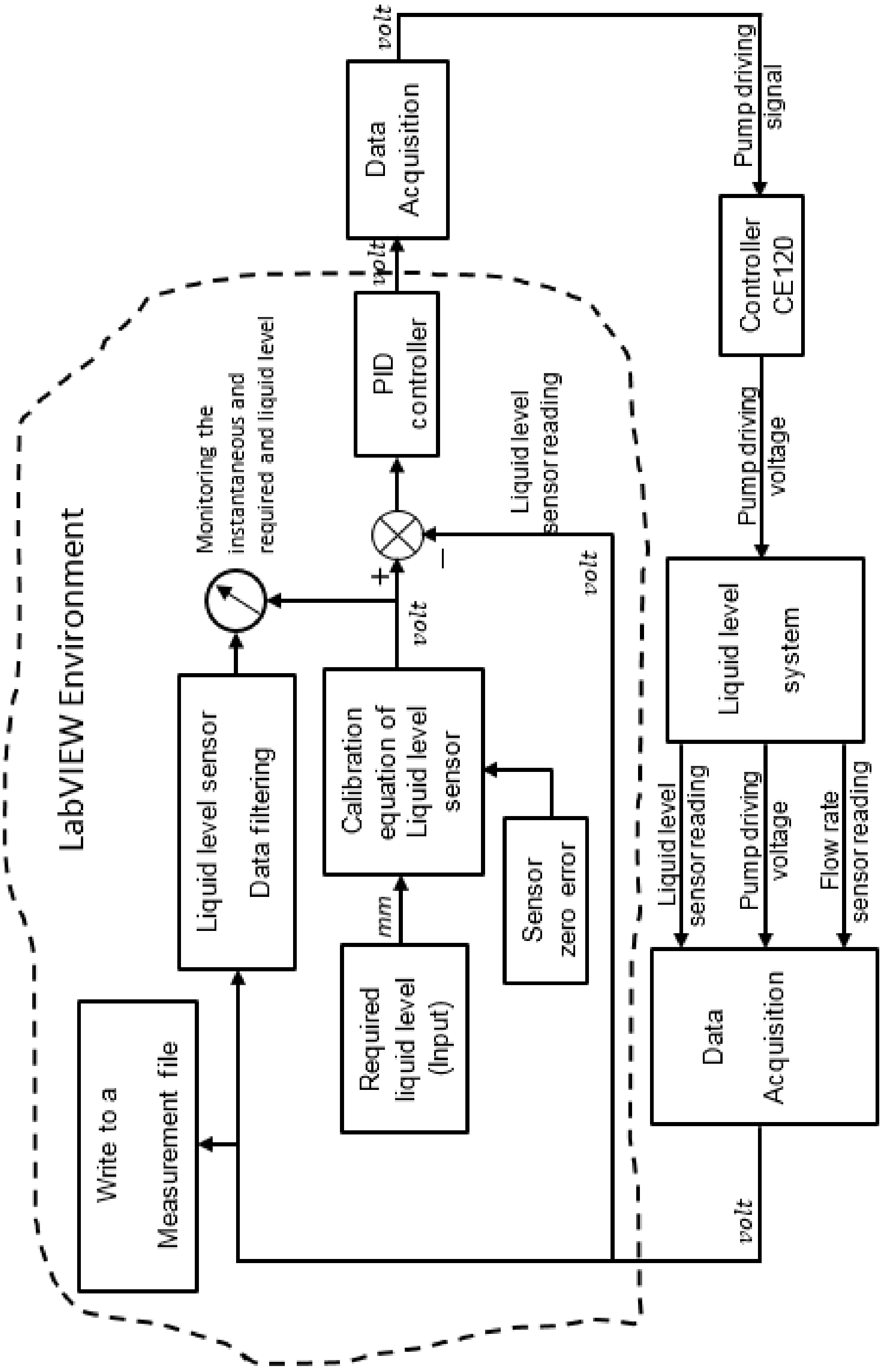


Figure 3.23 Block diagram of the operating and data acquiring of CE105 coupled tank system

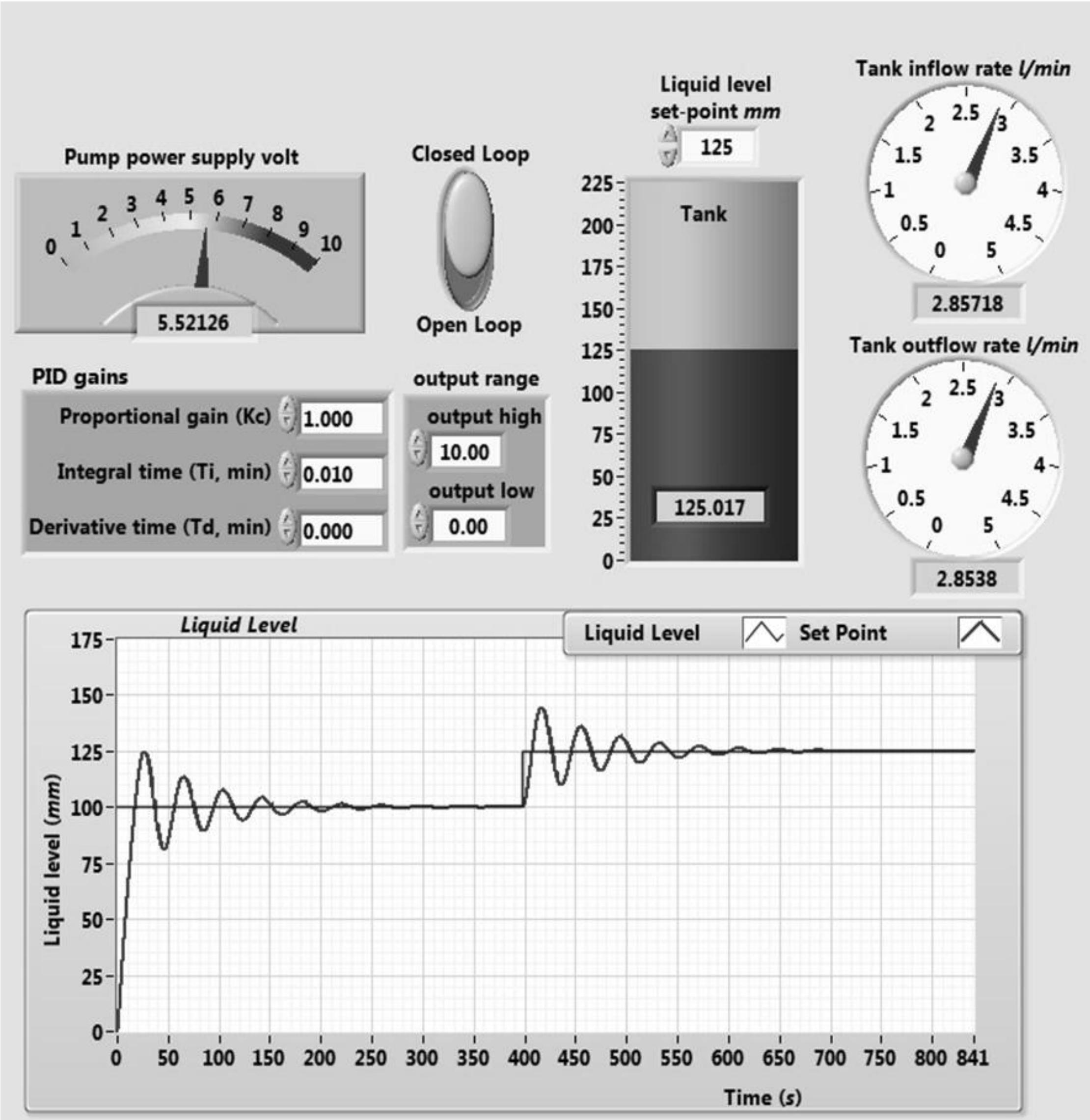


Figure 3.24 Front panel of CE105 simulation under LabVIEW environment

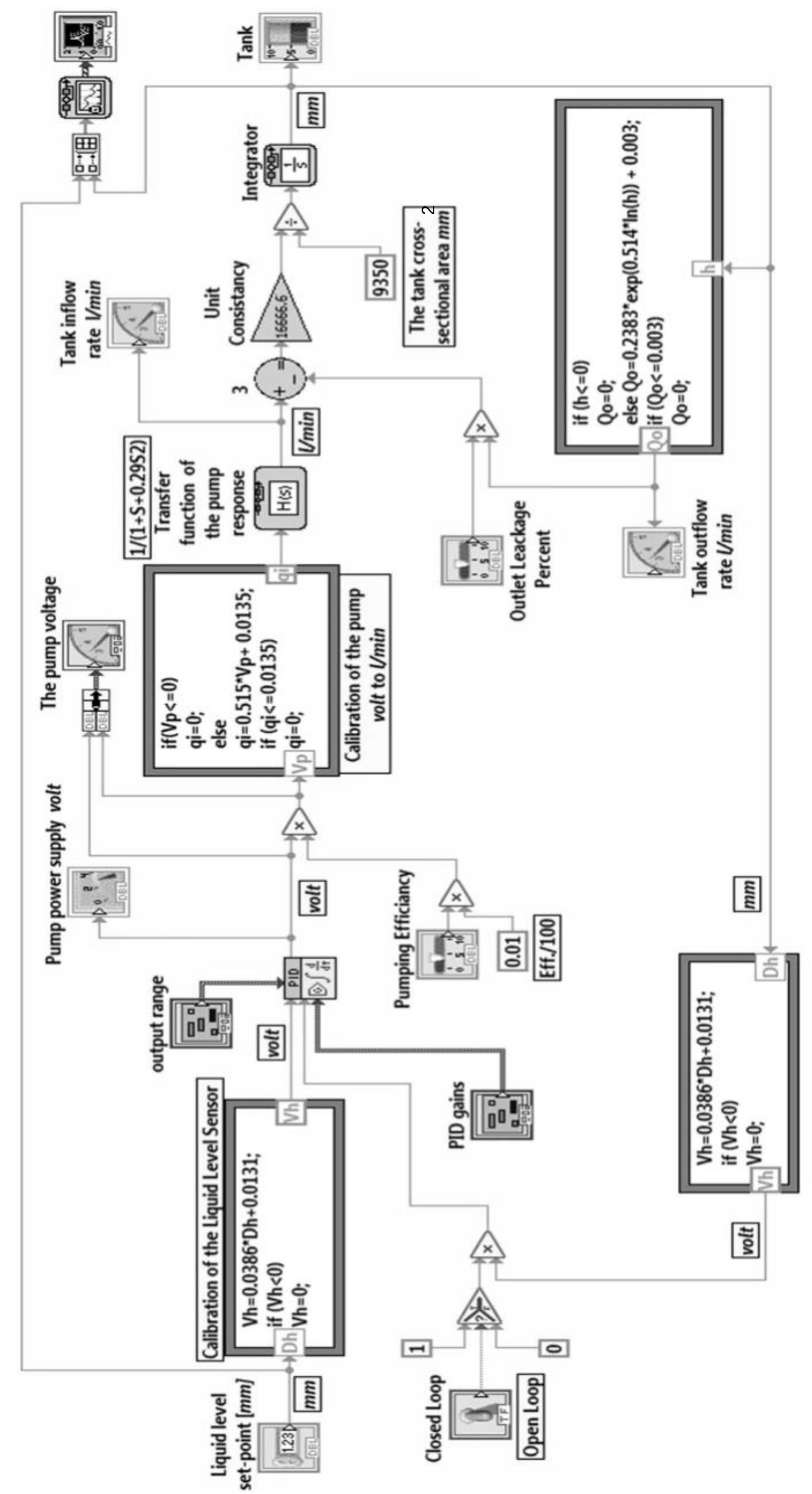


Figure 3.25 Block diagram of the simulation of CE105

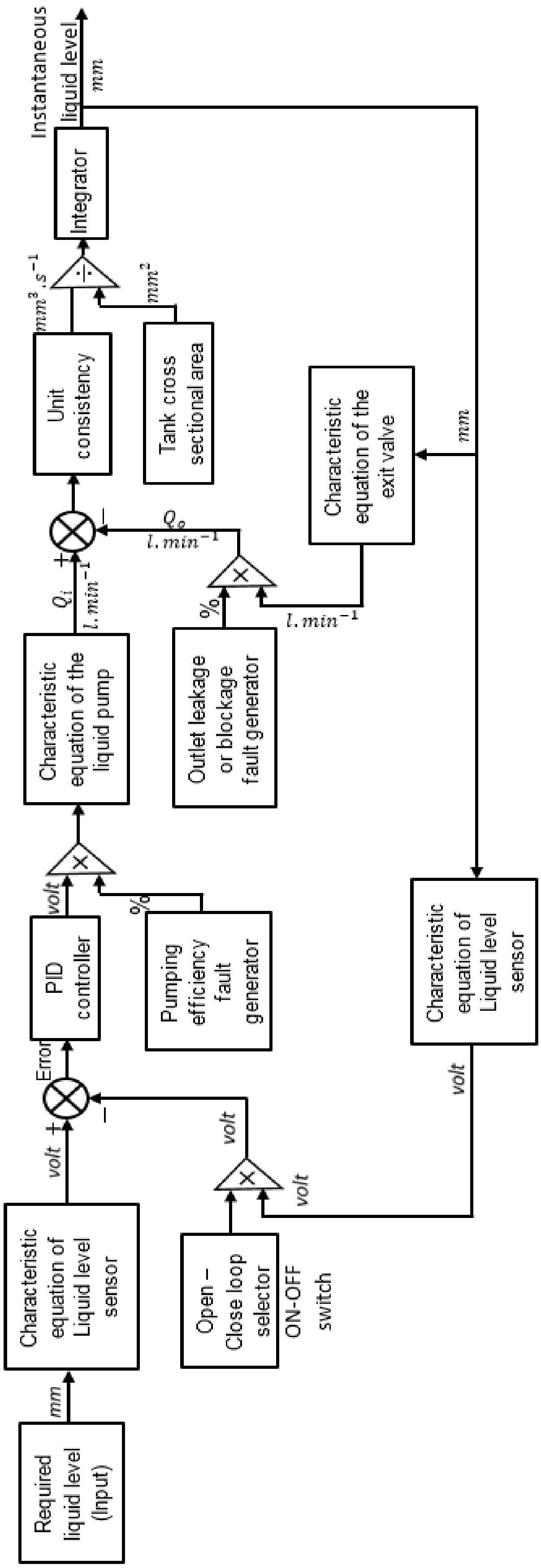


Figure 3.26 Block diagram of CE105 simulation

3.9 Controlling of CE105

Controlling of (LLTS) is classified as one of the most challenging benchmark control problems because of its nonlinear and non-minimum phase characteristics (Mahapatro 2014). Comprehensive simulation of a system was built to give an adequate conception of how it behaves under different operation scenarios, including when some fault sources have been added. For that, it is considered that facts, such as those reported in Chapter 4 of this thesis, which was developed over prolonged periods. During these periods the tank level control system can be operated with varying permutations of operating demand profiles. These may range from a single set point demand for the duration through to a variety of time-varying operating profiles. The simulations reported are used to accelerate the timescales of evaluating the monitoring and tracking the system and controller signals. Such is to have prior knowledge of the system response due to different operational scenarios.

Figure 3.27 and Figure 3.28 presents the system response when the required liquid level increased from 100 to 125 *mm* or decreased from 125 to 100 *mm* respectively as a step function. The red line, in Figure 3.27 and Figure 3.28, refers to the instantaneous liquid level that measured using the pressure sensing liquid level sensor. This signal was measured in *volts* and then converted to *mm* before presenting in both figures according to the sensor characteristic equation. In these figures, the continuous blue line represents the simulation result of the liquid level system as a response to the same required demand. The dashed line refers to the required liquid level for the simulation and the test rig. On these figures, there is a reasonable similarity between the behaviour of the CE105 apparatus as a real mechatronic system and the simulation result when increasing or decreasing the required liquid level.

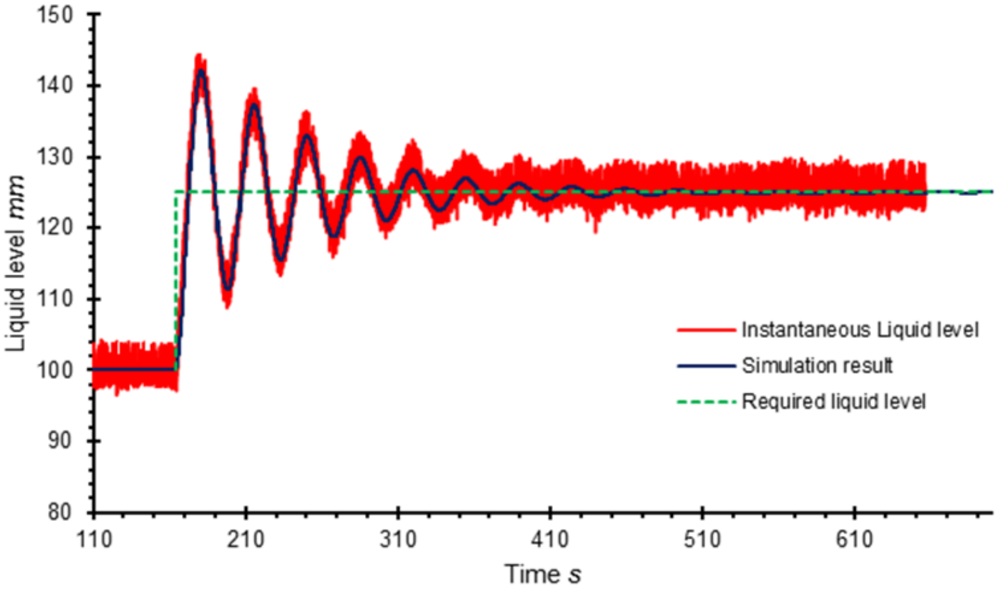


Figure 3.27 The response of CE105 liquid level system due to increase the required liquid level from 100 to 125 mm

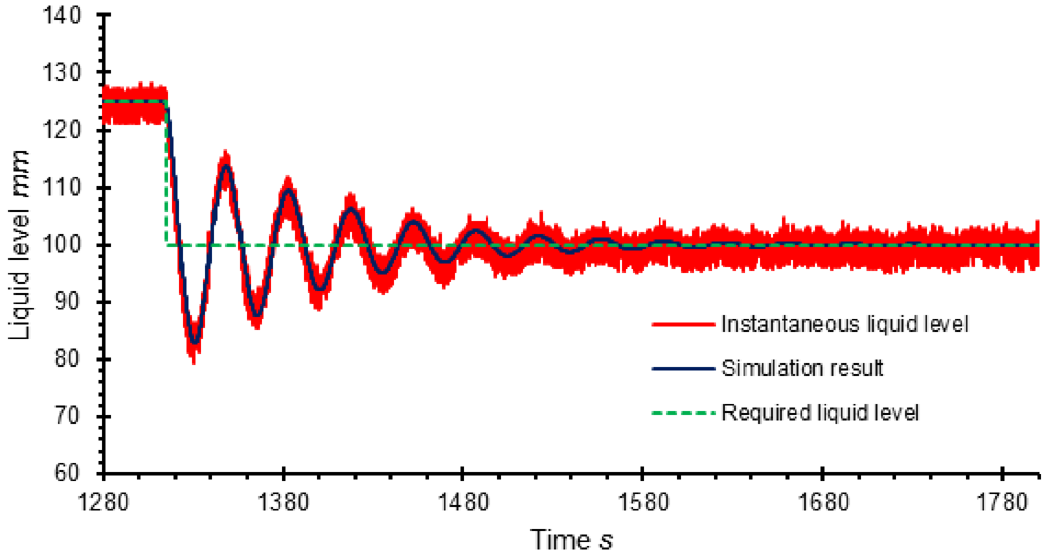


Figure 3.28 The system due to decrease the liquid level from 125 to 100 mm

3.10 Summary

Liquid level system, which is usually presented as a linear system, is studied as a feedback-controlled non-linear mechatronic system. This system mathematical-model was derived depending on Bernoulli's Equation and Lavoisier law of mass conservation. CE105 coupled tank system consists of several types of transducers and components. The characteristic equation of each of them shows a nonlinear behaviour. From these calibration equations, a detailed simulation under LabVIEW environment was built. By comparing the response of the virtual system and the CE105 coupled tank system, the later was exceptional showed a linear behaviour, which is unusual for a real system. The investigation showed that the discharge valve position was behind this linearity, which it might be called mechanical design to linearise the system. By directing the drained water through another valve that was located in a consistent position, the system showed a nonlinear behaviour that consistent to its simulation results. This consistency was valid for different operating scenarios, and hence it can be satisfactory moved to next chapters and used this virtual system to study its prognostic and health condition monitoring due to several kinds of proposed fault sources.

Chapter 4 presents a novel algorithm to diagnose the entire system health condition based on the system controller signal.

Chapter Four

Diagnostic of a Liquid Level System

4.1 Introduction

Chapter 4 presents fault diagnostics of closed-loop mechatronic systems in general and the liquid level system in particular. It is widely accepted in a closed-loop controlled system that the controller masks any hidden fault developed with the time while the control signal is less than its maximum allowable value. The layout of Chapter 4 is as follows:

Section 4.2 reviews literature related the diagnostic of a liquid level system and main steps of a health condition-based maintenance programme. Section 4.3 presents the requirements to diagnose liquid level systems by dividing it into two main sides depending on the liquid pressure carried in each part. The expected fault sources that may occur in each of them is presented in Section 4.4. Because of this chapter deals with the virtual system, Section 4.5 discusses the simulation of fault sources of CE105 under LabVIEW environment. Section 4.6 reviews the simulation results with a degradation of the pumping efficiency and leakage at the low-pressure side as a step function. These results are discussed in detail in this section. Sign chart algorithm (SCA) as a new controller-based health monitoring approach is presented in Section 4.7. Section 4.8 and Section 4.9 presents the virtual system response due to different fault sources as ramp functions. PID controller parameters are kept at their default values that set by LabVIEW. At the end of this chapter, Section 4.10 concludes the benefits of using the novelty monitoring tool (SCA) to snap the deterioration when it just starts, which provides an ability to evaluate the remaining useful life of the system and the type and severity of the hidden faults.

Technology advances have impacted upon monitoring, diagnostic and prognostic activities for increasingly sophisticated industrial systems and their operations. For integrated mechatronic systems, the facility provided by a dynamic simulation model, as the system experiences deteriorating faults, has to be investigated. For informed data-driven prognostic extrapolations, the long-term, time-varying operational profile of the mechatronic system requires recording and analysis. The contribution reported in this chapter is related to demonstrate an innovative Sign Chart Algorithm (SCA) operating in real time allows to monitor the liquid level system. This algorithm was implemented on a CE105 liquid level system with a PC running the actuators via NI USB-6008 data acquisition device. The simulation is used to accelerate the timescales of evaluating the monitoring and tracking the system and controller signals for healthy and faulty behaviour for several operating condition scenarios. By utilising LabVIEW software, a graphical user interface (GUI) has been developed to acquire, operate and monitor the collected data from the system sensors and to display the instantaneous liquid level. A Sign chart algorithm was developed and used as a controller-based health-monitoring approach. The SCA depends on the PID output signal and the liquid level demand to monitor the system health. Results are reported and discussed for, leakage, blockage and deteriorating of the pump performance faults.

4.2 Literature review

Systems during the history of the rudimentary equipment up to nowadays modern complex systems need to have maintenance during their lives. The earliest sort of maintenance is called run to failure maintenance technique or corrective maintenance, which takes place when a system fails to accomplish its task efficiently. A later technique is a planned or time-based maintenance. This approach sets a statistical periodic interval time to have maintenance even the system is in a healthy status. According to the quick development of modern advanced technologies, systems have become progressively complex whereas higher reliability and better quality are still required. As discussed in Chapter 2, this makes the preventive maintenance more expensive in comparison with what it was in the past. Hence, to deal with such situation, a new maintenance approach based on the system health condition needs to be implemented. Accordingly, this approach is called Condition-Based Maintenance (CBM). (Jardine, Lin et al. 2006) briefly summarised and reviewed some modern research in diagnostics and prognostics of CBM implemented mechanical systems. They emphasised data processing and maintenance decision making with their models, algorithms and technologies. Moreover, they defined the CBM as a maintenance programme, which recommends maintenance decisions based on the information that collected from the condition-monitored system. Liquid Level Tank System (LLTS), as one of the real mechatronic systems, exposes to one sort of fault or more during its service life.

Before designing a controller, it is essential to understand the system behaviour under different operating scenarios. LLTS is commonly controlled by using a conventional Proportional – Integral – Derivative (PID) controller, this kind of controller will be discussed in Chapter 6. Such a feedback controller minimises the difference between the required demand and the related plant measured variable, which is called an “error”, by regulating the process-controlled inputs. Furthermore, every single element of a PID controller refers to a particular action taken on the error (Kumar and Dhiman 2011).

Product costs are reduced by implementing an active maintenance programme. This proposed efficient approach could be achieved by decreasing the number of unnecessary planned preventive maintenance activities.

Any CBM programme contains three main steps (Lee, Abujamra et al. 2004), as can be seen in Figure 4.1:

1. Data acquisition that means collecting data relevant to the system health monitoring.
2. The second step is processing the collected data to understand the current system condition.
3. Lastly, a decision-making algorithm to recommend a suitable maintenance activity.

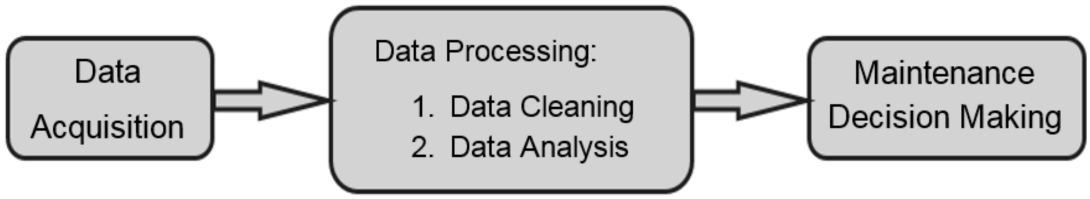


Figure 4.1 The main steps of a condition-based maintenance programme (Jardine, Lin et al. 2006)

Accordingly, simulating a real system gives an adequate conception of how this system behaves, especially when some fault sources are added. For that and considering that facts, such as those reported in this chapter, develop over prolonged periods. During these periods, the tank liquid-level control system may be operated with varying permutations of operating demand profiles. These are ranged from a single set point demand for the duration through to a variety of time-varying operating patterns. Simulations provide a prior knowledge of the system behaviour for different operational scenarios. Furthermore, faults diagnosis and a remaining useful life estimation could be achieved in advance with the aim of reducing uncertainties of predicting the future behaviour of the system.

(Luo, Pattipati et al. 2008) stated that monitoring the instantaneous health condition of each single element prognosis (degradations tracking and a remaining useful life estimation) of a whole system is recognised as a difficult task because of:

1. The uncertainty of the result in the inference processes.
2. Fault propagation of the cross-subsystems.
3. The system complexity.

High technology machines become increasingly complex with several kinds of actuators and sensors. Modern aeroplanes, automobiles, high-technology products manufacturing lines are some examples of complex mechatronic systems. For them, it is not easy to monitor the entire system health condition by only observing their outputs. Meanwhile, an efficient approach to a whole system health monitoring and tracking the remaining useful life might be achieved by observing a limited number of critical components; this then infers the remaining useful life of the entire system. Several physical properties have been used in model-based health assessment, such as crack propagation and vibration. Monitoring a crack propagation of gear for a helicopter transmission gear system is a critical element of health monitoring system to predict the remaining useful life of the entire aeroplane (Luo, Pattipati et al. 2008). Serious failures in complex machines of industrial factories can be caused by cracks in the system mechanical components. (Pennacchi and Vania 2008) presented a model-based diagnostics approach for gas turbines failure identification. From their analysis of shaft vibrations caused as result of crack propagation during load coupling of gas turbines, they successfully obtained good diagnostics results that lead to prevent catastrophic failures. Filters are an important component in industrial activities that deal with fluid. The filtration process is using to clean and/ or trapping suspended particles from a served fluid. This important process is used in many engineering applications, such as automotive, chemical industry, nuclear plants and water treatment. A physics-based model for filter clogging phenomena was presented in (Jennions, Camci et al. 2015). (Zio and Peloni 2011) presented particle filters based prognostics framework for crack propagation due to dynamic fatigue. (An, Choi et al. 2013) provided a tutorial on particle filters with the implementation of MATLAB code. Moreover, (Jouin, Gouriveau et al. 2016) presented a comprehensive review. Similarly, liquid level system, as a part of a cooling unit, assumed to be a critical component of petrochemical industries, chemical reactors, thermal power plants and nuclear reactors for example.

In condition monitoring tasks of closed-loop controlled systems, it is widely accepted that the control actions will initially mask the early stages of progressive faults. A PID-based feedback control system will mask any degradation in the plant measured variable caused by faults. A liquid level for example, in the presence of a PID controller, will not be affected by a fault type and strength until it reaches a certain threshold. Accordingly, monitoring the behaviour of the controller output signal could be a key to monitor the overall system condition. Such because the PID signal has been affected as a result of set-point changing and faults progression (Al-Khafaji and Grosvenor 2016).

A wide range of application strategies and approaches over the past several decades have been developed. Moreover, they are applied to perform manual, semi-automated, or fully automated system health monitoring (i.e., fault diagnosis and system prognosis) on critical systems in defence and commercial markets (George, Frank et al. 2006).

(Daigle, Kulkarni et al. 2014) emphasised the importance of a model that describes the nominal and faulty behaviour of a system, and how the latter progresses with the time causing the end of useful life of the system. They built their study on a pneumatic-actuated valve. They developed a new model-based valve prognostics approach that estimates fault progression and predicts remaining useful life based only on valve timing measurements.

(Luo, Pattipati et al. 2008) developed an integrated prognostic process based on data collected from model-based simulation under healthy and faulty conditions.

The healthy behaviour of CE105 coupled tank system that shown in Figure 4.2 was presented in Chapter 3. In the following sections, diagnosis of this system is presenting including a new diagnostic tool.

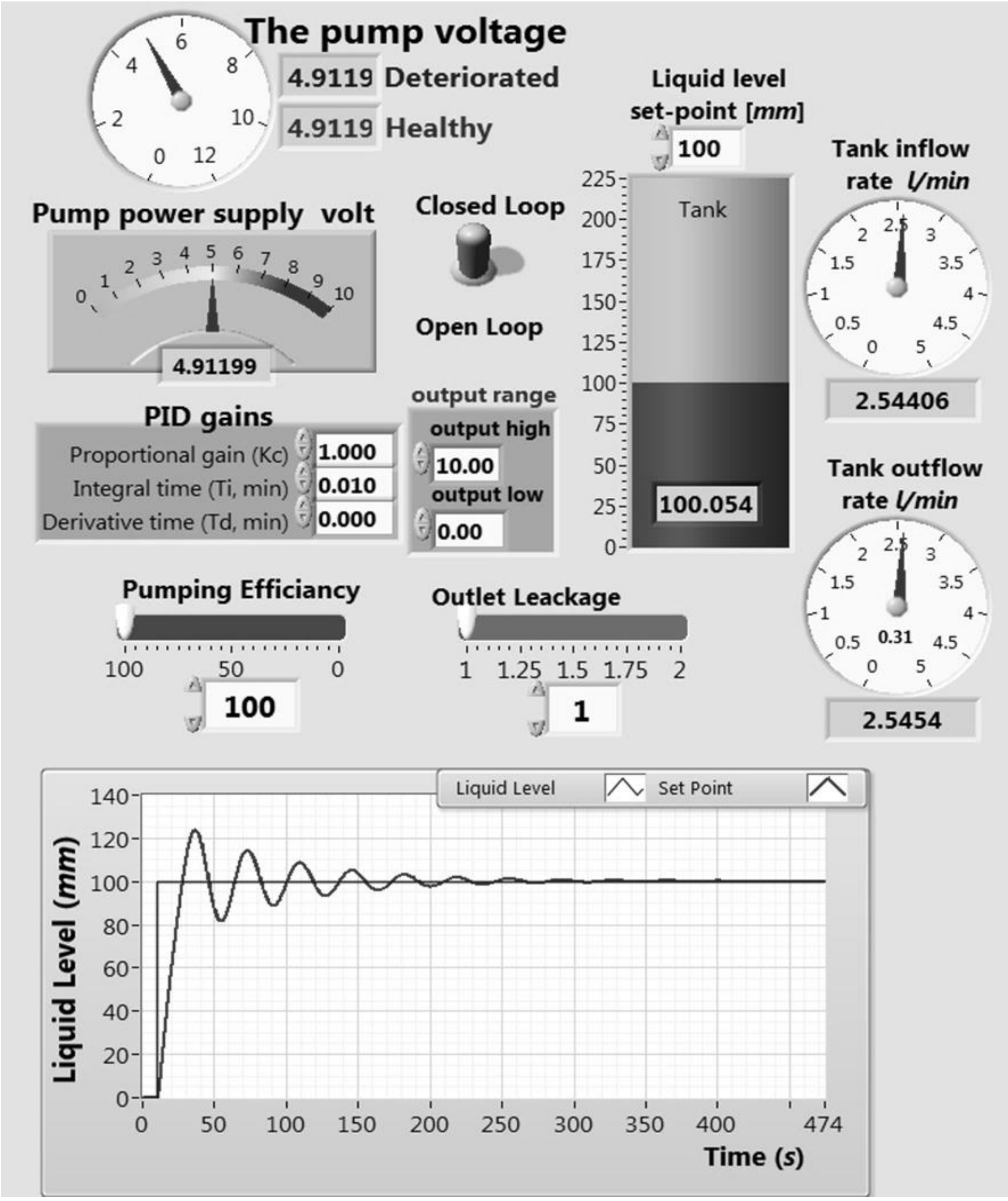


Figure 4.2 Simulation front panel of healthy CE105 with fault sources

4.3 Diagnosis requirements for CE105

CE105 coupled tank system as a mechatronic test rig of this study was described in detail in Section 3.3. In order to study the faulty behaviour of this system, it needs to divide it into two main sub-systems, a high-pressure section and a low-pressure section.

4.3.1 High-pressure section

The high-pressure section contains the system pump, the rotameter, liquid flowrate sensor and the tank inlet pipe, as can be seen in Figure 3.3. These parts, which form the tank inlet components, are exposed to a relatively higher pressure caused by the pump, which depends on the pump characteristics, than the rest equipment.

4.3.2 Low-pressure section

The low-pressure section consists of the system tank, drain line and the outlet (drain) valve. It so called, because these components are exposed to a pressure of the liquid head in the tank, which is assumed to depend only on liquid level and the liquid characteristics.

4.4 Fault sources of LLTS

As a result of ageing or long-term usage, the system behaviour might be deteriorated due to one or more, abrupt and/ or incipient faults. It needs to consider the diagnosis requirements that presented in Section 4.3 to classify the LLTS fault sources.

A. Faults in the high-pressure section can be classified into two categories:
    1. Abrupt fault: an example of such kind of fault is leakage due to a breakdown of the tank inlet pipe to the atmosphere. If this fault occurs, and because of this part is connected to the pump outline, which provides relatively high pressure and high flow rate depending on the outline resistance, it may lead to a massive leakage and progress in a high pace with the time.
    2. Incipient fault: this type of fault is progressing slowly with the time. The pump internal leakage or impeller wear are examples of such fault, which are represented as progressive degradation in the impeller area (Biswas and Mahadevan 2007); (Daigle and Goebel 2011). Bearing wear can be considered as an incipient fault progression in whichever type of bearings are used, e.g. radial or thrust bearing (Daigle and Goebel 2011).

B. It is assumed that a fault in the low-pressure section, i.e. tank, drain lines and the outlet valve, occurs in two different ways.

1. The first sort of fault occurs when the outlet valve setting has been unintentionally changed to a new set position, which means it has set by an operator or an accident to cause a significant change of outflow rate. This sort of fault may occur alone or couple with a breakdown of the drain line, which leads to a massive leakage. While this portion carries a low-pressure liquid, there is a possibility to develop an abrupt failure.
2. The second type of fault is assumed to be time-dependent, and usually, this fault has a slow progression pace. A minor leakage is due to wear at internal elements of the outlet valve and /or other parts of this section. Moreover, any blockage leads to increase the resistance to the liquid flow through the outlet restriction are some examples of this sort of faults. Table 4.1 reviews two types of fault and their proposed sources and how to simulate each of them in the simulation.

Table 4-1 Faults types and sources and how to simulate them in the simulation

<table>
<tr><th colspan="2">Fault</th><th>Simulation as</th><th>Fault strength</th></tr>
<tr><td colspan="2">Degradation of the pumping efficiency that caused by:</td><td rowspan="14">Abrupt or incipient function depending on the fault severity and its progression rate with the time. Continuous progression rate can be simulated as a ramp function with an adjustable slope to represent the deterioration speed.

But the abrupt fault that is terminating or changing suddenly and settled at its new value can be represented as a step function

Impeller wear due to corrosion of a centrifugal pump is an example of an incipient fault because it is deteriorated with the time. Meanwhile, broken and lose a piece of the impeller can be simulated as incipient fault due to the previous definition.</td><td rowspan="14">The different slope value of a ramp function simulates different deterioration speed.

While the step function value mimics a sudden fault strength.</td></tr>
<tr><td>1</td><td>Degradation of the electrical pump efficiency</td></tr>
<tr><td>2</td><td>Degradation of the mechanical efficiency</td></tr>
<tr><td>3</td><td>Bearing deterioration</td></tr>
<tr><td>4</td><td>Pump internal leakage</td></tr>
<tr><td>5</td><td>Seal deterioration</td></tr>
<tr><td>6</td><td>Pump internal wear</td></tr>
<tr><td>7</td><td>Leakage at the high-pressure side</td></tr>
<tr><td>8</td><td>Blockage at the high-pressure side</td></tr>
<tr><td colspan="2">Leakage or blockage fault at low-pressure side caused by:</td></tr>
<tr><td>9</td><td>Leakage at the discharge pipeline</td></tr>
<tr><td>10</td><td>Blockage at the discharge pipeline</td></tr>
<tr><td>11</td><td>Damage to the internal parts of the drain valve (increasing the discharge)</td></tr>
<tr><td>12</td><td>Leakage from the tank</td></tr>
</table>

4.5 Simulation of fault sources of CE105 under LabVIEW environment

A system simulation gives a reasonable conception of how this system behaves under a healthy condition or when some fault sources are added.

Simulation is used to accelerate the timescales of monitoring and tracking the system condition and controller signals for normal and faulty behaviour at several operating and condition scenarios.

Degradation of the pumping efficiency, mechanical and/ or electrical, which is affecting the pump performance has been represented in this research as a percentage of nominal pumping efficiency. The current pumping efficiency can be evaluated by comparing the current liquid pumping rate with its nominal value at the same operating conditions according to Equation (4.1).

$$Pumping\ efficiency = \frac{Current\ pumping\ rate}{Nominal\ pumping\ rate} * 100\% \qquad (4\text{-}1)$$

This efficiency value as a constant can be feed to simulation as an initial value, as can be seen in the simulation front panel Figure 4.2 and monitor the system behaviour due to any other faults.

At the first time of use, the efficiency might be 100%, and hence it is introduced to the simulation programme as a constant value. Later on, the recorded efficiency when the simulation was halted needs to introduce to the programme instead of the 100% for the next run if there is any change. The estimated value of the fault ramp function, which will be discussed in Section 4.8, is subtracted from the nominal efficiency and the resulting multiply by the PID signal to prepare the voltage supplied to the system water pump.

Similarly, faults, leakage or blockage, at the low-pressure or drain section is represented as a per cent out of the nominal tank outflow rate, as shown in Figure 4.2.

4.6 Result and discussion

Parts of results and their discussion are presented in the following:

1. For a healthy system where the pumping efficiency is 100% of its nominal value and the outflow rate equals its designed value and as can be seen in Figure 4.2, the system reached its steady-state at its set point (100 *mm*) after about 400 *sec*. This figure reveals that the inflow rate is equal to the outflow rate and the power supplied to the pump is about 4.91 *volt*, which is calibrated to be about 2.54 $l.min^{-1}$.

2. As revealed in Figure 4.3, the system reached its set point regardless of the reduction of the pumping efficiency by 25%. On the other hand, the pump worked hard and consumed a higher amount of electricity to achieve the system requirements and reach the required demand. As this figure reveals, the pump power supply increased to be 6.54 *volt* in comparison with the nominal voltage of 4.91 *volts*. When the pumping efficiency decreases by 25% for example, the PID controller output signal will be increased by the same ratio to mask this degradation.

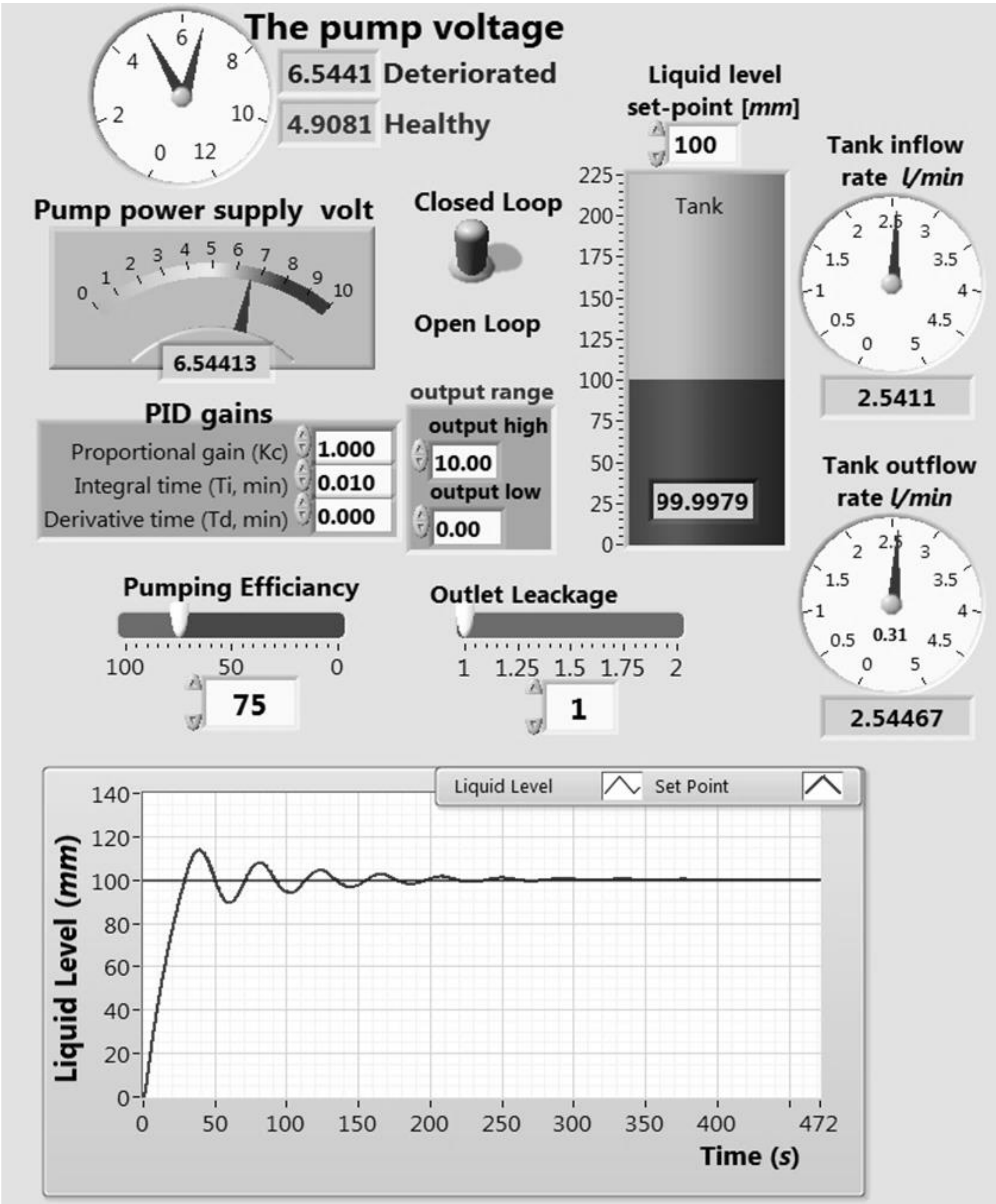


Figure 4.3 CE105 simulation response at 25% pumping efficiency reduction

3. For 100 *mm* liquid level demand, if the pumping efficiency reduces by 55% for example, from its nominal value, the drop in liquid level will be 15.7% from its demand, as it presents by Figure 4.4. Moreover, as can be seen in this figure, the pump worked at its maximum power or in other words, the PID controller reached its saturation output voltage, i.e. 10 *volts*. Additionally, at the steady-state, the outflow rate is equal to the inflow rate, but both of them are less than the desired amount.

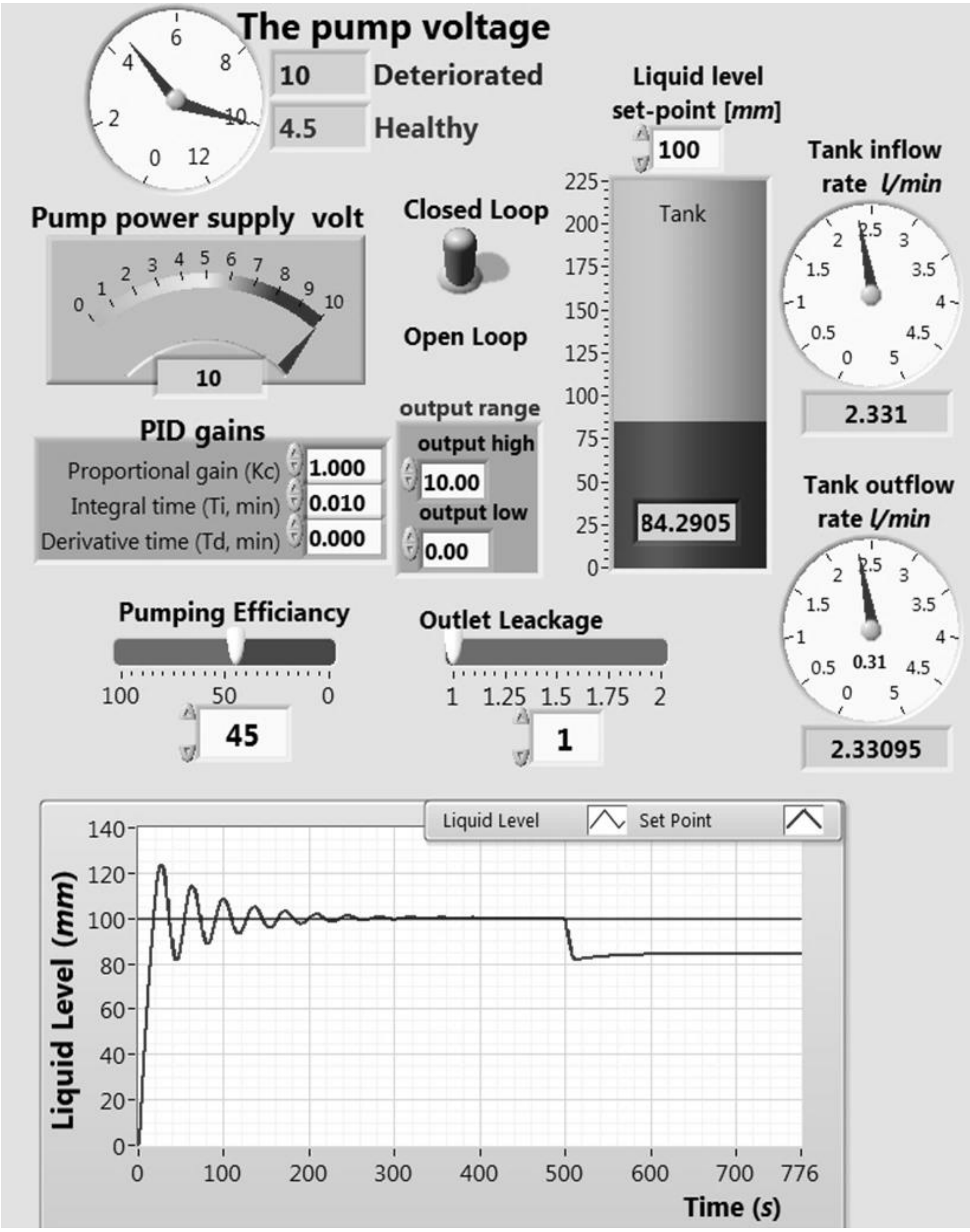


Figure 4.4 CE105 simulation response when the pumping efficiency degraded by 55%

4. Now, if the pumping efficiency was at its nominal value, i.e. 100%, and if the outflow rate increased as a result of leakage at the low-pressure side by 40% for example, the liquid level would achieve its set point. Meanwhile, the water-pump worked hard as the PID output voltage increased in order to mask the difference between the healthy and ill system, as depicts in Figure 4.5.

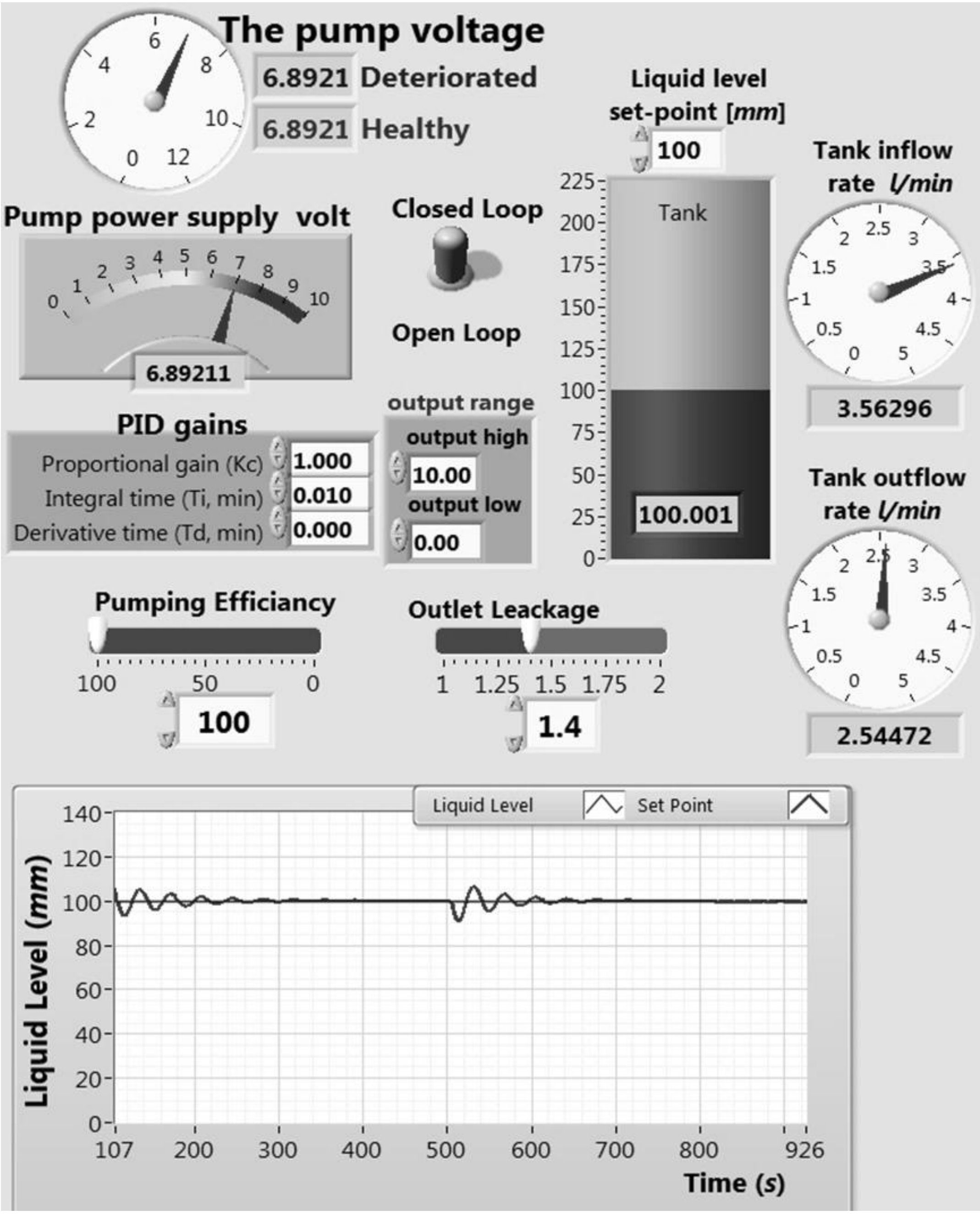


Figure 4.5 CE105 simulation response due to leakage at the drain side by 40% of the nominal discharge

5. Figure 4.6 illustrates that the liquid level would be affected when the amount of leakage at the low-pressure portion increased by 120% of the required outflow rate, the reduction in the liquid depth would be only 14.57% to be 85.43 *mm*. Here, the pump worked hard as the PID provided an additional voltage until it reached its saturation value (10 *volts*).

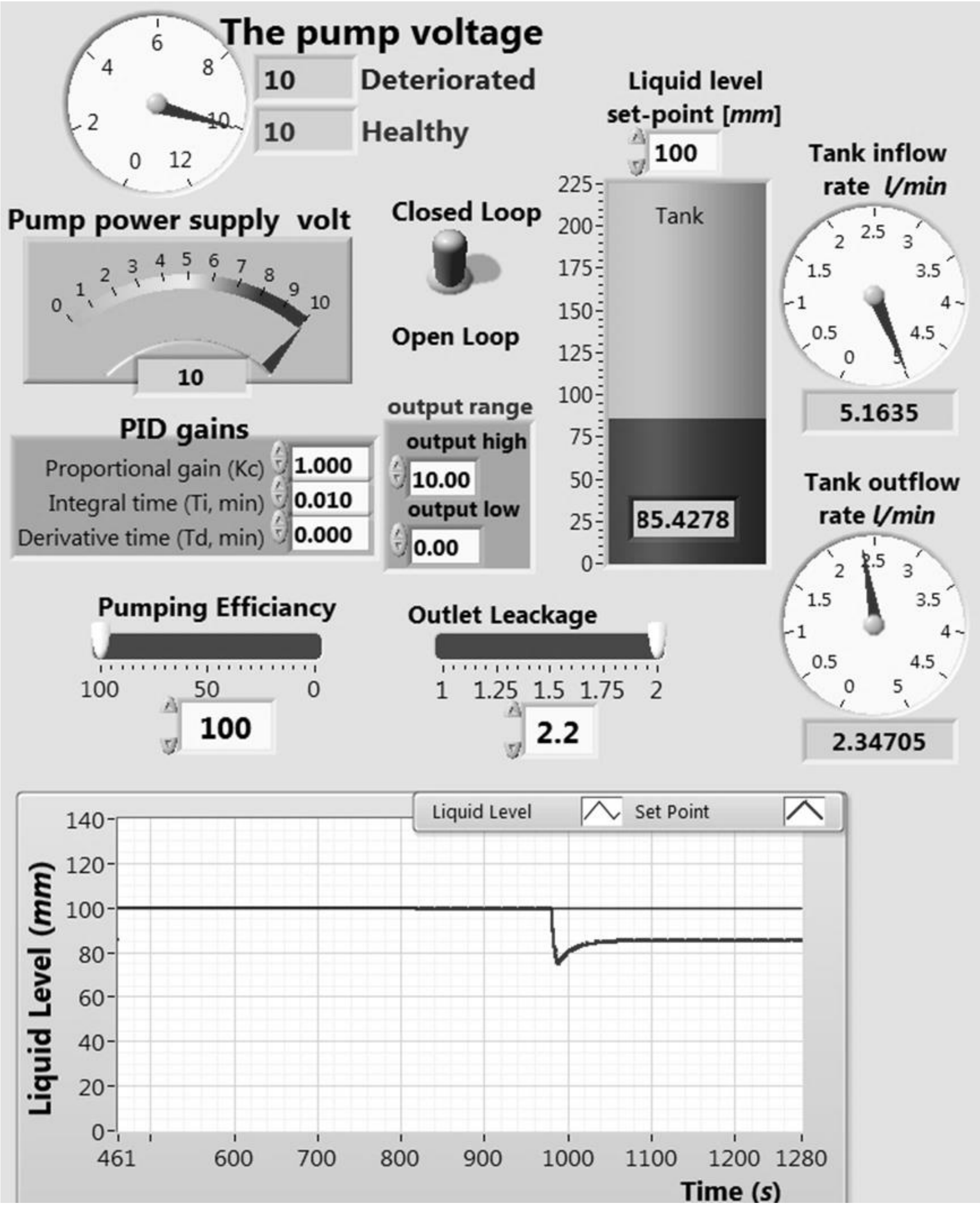


Figure 4.6 CE105 simulation response due to leakage at the drain side by 120% of the nominal discharge

Figure 4.6 reveals that, while the pump worked at its maximum pumping rate of 5.16 ($l.min^{-1}$), it could not be able to cover the required free out flowrate 2.54 ($l.min^{-1}$) at 100 *mm* liquid level in the presence of a greater than 103% leakage.

6. In reality, if the liquid discharge is reduced to be a half of the nominal drain value at 100 *mm* due to a blockage at the low-pressure side of the system, for example, the required liquid level will not be affected, as can be seen in Figure 4.7. For such kind of faults, it needs to set a minimum allowable PID output low voltage to 2 *volt*s, for example, depending on the minimum acceptable driving voltage of the pump at which it starts pumping.

Accordingly, in the presence of a PID controller for closed loop LLTS, the liquid level will not be affected by faults such as a degradation of the pumping efficiency and leakage or blockage until the fault intensity reaches a specific threshold. This threshold depends on the PID output rage, the high and the low output, which can be predefined on the programme GUI according to the pumping driving voltages.

7. Figure 4.8 reveals that at 100 *mm* required a liquid level, as the pumping efficiency reduced downward to 49%, the PID controller hastens to mask the lack of the liquid inflow rate following Equation (4-2).

$$V_{PID} = \frac{491.33}{\eta_p} \tag{4-2}$$

$Where, V_{PID}$ is the output voltage of the PID controller. When the PID signal reaches its saturated value, i.e. 10 *volt* which corresponding to 49% pumping efficiency, the output voltage will remain at this maximum value for any further reduction of the pumping efficiency, as can be seen in Figure 4.8.

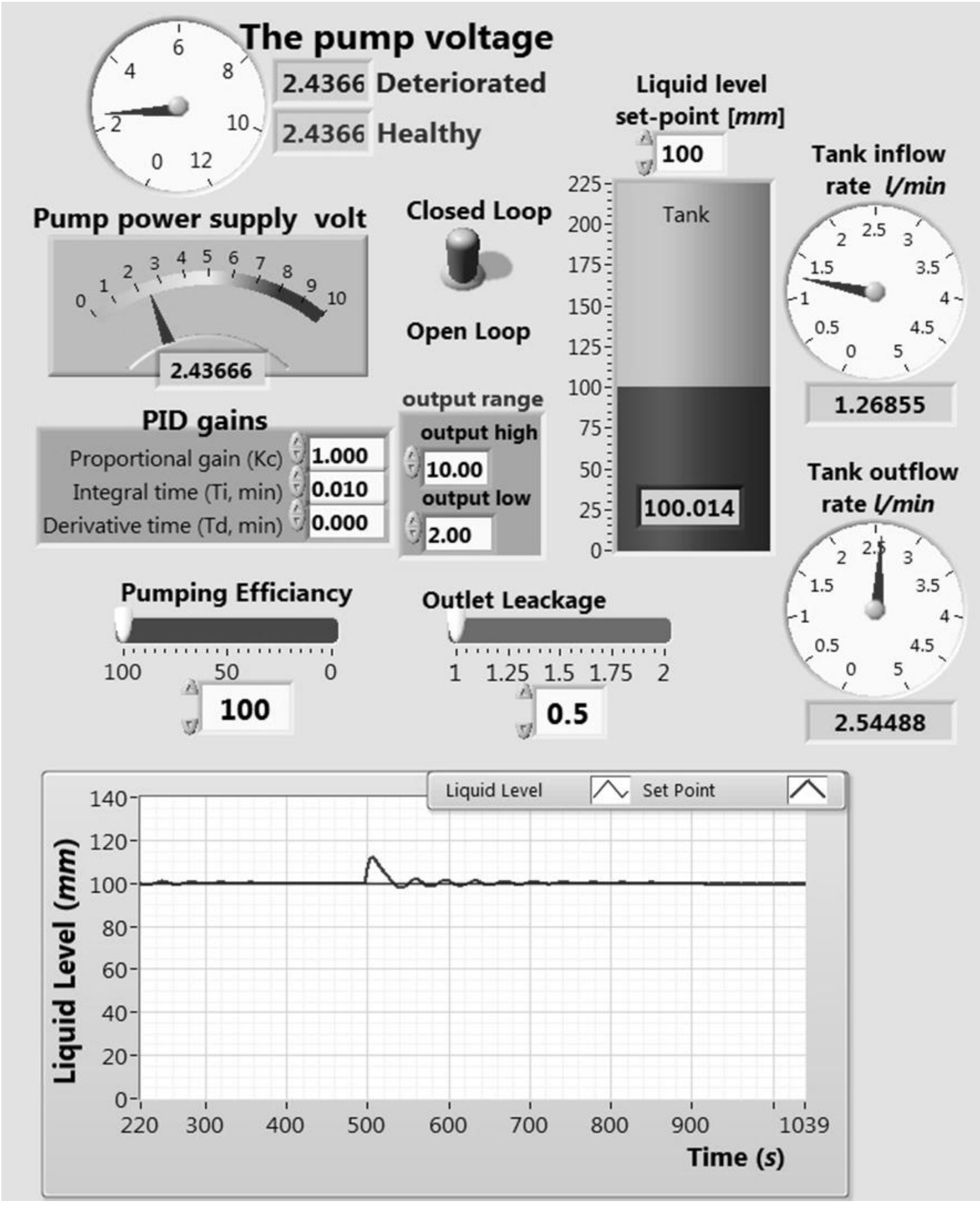


Figure 4.7 CE105 simulation response due to a blockage at the drain side by 50% of the nominal discharge

8. At the same time, the liquid level settled at its required demand until the PID signal reaches its saturation value. As the pumping efficiency continue degraded after this threshold, the liquid level is decreasing accordingly, as shown in Figure 4.8, following Equation (4-3).

$$h = 0.0394\eta_p^2 + 0.1058\eta_p - 0.225 \tag{4-3}$$

Where *h,* is the liquid level in *mm* and η_p is the pumping efficiency.

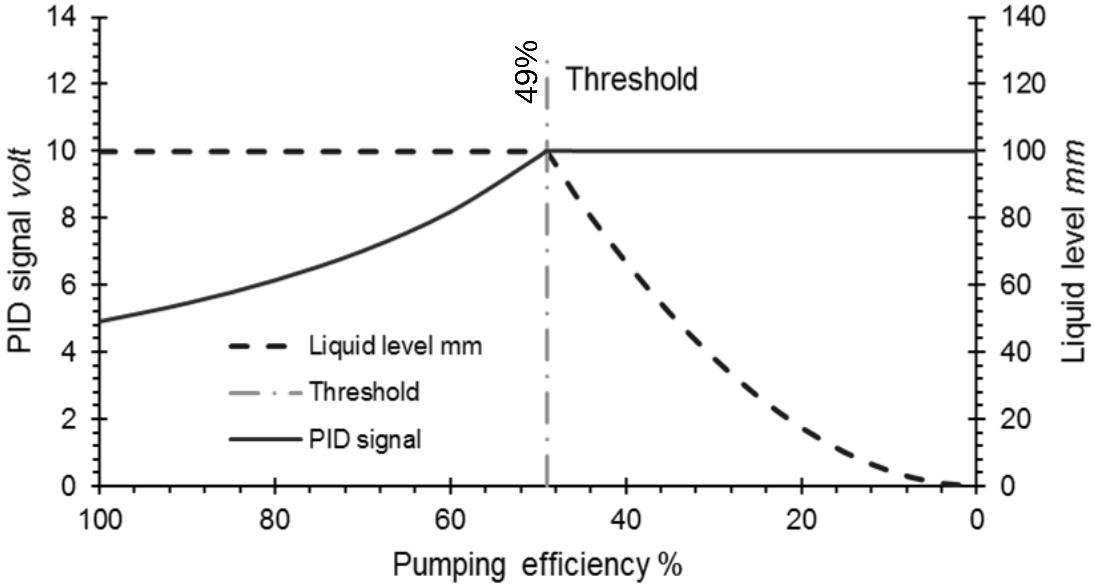


Figure 4.8 PID signal and liquid level as functions of the pumping efficiency

9. As can be seen in Figure 4.9, the PID output voltage depends on the output leakage at the low-pressure side as a percentage out of the nominal discharge, which the latter is a function of the liquid level as discussed in Chapter 3. As the amount of leakage increases as shown in Figure 4.9, the PID output voltage increases linearly following Equation (4-4).

$$V_{PID} = 0.0494Q_{Leak} + 4.915 \tag{4-4}$$

Where, Q_{Leak} is the leakage percent.

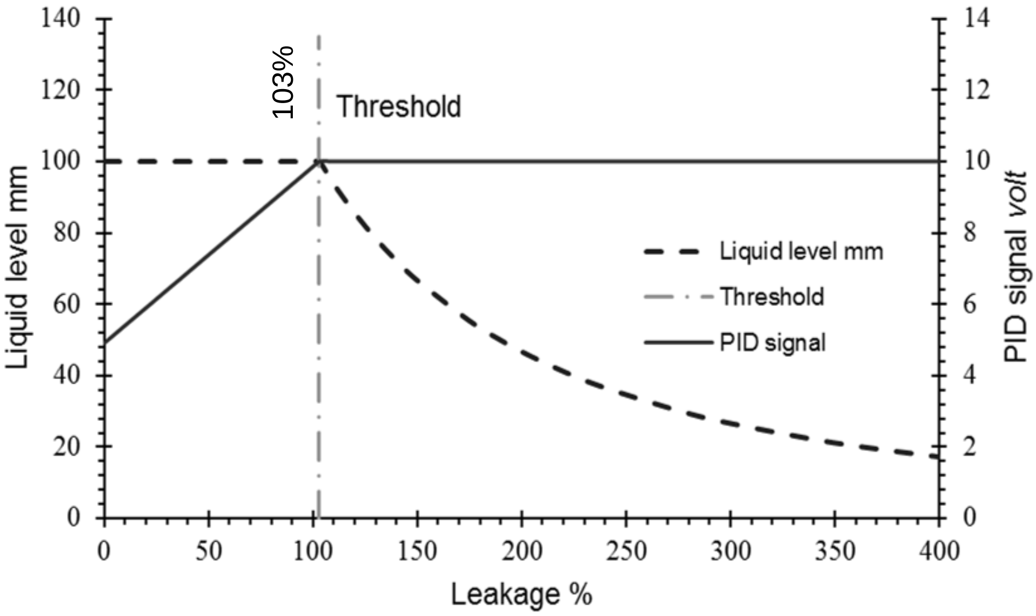


Figure 4.9 Liquid level and PID signal as functions of leakage per cent

When the leakage per cent equals 103% the nominal discharge, the PID output voltage will reach its saturation value of 10 *volts*. However, if the leakage amount becomes more than the nominal outflow rate by 3% or more, the PID output voltage will not be able to cover the deficiency of liquid level caused. Accordingly, and as can be seen in Figure 4.9, the degradation of the liquid level will follow the following Equation (4-6).

$$h = \frac{8159.854}{Q_{Leak}^{0.9138}} - 17.56 \tag{4-6}$$

A blockage, at either low-pressure or high-pressure side, as a fault is similar to leakage, but the amount of liquid goes into the tank becomes greater than it needs to settle the liquid level at its required demand. In such situation, the controller hastens to reduce its output signal to have a convenient pumping rate. Accordingly, the PID voltage will be degraded continuously as a result of discharge deterioration according to Equation (4-7) until the controller reaches its saturation minimum value, in this case, 2 *volts* at blockage of 58% of the nominal discharge value, as can be seen in Figure 4.10.

$$V_{PID} = 4.983 Q_{Blockage} - 0.06 \tag{4-7}$$

The liquid level will not be changed as a result of blockage as shown in Figure 4.10.

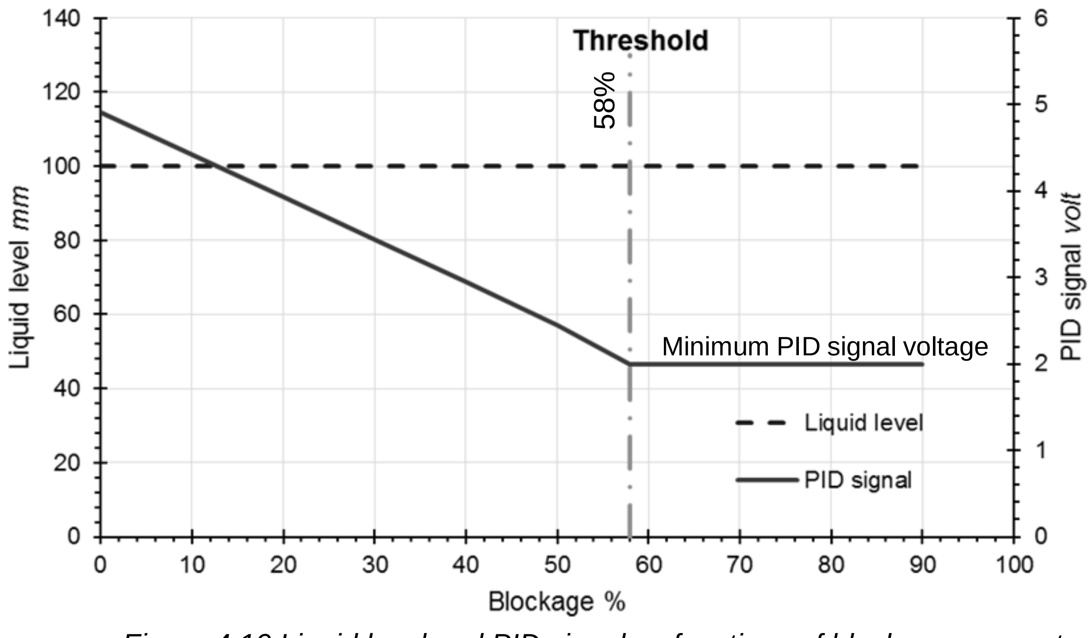


Figure 4.10 Liquid level and PID signal as functions of blockage per cent

It can be concluded that the PID controller could mask any fault occurs at the high-pressure or the low-pressure side of the closed loop controlled LLTS until the PID signal reaches its maximum or minimum saturated values or predefined limits.

4.7 Sign chart algorithm

In literature, most PHM research are based on component health condition rather than the whole system. However, modern complex engineering systems contain individual interactive components that can impact the system behaviour exceptionally severely when they fail. Hence, developing a whole system PHM methodology is as important as component and subsystem prognostic and health management methodology (Sankavaram, Kodali et al. 2016). As the system PID controller is sensitively response to any change in the system behaviour, Sign chart algorithm can be assumed as a whole system health-condition monitoring tool as discussed in Chapter 4. Modern industrial processes contain a wide range of elements, sub-systems and transducers. The entire system health can be monitored by collecting and analysing the acquired data from these elements. Usually and according to the system complexity, data from a process under continuous monitoring may become huge, especially when it contains analogue signals sampled at a high rate. Data acquisition systems have been developed over time from limited electromechanical recorders, which contain no more than four channels to fully electronic systems capable of measuring hundreds of variables simultaneously. Recording signals in early systems was done by using permanent media such as paper charts or magnetic tapes. Nowadays and since the advent of computers, particularly widely-used personal computers, the amount of available data and the speed with which they could be collected increased dramatically (Measurement 2012).

It seems to be that equipment may fail unexpectedly, but in fact, machines usually go through some measurable processes of deterioration before their failure. For these operator-invisible degradation steps, significant efforts of researchers and technology have been spent to develop this field to make such information being visible. According to the modern technology, many advanced sensors and computer-aided equipment be able to deliver information about the system condition. Unfortunately, these data have only small practical applications. While there are some applicable smart devices, there is a lack of continuous flow of information from condition-monitored systems. The reason beyond this could be the acquired raw data are not in a comfortable form to be used. It might not apply to provide each equipment with a high-technology computer to deliver, analyse and decision-making purposes. A network that connects all the electronically monitored equipment with one master computer could be a suitable choice to have an entire system performance and condition monitoring. For existing modern machines, there is a deficiency of infrastructure for acquiring data over a network, managing and analysing them even the system devices were networked. Problems may occur during data transformation between the system and the processing computer. Because these raw signals are inherently carrying a significant level of noise that confuses the analyser. Moreover, data transformation and processing speed are some additional examples of such problems. If smart machines are connected to have a remote condition monitoring; and if their acquired data is cleaned, modelled and analyse continuously via smart systems then it might be possible to upscale from traditional preventive maintenance to an intelligent prognostic approach.

(Lee, Ni et al. 2006) defined this intelligent prognostic as “a systematic approach that can continuously track health degradation and extrapolate the temporal behaviour of health indicators to predict risks of unacceptable behaviour over time as well as pinpointing exactly which components of a machine are likely to fail”.

(Tian, Feng et al. 2014) Investigated a motor current signal from electric control systems for fault diagnosis of centrifugal pumps without installing additional measurement instruments. They concluded that the impeller fault of a centrifugal pump could be diagnosed using remotely measured electric current signals.

For a PID-based control system, it will be worth to create a new efficient algorithm to track the PID signal as it is sensitively being affected by any changing in the system parameters.

Sometimes, collecting and processing all the acquired data to monitor a health condition of a system is not necessary. It needs to think of a new monitoring methodology to save time, power consumption and effort. An algorithm depends on continuous monitoring of the controller output signal might be helpful. A Sign Chart Algorithm (SCA) may provide a useful monitoring tool to track a closed-loop system health-condition, as shown in Figure 4.11. This algorithm compares the controller output signal at a time (*t*) with that at the time (*t-1*) and returns the result as a simple chart to have visual monitoring tool. Figure 4.12 shows the principle of the SCA. This novel algorithm returns zero if the two signals are equal to each other, which means the system is at a steady-state and in a healthy condition. Meanwhile, it returns different values (+1, -1) according to the trend of the controller signal to point the related part of data that the system analyser needs to deal with. For a liquid level system, the SCA can be used for any operating scenario to track the following:

1. Increasing the required demand, (human-made or unintentionally).
2. Decreasing the required demand, (human-made or unintentionally).
3. Degradation of the pumping efficiency, high-pressure side.
4. Leakage or blockage at the low-pressure side.
5. Leakage or blockage at high-pressure side.

This algorithm can be used to monitor a PID output signal by comparing the current voltage $V_{PID}(t)$ with the previous value $V_{PID}(t-1)$, as follows:

$$Sign = \begin{cases} +1 & if\ \ V_{PID}(t) > V_{PID}(t-1) \\ 0 & if\ \ V_{PID}(t) = V_{PID}(t-1) \\ -1 & if\ \ V_{PID}(t) < V_{PID}(t-1) \end{cases} \tag{4-8}$$

The SCA, according to Equation 4.8, returns zero if the system at its steady state when there is no change in the controller instantaneous output signal as can be seen in Figure 4.11. Such algorithm returns other values (+1, -1) several times depending on the fault type and its progression pace (fault intensity). Accordingly, when a fault occurs, it could be easy to diagnose the type of fault and the trend of it regarding time. The SCA provides a summarised operating profile, e.g. how often a fault occurred and for how long it stayed; and how often the liquid level was changed during an operating period.

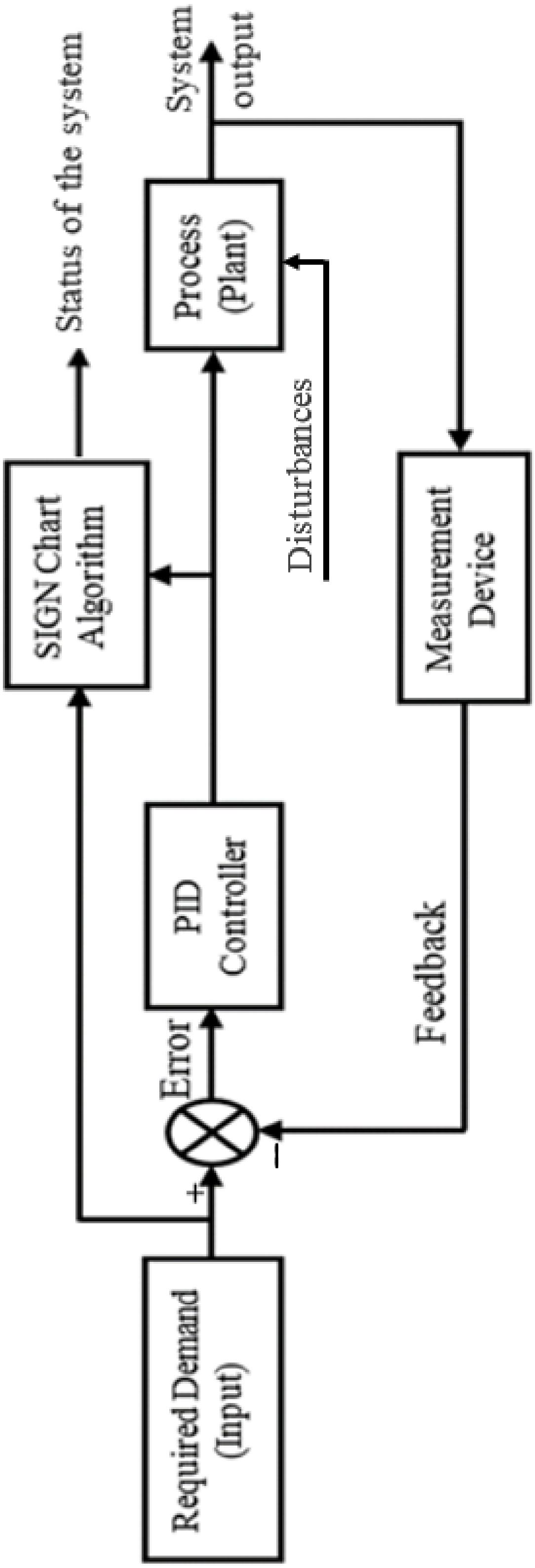


Figure 4.11 The principle of a closed-loop control system with a Sign chart algorithm

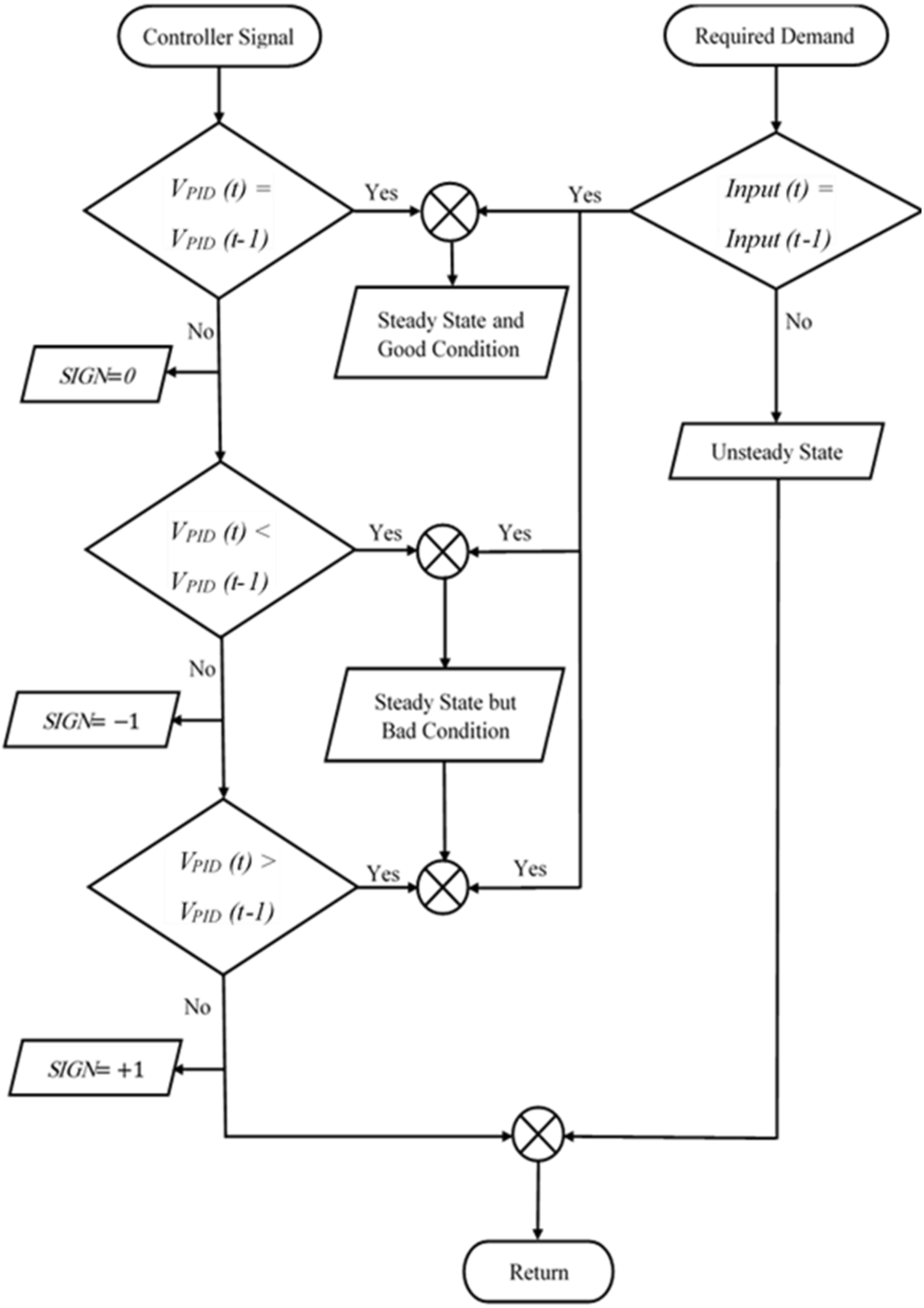


Figure 4.12 Sign Chart Algorithm

In a PID closed-loop controlled system, it needs to specify a process variable and a set point. The process variable, for this system, is an instantaneous liquid level which it needs to be controlled and monitored. Meanwhile, the setpoint is the desired liquid level and consequently the liquid outflow rate. A PID controller determines its output signal by comparing the set point with the process variable value, which is so-called “error”. This output value as a voltage supplied to the system liquid electric-pump, which in turn drives the process variable to achieve the setpoint value.

In this study, a non-linear single tank system was simulated under LabVIEW environment. Additionally, some fault sources were added in order to study their impact on the overall system nominal and faulty behaviour.

In complex systems, Maintenance and repair have an enormous impact on the total cost of the final products. Efficient techniques for diagnosis and prognosis have to be adapted to detect, isolate and anticipate faults. A simulation of a liquid level system, for example, gives a reasonable conception of how this system behaves when some faults could happen in different parts of this system. There is a shortage in studying the characteristics of this system when it exposed to a fault, i.e. a healthy and ill-behaviour condition.

(Al-Khafaji and Grosvenor 2017) stated that the liquid level in a PID-controlled tank system, for example, will not be affected by either the fault type and strength until the latter reaches a certain threshold. This threshold could be a saturation output voltage of the PID controller; the maximum permissible pumping rate; or an operator predefined limit. As the system works correctly, any change due to its parameters value or some faults progression will be resulted based on the PID output signal.

Sign Chart algorithm (SCA) provides an ability to diagnose system faults, monitor the system health and may use predict the remaining useful life.

4.8 Case Study

In this study, a PID controller under LabVIEW environment was used to preserve the desired liquid height and hence the required discharge. Liquid level and outlet valve opening have a direct interactive impact on the liquid free outflow rate. The specifications of the coupled tanks apparatus CE105 were used to build a detailed closed-loop simulation incorporated with the system elements' calibration equations that described in Chapter 3. Simulation parameters, which need to be set to run the simulation are as shown in Table 4.1. PID parameters were set by LabVIEW as default values. For the purposes of this PhD research, these values would not be changed because it dealt with the health monitoring rather than the system response to achieve the required demand. But, the PID output high and low voltages were set according to their corresponding values using to drive the system's water pump. This simulation shows response as similar to the test rig CE105 does at the same system's parameters, as shown in Figure 3.24 and Figure 3.26.

Table 4-2 The parameters were used for the simulation purpose

<table>
<tr><td colspan="2">The liquid level set point</td><td colspan="2">100 and 125 mm</td></tr>
<tr><td rowspan="4">PID parameters</td><td>Proportional gain (K_c)</td><td>1</td><td rowspan="3">Set as default values by LabVIEW</td></tr>
<tr><td>Integral time (T_i, min)</td><td>0.01 min</td></tr>
<tr><td>Derivative time (T_d, min)</td><td>0 min</td></tr>
<tr><td>Output high and low voltage</td><td colspan="2">10 and 2 volts respectively</td></tr>
</table>

4.9 System response due to different fault sources

Figure 4.13 presents a detailed flowchart of the virtual system that can be used for a wide range of operation and fault scenarios as shown below:

1. The input function (required demand) as a step or ramp function with a changeable slope.
2. A closed loop control system using PID.
3. Degradation of the pumping efficiency as a fault source (incipient and abrupt).
4. Sign chart algorithm.
5. Incipient and abrupt leakage or blockage at the low-pressure side as a fault source.

A ramp function with an ability to change its slope has been implemented in simulation to mimic the degradation in the pumping efficiency. When this function activates at any time during the simulation, it will subtract the slope value of the ramp function from the amount of voltage supplied to the water pump every single cycle. The control and simulation loop iterates the simulation under LabVIEW environment according to the pre-defined step size, which is equal to 0.01 *sec* for the purpose of this research. In the high-pressure section, a ramp function was used to simulate a time-dependent fault progression. This degradation in the pumping efficiency occurs according to the deterioration in the pump electrical and/ or mechanical efficiency and an internal leakage at the pump due to wear in its elements, for example. The reduction in the pumping outflow rate is a result of such fault for the same supplied voltage. Consequently, liquid level will drop even for a short distance, the operator may not recognise it by a necked eye. In a closed-loop control system, the controller hastens to increase the supplied voltage to reparation the lack of liquid flow rate. In the simulation of this research, reducing the pump voltage is analogous to the flowrate deterioration. Running the simulation continuously in the presence of such fault as a ramp function leads to accumulating the reduction of the pumping efficiency even minimal values.

The incipient fault progression for each side was represented as a ramp function with an ability to change its slope as shown in Figure 4.14. Changing the slope of the ramp function gives an ability to simulate different paces of the fault deterioration rate.

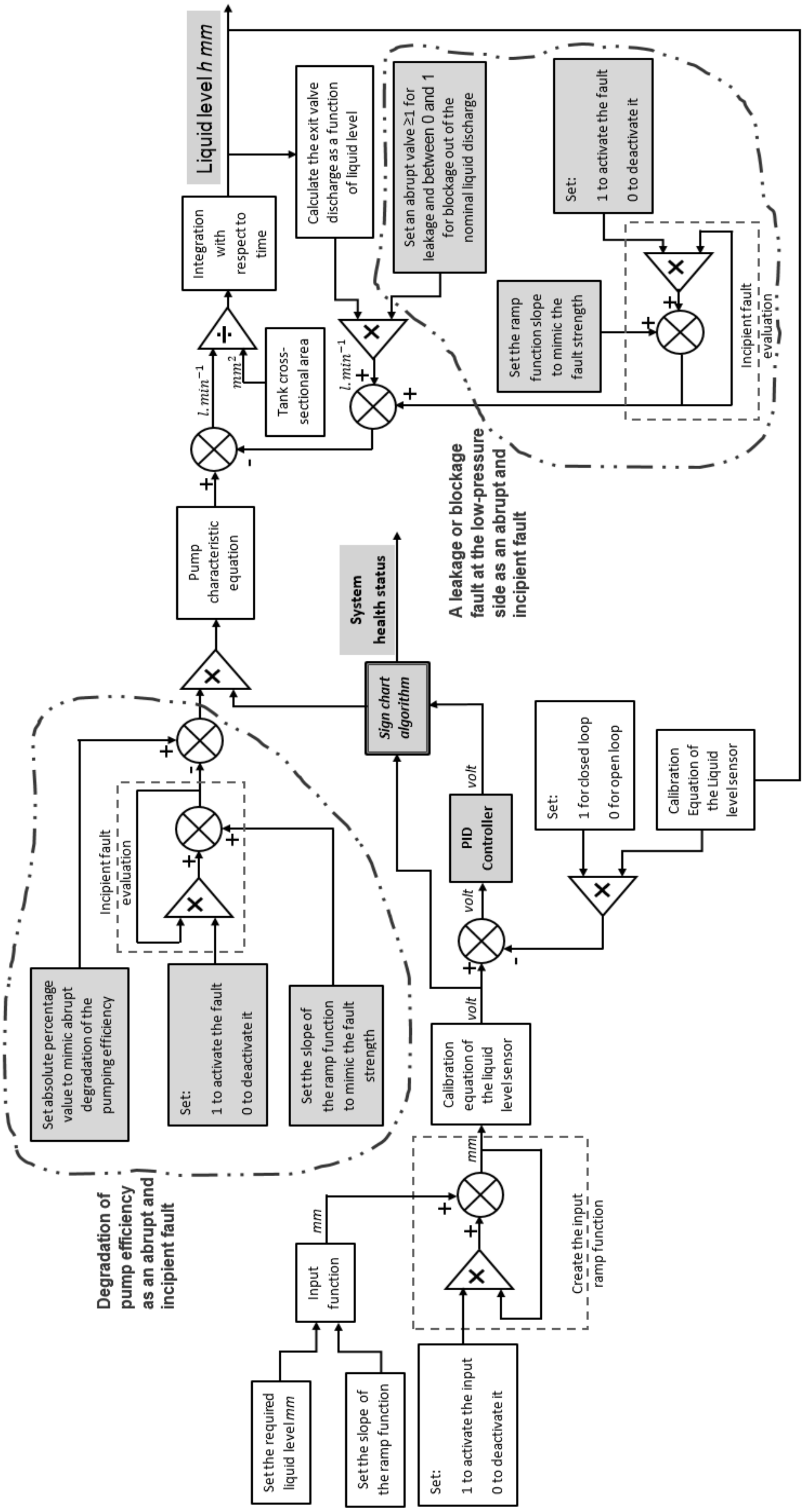


Figure 4.13 A detailed flow chart of the virtual system

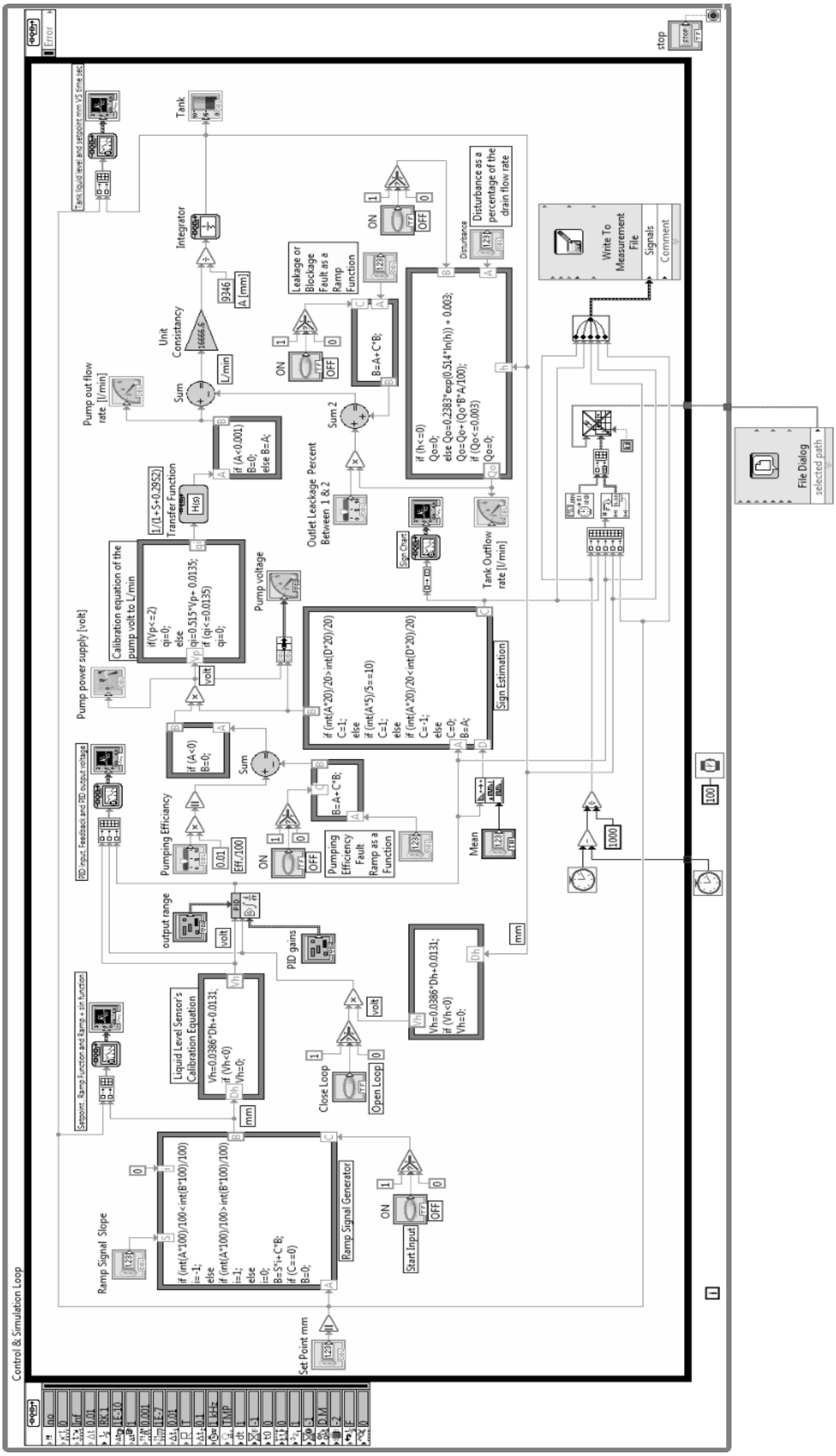


Figure 4.14 Simulation block diagram under LabVIEW environment

1. When a liquid level in a tank of a healthy system changed from its steady-state height at (100 *mm*) to (125 *mm*) as a step input function, the system response started fluctuating depending on the setting of the PID parameters. For the purpose of this study, PID parameters were kept at their default values, set by LabVIEW 2014 programme, as shown in Table 4.1. Because of the fluctuation that is shown in Figure 4.14, the SCA returns (+1, 0, -1) values, as can be seen in Figure 4.15. When the system reaches the new steady-state, the Sign algorithm returns zero uninterruptedly.

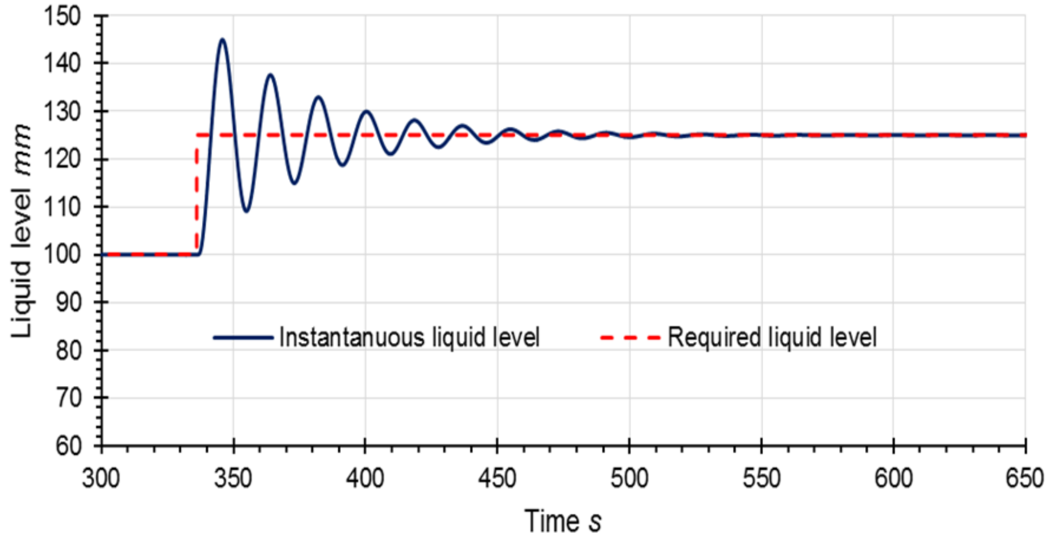


Figure 4.15 Increasing the liquid level

2. Similarly, if the required demand at steady-state decreases from (125 *mm*) to (100 *mm*), The SCA will provide an inverse shape of that when the demand increases, as can be seen in Figure 4.16 and Figure 4.17.

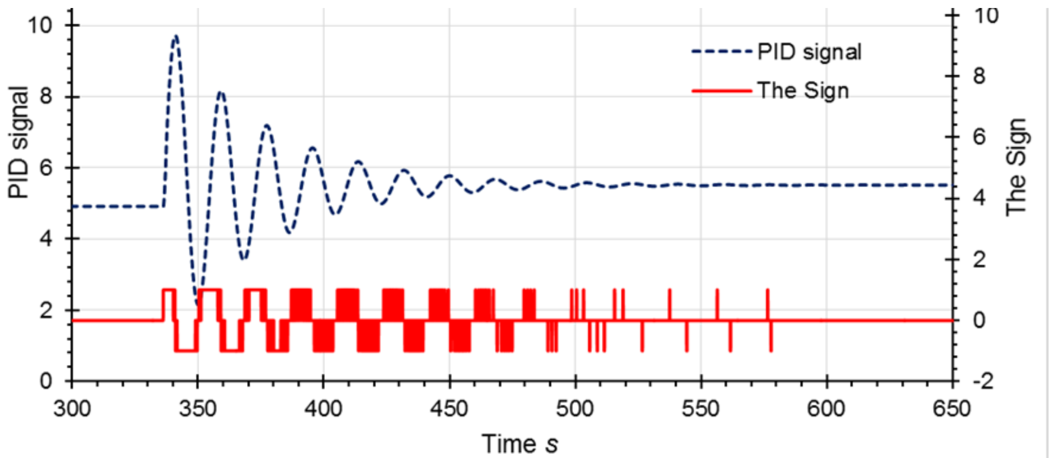


Figure 4.16 The Sign chart and the PID signal as a response to increasing the liquid level

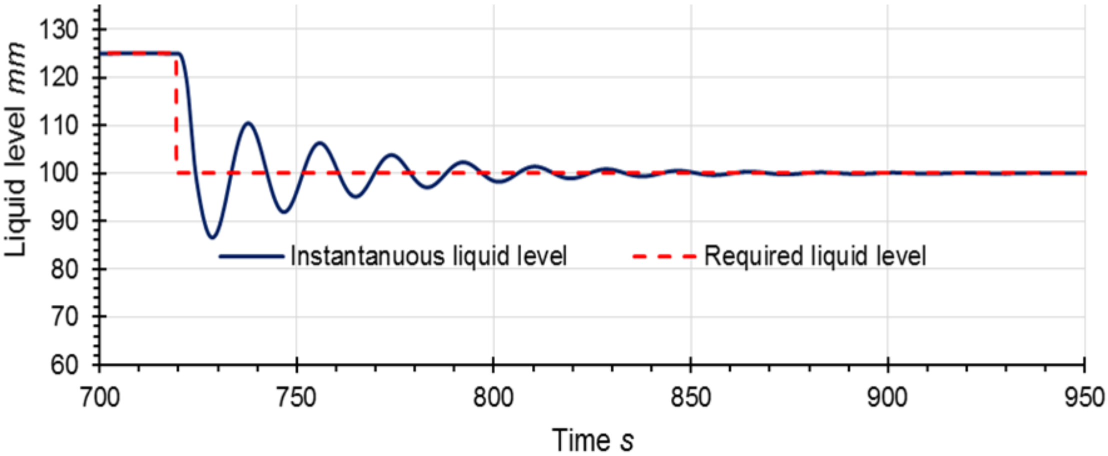


Figure 4.17 Decreasing the required demand

It seems to be easy to realise whether the demand has been increased or decreased, at any operation stage, by tracking the Sign chart.

3. At steady state, where the liquid level is 125 *mm* and when leakage fault, which was simulated as a ramp function with a slope equals to ($1*10^{-5}$). When this fault was started at the low-pressure side, applied at the time (130 s), there was no change apparent in the liquid level, as shown in Figure 4.18. The chosen slope of the ramp function was to speed up the simulation only, and it does not reflect any practical deterioration of a real system. The reason for the liquid level stability could be attributed to; the PID controller masks the liquid level deficiency by increasing the pump voltage, as can be seen in Figure 4.19. By contrast, the SCA responded immediately by returning (+1) as a result of the PID signal increment, as shown in Figure 4.19.

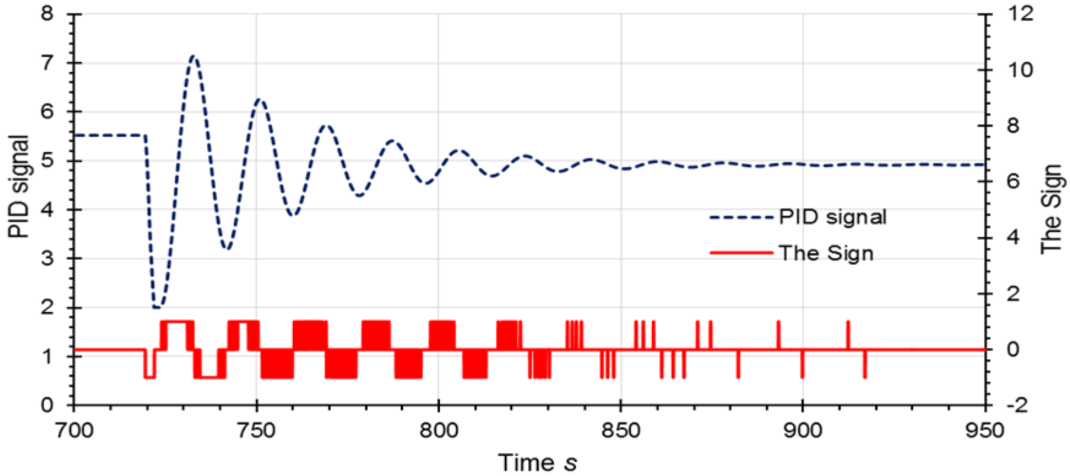


Figure 4.18 The Sign chart and the PID signal as a response to decreasing the required demand

4. Similarly, if the fault is a blockage rather than leakage at the low-pressure part of the system, the SCA returns (-1) as a result of the controller signal reduction, as can be seen in Figure 4.20 and Figure 4.21. By comparing Figure 4.19 and Figure 4.21, it might easily recognise whether the fault is leakage or blockage.

Fixed spaces between the vertical lines of the Sign chart in Figure 4.19 and Figure 4.21 refer to a linear system-response due to this sort of fault in particular.

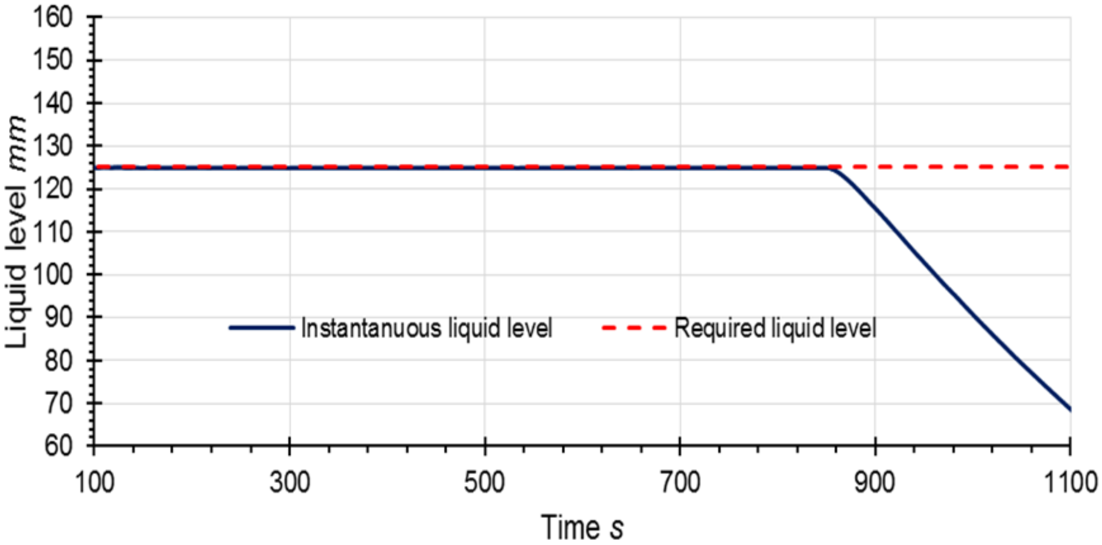


Figure 4.19 The required and the instantaneous liquid level during a leakage fault at low-pressure side with a progression slope = $1 * 10^{-5}$

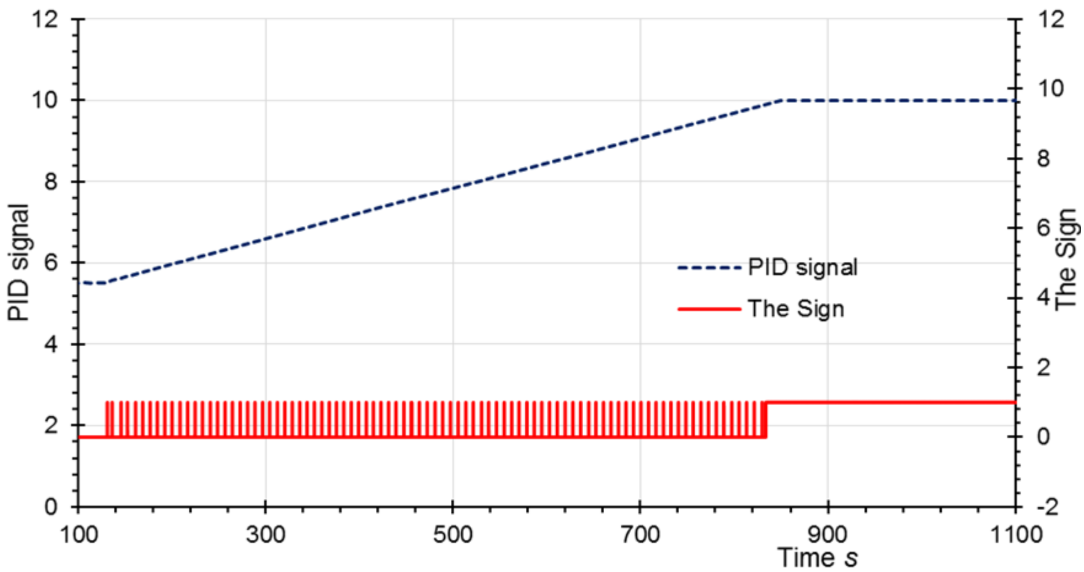


Figure 4.20 The Sign chart and the PID signal during a leakage fault at low-pressure side with a progression slope = $1 * 10^{-5}$

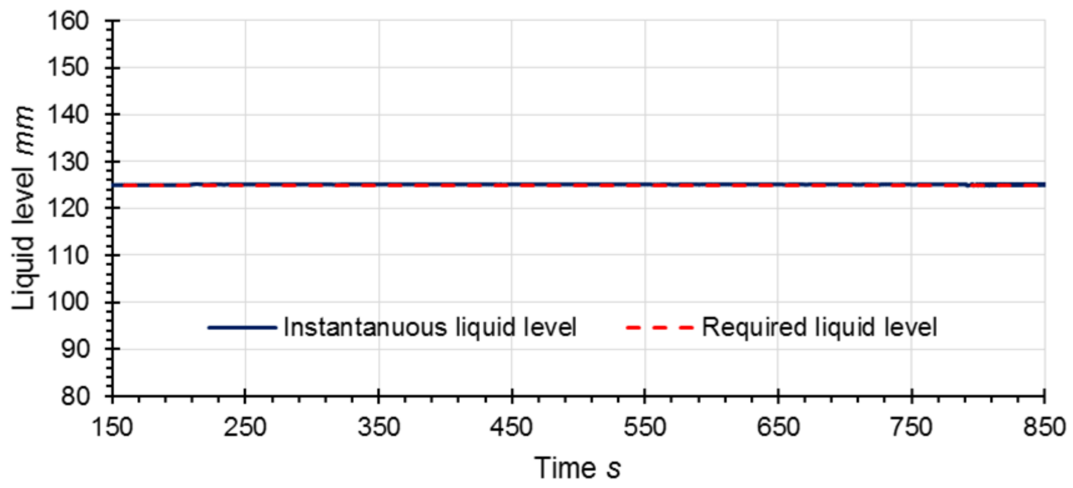


Figure 4.21 The liquid level during a blockage fault at low-pressure side with a progression slope $=-(1 * 10^{-5})$

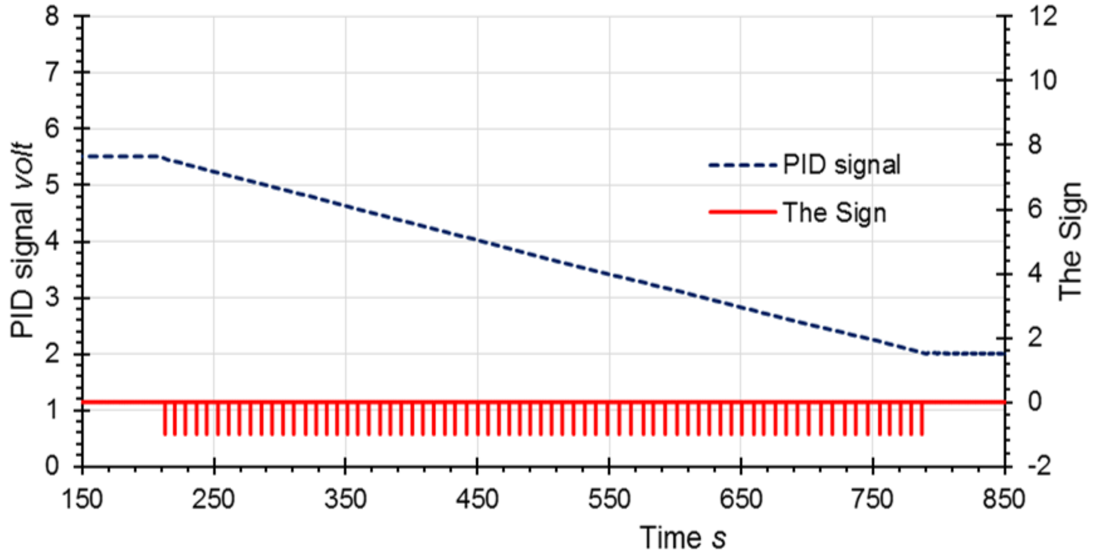


Figure 4.22 The sign chart and the PID signal as a result of a blockage fault at low-pressure side with a progression slope $=-(1 * 10^{-5})$

5. Moreover, Figure 4.18 and Figure 4.20 show that the liquid level will not be affected by the fault progression until the PID signal reaches its maximum set value, i.e., (10 *volts*) or its minimum set value, i.e., 2 *volts* for example. Beyond this threshold in Figure 4.18, the PID controller fails to mask the fault and hence, the liquid level drops as a result of the leakage deterioration. Meanwhile, when the PID signal reaches its saturated output low value, the PID fails to cover the blockage effect. For these two kinds of faults, the SCA returns a continuous (+1 or -1) for the leakage or blockage faults respectively.

6. Figure 4.22 and Figure 4.23 show the same previous fault, but its deterioration rate is five times slower than it was in point 3 above. Figure 4.18 and Figure 4.22 show that the liquid level will not be affected because of the fault progression until the PID controller reaches its maximum voltage, i.e., (10 *volts*). Beyond this threshold, the PID controller failed to mask the fault, and hence, the liquid level drops as a result of this fault deterioration. When the PID voltage reaches its saturation value, the SCA returns (+1) continuously, as shown in Figure 4.23.

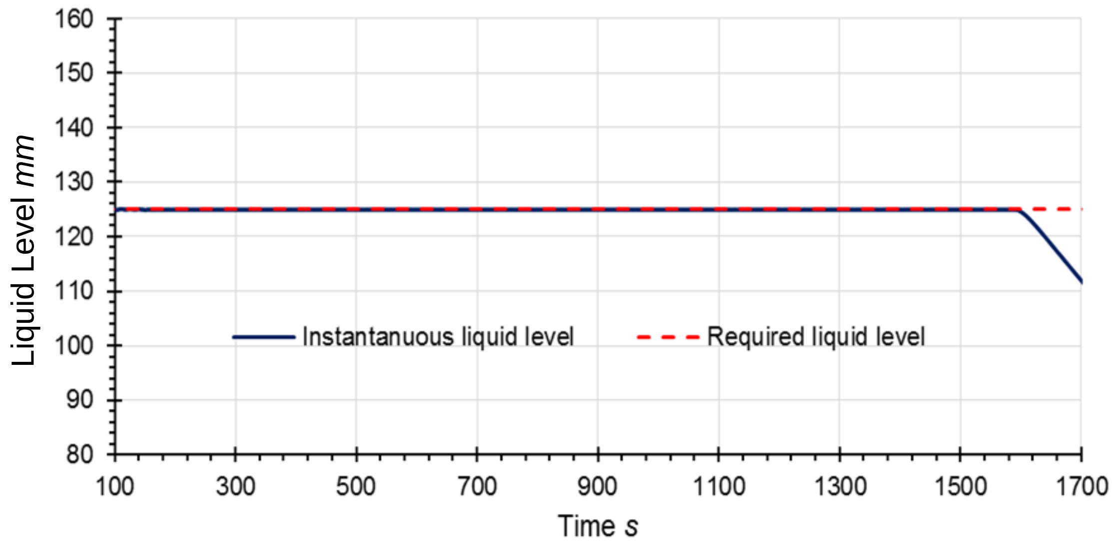


Figure 4.23 Liquid level during a leakage fault at low-pressure side with a progression slope = $5 * 10^{-6}$

7. A fault at the high-pressure part of CE105 was represented as a deterioration of the pumping efficiency. This degradation was mimicked as a ramp function with a slope equal to $5 * 10^{-6}$ for the purpose of simulation. The behaviour of the liquid level is as shown in Figure 4.24 and the SCA and the PID signal response is as shown in Figure 4.25. The trend of the PID signal is as similar as that when a fault occurred at the low-pressure side. The PID hastens to cover any change due to a fault until the controller reaches its high saturated value.

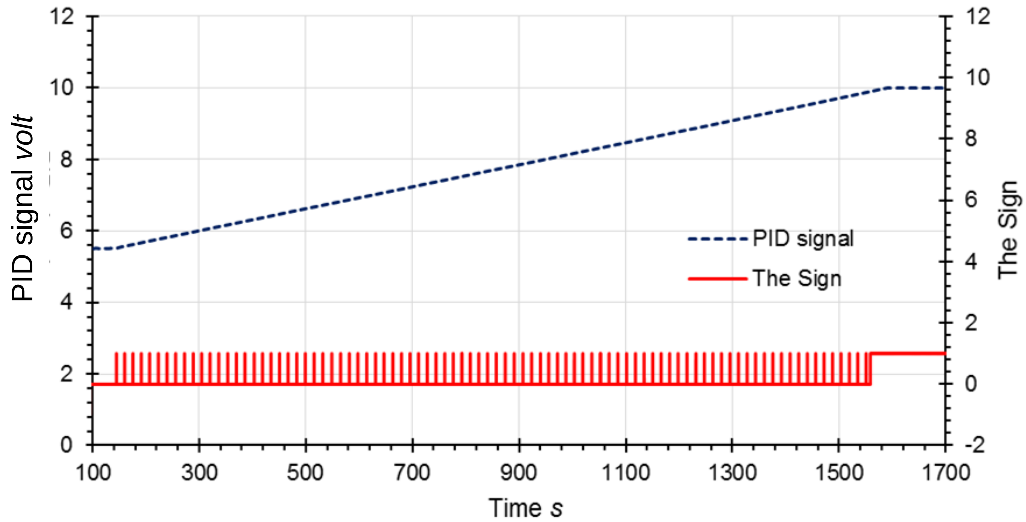


Figure 4.24 The sign chart and the PID signal as a result of a leakage fault at low-pressure side with a progression slope = $5 * 10^{-6}$

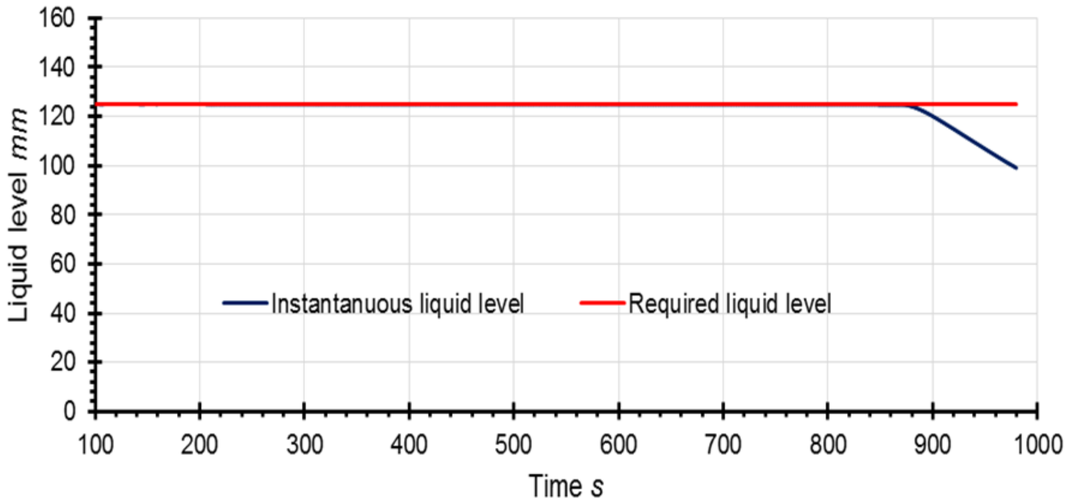


Figure 4.25 The liquid level response as a result of the degradation of the pumping efficiency, the ramp function slope = $5 * 10^{-6}$

8. While the progressive fault function at the low pressure and the high-pressure side was mimicked as a linear ramp function, the system response due to this fault at the drain side is linear. Meanwhile, the system shows a nonlinear response due to a linear fault at the high-pressure side, as can be seen in Figure 4.23 and Figure 4.25 for the same fault intensity. Accordingly, the SCA provides a new system health-monitoring tool to diagnose its deterioration.

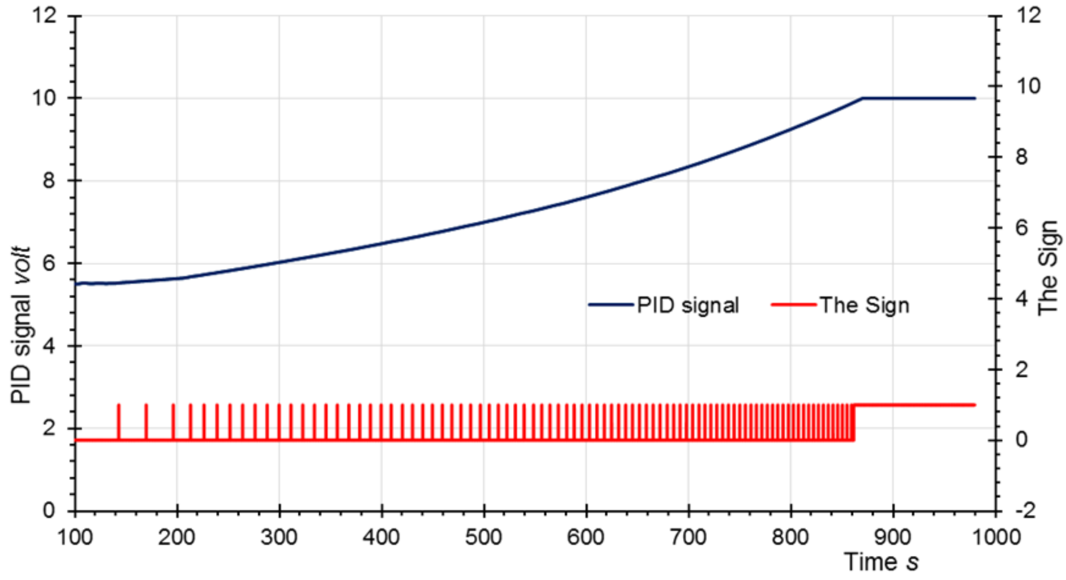


Figure 4.26 The liquid level response as a result of the degradation of the pumping efficiency, the ramp function slope = $5 * 10^{-6}$

9. If the pumping efficiency deteriorates at five times slower than that shown in Figure 4.24 and Figure 4.25, the system shows a corresponding response as can be seen in Figure 4.26 and Figure 4.27. The distances between the vertical lines of the Sign chart become shorter with the time to indicate that the PID signal is not linear. It could be easy to recognise this difference by having a quick look at the two figures.

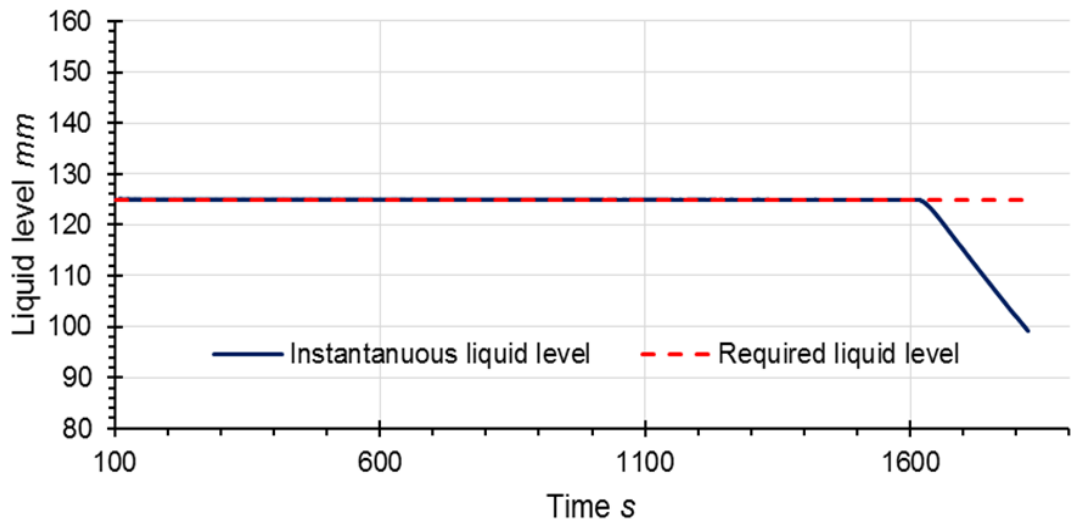


Figure 4.27 The liquid level response as a result of the degradation of the pumping efficiency, the ramp function slope = $1 * 10^{-6}$

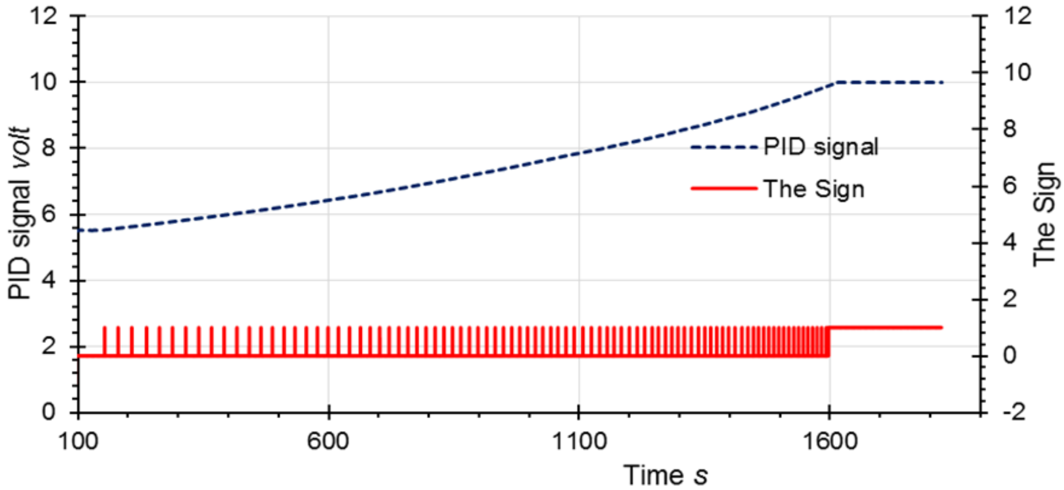


Figure 4.28 The Sign and the PID signal response due to deterioration of the pumping efficiency, the slope = $1 * 10^{-6}$

10. By comparing Figure 4.27 where the ramp slope is $1*10^{-6}$ with Figure 4.25 where the slope is $5*10^{-6}$, it can be concluded that the system behaves similarly in both cases. Despite this, the total time taken by the PID controller to reach its saturation value, i.e., (10 *volts*) is much longer in the former than in the latter. Consequently, this can provide an ability to estimate the type and the deterioration rates of faults. Moreover, there is an ability to evaluate the remaining useful life of a closed loop-controlled system associated with the Sign chart algorithm and the PID signal as demonstrated in Chapter 5.

4.10 Disturbance

The disturbance is unwanted input signal that has an effect on the output signal. One of the most important effects of feedback in control system is to reduce the impact of such disturbances. Any unintentional temporary change of the liquid properties or the flow characteristic or valve status and its setting can be considered as a disturbance. It is crucial to deal with such possible disturbance to have an efficient control system. Moreover, an effective health monitoring system needs to deal with this situation to diagnose and recognise it. Many control systems are subject to external disturbance signals that cause the system to provide an inaccurate output. The effect of distortion, noise and unwanted disturbance can be effectively reduced by using feedback systems (Dorf and Bishop 2005). The disturbances as an unwanted input signal will affect the liquid outflow rate, for the purpose of this research, the disturbance was simulated as a percentage of the outflow rate as can be seen in the flowchart and block diagram that are shown in Figure 4.11, Figure 4.13 and Figure 4.14.

The simulation was run and waited until the system reached its steady state, and the disturbance was activated with 10% of the nominated liquid outflow rate. Because the PID signal was less than its output high range and in the presence of disturbance, the system response is similar to an abrupt fault occurred at low-pressure side. A shown in Figure 4.29, the liquid level was fluctuated depending on the system and PID parameter when a disturbance applied, but it settled at its required liquid level. The system showed the same response when the disturbance was deactivated.

By comparing Figures (4.19 – 4.28) and Figures (4.29 and 4.30), it can be easily recognised that the liquid level changing in the latter was because of disturbance rather than a fault as in the formers. The Sign chart in Figure 4.30 shows that there was an abrupt increasing and then decreasing of the PID signal as a result of activating the disturbance generator and deactivating it.

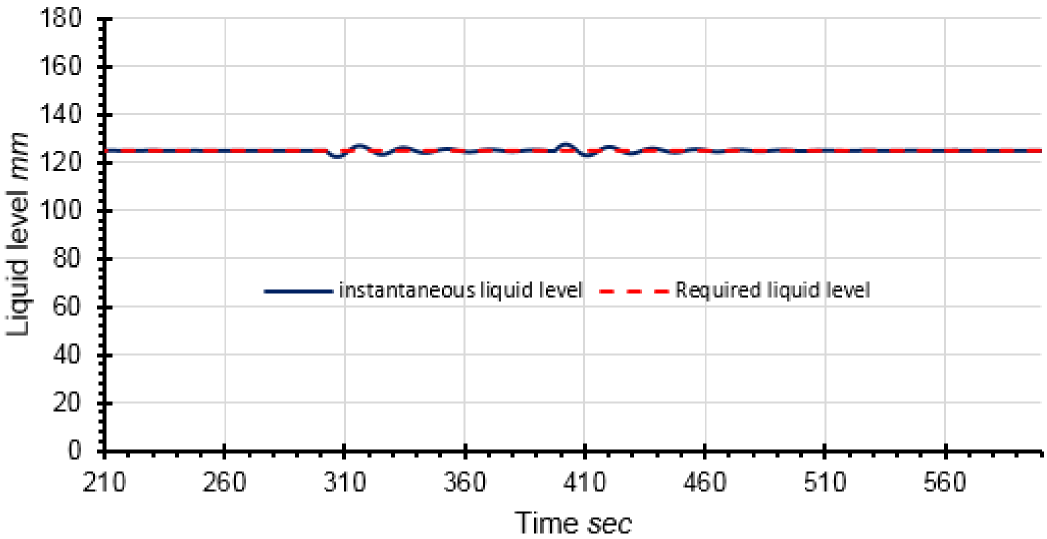


Figure 4.29 Instantaneous liquid level due to disturbance

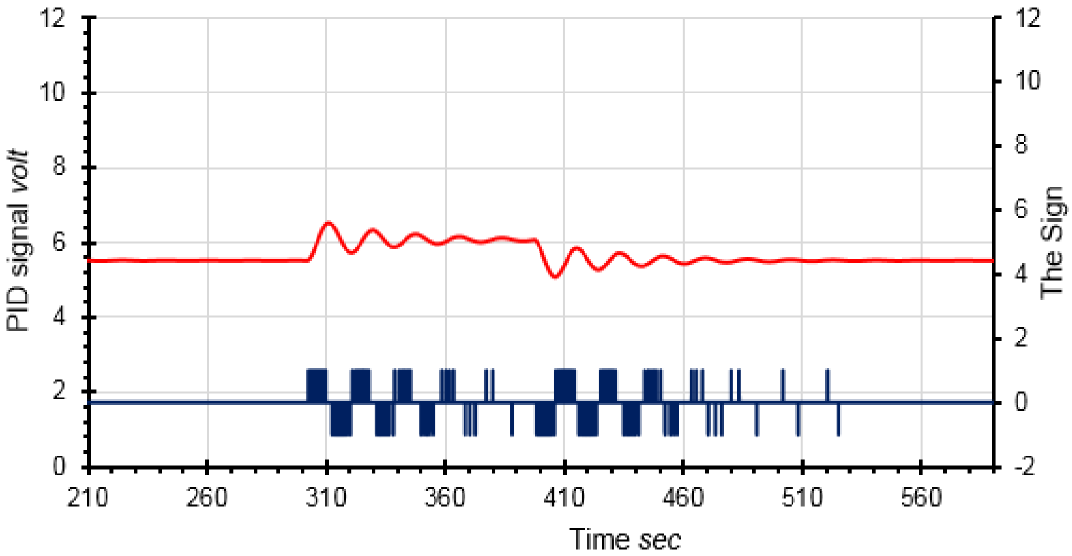


Figure 4.30 PID signal and the Sign chart as a result of disturbance

4.11 Summary

Depending on the system parameters and for a closed-loop PID controlled liquid level system, the liquid level will not be affected by any fault regarding the pumping efficiency and leakage or blockage and their intensity until the controller reaches a specific threshold. The PID controller hastens to increase or decrease the driving voltage supplied to the system water pump in order to rise or decline the pumping rate to cover any changes at the liquid level out of its demand. This behaviour is applicable until the controller reaches its saturated high or low value, or in reality, the maximum or minimum permissible pumping rate. When the controller reaches or exceeds this threshold, the liquid level will decrease as a result of the fault sort, trend and strength.

The PID controller increases the driving power supplied to the pump in order to boost the liquid pumping rate to mask any reduction in the required liquid level. This change could be a human-made mistake or caused by faults. The SCA converts the PID signal into a simple chart with sufficient details to have an efficient long-term health monitoring system. From this chart, the system health condition can be easily monitored and tracked any change that caused by operator or fault. Traditional monitoring algorithms depend on a massive amount of data collected from the system sensors combined with complex analytical approaches. In contrast, this novel Sign chart algorithm provides a simple chart with values (+1, 0, -1) depending only on the controller signal trend and the required demand changing, rather than install additional measuring instruments, to monitor the system performance efficiently. As the SCA provides zero at steady-state, it could be easy to track the system operation history. Moreover, this monitoring algorithm can be automated to monitor a system continuously while it is in-service and sent an alarm or a report when something novel occurs. The report file can be easily sent via internet for its small size in comparison with that of the enormous amount of data acquired from all sensors.

The novelty of this chapter is to snap the deterioration when it just starts via the Sign chart algorithm in order to assess the system remaining useful life. Additionally, by using the SCA, there is an ability to diagnose the sort of fault, intensity and any other changes in the required demand. Moreover, on the SCA, it can easily differentiate between different kinds of controller response due to changing the set point or fault or even a disturbance.

After flagging an unusual event on the controller signal by SCA even hidden faults, it needs to track the signal trend and extrapolate it to a specific threshold to evaluate the remaining useful life as presentes in next chapter.

Chapter Five

Prognostic of a Liquid Level System

5.1 Introduction

This chapter presents a review of the background and theory behind the prognostic of the liquid level system based on the control signal for the development of health monitoring and prognostic algorithm. The layout of this chapter is as follows.

Section 5.2 reviews a brief introduction of prognostic of mechatronic systems and the difficulties behind tracking the degradation and estimation of the remaining useful life of an entire system. Moreover, it reviews the prognostic definition that usually used in literature. The relationship between diagnostics and prognostics as the main parts of prognostic and health management is presented in Section 5.3. Section 5.4 discusses the benefit of applying suitable prognostic approaches. CE105 coupled tank system is controlled using PID controller. Section 5.5 describes the PID signal as a key to monitor the system health condition and evaluate its trend. Section 5.6 presents a test operating scenario, which consists of different kinds of liquid level requirements and several fault sources and severity. Then Section 5.7 presents the results by simulating the previous section and discuss them in detail. Depending on the PID signal trend, the evaluation of the remaining useful life is presented in this section at every single stage of the operating scenario.

5.2 Prognostic of mechatronic systems

Reliability and robustness of any system can be increased through modelling and simulate the process at its design stage. This advancement leads to the integration of system model-based diagnostics and prognostics. Generally, real systems inherently examine some failure, due to wear for example, during their working life (Barbera, Schneider et al. 1996).

(Coble, Ramuhalli et al. 2015) stated that, operation and maintenance costs cover approximately 60–70% of the overall generating cost in nuclear power plants, while fuel costs only 15–30%. Furthermore, labour costs approximately 80% of the operation and maintenance costs in the United States nuclear power plant.

According to this significant facts, using PHM has potential to impact the economics of maintenance for active components (e.g., pumps, valves, motors) and passive structures (e.g., concrete structures, reactor vessels, buried pipes) (Bond, Doctor et al. 2008).

Liquid level tank systems, for example, have many pieces of equipment, including a water pump, pipes, tanks, sensors, and valves that each may exhibit various types of performance degradation as a result of mechanical and/ or electrical faults. These faults may be caused by ageing, dirt or debris precipitation, erosion, friction, internal damage, blockage, cracks.

Prognostics considers the current health condition of a system and predicts its remaining useful life based on features that capture the incipient degradation in the operation of the system. Predictive capability is essential to improve safety, plan successful working scenarios, schedule maintenance activities, and reduce the overall maintenance costs (Brotherton, Jahns et al. 2000). Prognostics is a relatively new field in comparison with diagnostics, and it has become necessary for condition monitoring based maintenance. (Mathur, Cavanaugh et al. 2001) discussed the purpose of failure-based modelling in the overall decision-making problem and they proposed an approach to integrate model-based diagnosis and prognosis.

In general, the prognostic methods can be classified into three categories, data-driven, model-based that presented in (Chiang, Russell et al. 2001), and experience or knowledge-based that demonstrated in (Byington, Roemer et al. 2002) and (Byington, Watson et al. 2003). Each one of these approaches has its advantages and disadvantages, for that they are often used in combination in many applications where available. Tracking the degradation and estimating the remaining useful life, i.e. the prognosis of an entire system is infeasible because of:

- The model complexity,
- The uncertainty and
- sub-system fault propagation.

Typically, the system prognosis is assumed to be designed upon some critical components where their number and positions are depending directly on the system structure. Tracking these critical elements and estimate their remaining useful life provide a measure of the end of useful life of the entire system. In an individual part, the deterioration level and the remaining useful life are estimated according to the physical properties of these elements. For example, the theory of failure is utilised to study the crack propagation in structural components.

Developing prognostic models lead to a considerable amount of research has been achieved. These models can be used to predict the end of the engineering system useful life (EOL) and consequently the remaining useful life (RUL). Unfortunately, applying these models have limited success for industrial applications because of the above-described difficulties. During system design, models are subject to specific assumptions and approximations. Some of them are mathematical, while others relate to practical application issues such as the required amount of data to validate and verify a proposed model. Accordingly, a suitable model selection to have an effective practical application needs more than a mathematical understanding of each model type. It needs to know how a particular application intends to use this model and its required outputs.

In the contribution reported in this chapter, a Sign Chart Algorithm (SCA), which has been presented in Chapter 4, was developed. The SCA provides an ability to diagnose the system faults, monitor the system health and predict remaining useful life by using a mathematical data processing. The testing of the approach reported in this chapter relates to the simulation, which already has been experimental validated of a CE105 coupled-tank liquid level system in Chapter 3. The simulation created used the real-time control toolbox with LabVIEW 2014 software as discussed in Chapter 3 and Chapter 4.

There are several different definitions of prognostics in the available literature. (Sikorska, Hodkiewicz et al. 2011) proposed eleven different definitions of prognostics. Communally, those definitions stated that:

- prognostics is, or should be, applied at the component or sub-component level, as it is a difficult task to prognosis a whole system as a single unit.
- Prognostics contains predicting the deterioration time of a specific failure-mode from the fault start until the time of EOL. For a condition monitoring

system, it is assumed that there are completion rules between diagnostic and prognostic, as shown in Figure 5.1.

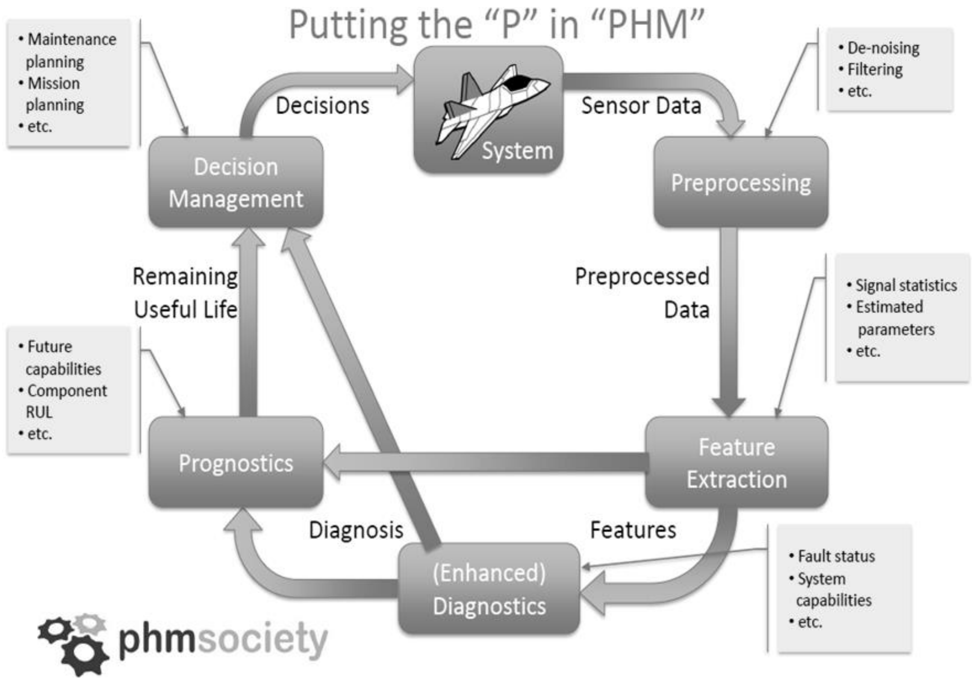


Figure 5.1 Prognostics and health management integrated parts (Clements 2011)

As soon as an indication of a fault has been triggered through the diagnostic approach, the remaining useful life RUL estimation should start from this point of time upward to the end of the system useful life.

(Saxena, Balaban et al. 2010) presented the prognostic and health management society PHM definition of prognostics as the estimation of remaining life of a component or subsystem. Prognostics evaluates the current health condition of equipment or subsystem and based on the condition of the future proposed operation scenario (load) and environmental exposure, the prognostics estimate the end of the equipment useful life. At which, this equipment will no longer operate within its stated specifications. These predictions are based on the following:

1. The failure mode analysis.
2. Early signs of fault and its condition triggered and an assessment of the current damage state.
3. Describing how the damage is expected to develop at the time.
4. Describing the effect of loads and operating conditions on the system.

5.3 Diagnostics and prognostics relationship

Condition-Based monitoring of a system consists of two main parts, diagnostic and prognostic. There is a slight difference in the literature as they are accepted that prognostics is related to diagnostics and highly dependent upon it, as can be seen in Figure 5.1. However, a separation limit between these two fields is not defined precisely. Diagnostics involves identifying and quantifying the damage that has occurred in the past up to this assessment time, while prognostics is concerned with predicting the damage that may occur in the future (Sikorska, Hodkiewicz et al. 2011). Diagnostics provide useful outputs by its own. Meanwhile, prognostic depends on diagnostic outputs (e.g. fault indicators, fault strength and rates of degradation) and therefore, prognostic cannot be performed in isolation, as shown in Figure 5.1.

This PhD thesis presents SCA as a tool used to capture a fault in the LLTS system as soon as it occurs while it is still showing a healthy behaviour. Meanwhile, prognostics will be activated after identifying and quantify the fault by the diagnostics approach to describe the trend of the system response due to a fault and accordingly estimates the remaining useful life.

When a new event triggered during operation within a system useful life, as shown in Figure 5.2, which leads to increase or decrease the fault degradation, and while this proposed prognostic approach is estimating the EOL, it can adapt its trend. As soon as a new abnormal event has been triggered, this approach starts evaluating its parameters and determining an updated EOL.

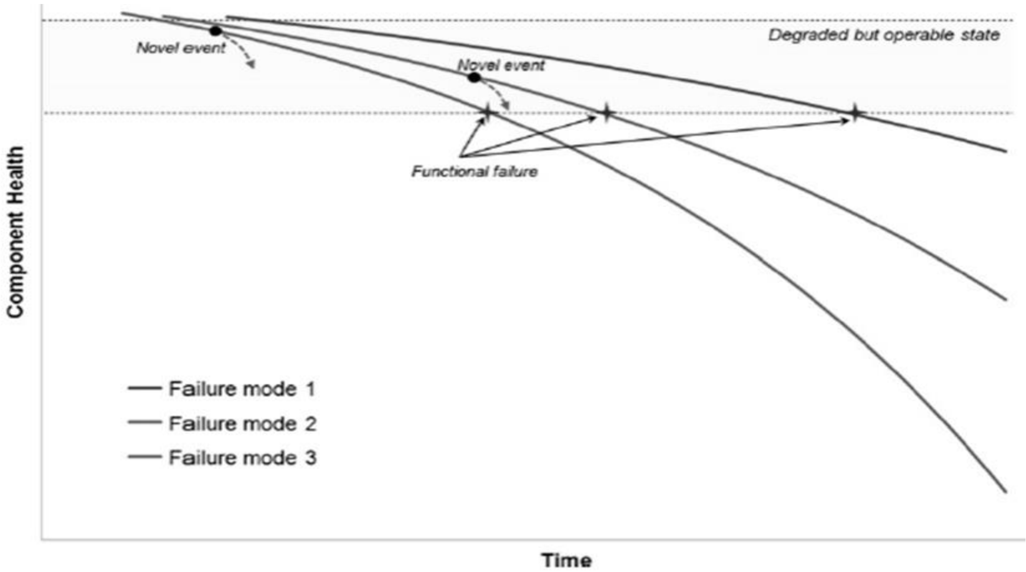


Figure 5.2 Description of different health degradation curves (Sikorska, Hodkiewicz et al. 2011)

5.4 Benefits of prognostics application

A significant amount of research has been done to develop different prognostic models, which can be applied to predict the remaining useful life of industrial systems. Nevertheless, the industrial applications of such approaches have had restricted success.

There is a wide range of objectives can be achieved with a suitable prognostics approach. Because there are different solutions and strategies are applicable for a different user application, users according to their perspective need to define the prognostic goals. (Saxena 2010) from his work at NASA Ames research centre presented the prognostics goals, at the annual conference of PHM society PHM 2010, in two main categories according to different views of management, as can be seen in Figure 5.3.

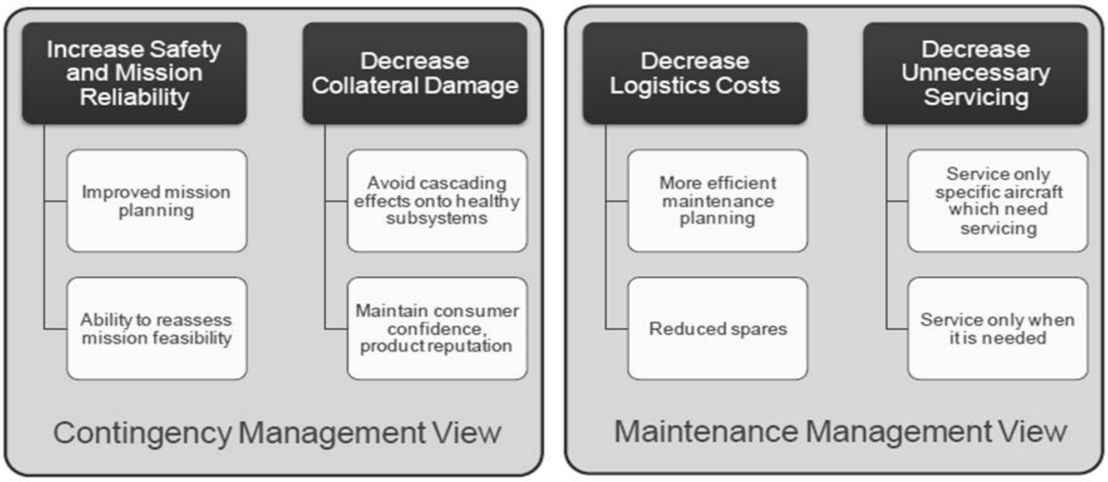


Figure 5.3 The prognostics goals tend to be achieved (Saxena 2010)

5.5 The PID signal trend:

5.5.1 Describing the PID signal

Sign chart algorithm provides a continuous health monitoring tool based on the PID signal as any change in its trend; the SCA will flag it. The contribution presented in Chapter 4 was about a novel approach to catch any variation of the controller signal and its intensity caused by manipulating the liquid level, faults even hidden one and any disturbance. Meanwhile, the contribution of this chapter is a controller-based prognostic approach. This algorithm is continuously observing the PID signal trend to build its mathematical model and then extrapolate it to a specific threshold to evaluate the remaining useful life of the system. A liquid level tank system has several kinds of elements, sensors and actuators, as described for CE105 in Chapter 3. Quantities and types of these transducers depend on the size and complexity of the process and operating scenario. For modern computerised systems, information from sensors and actuators can be electronically recorded and monitored. Although nowadays-technology provides massive electronic data storage media that can be used in the site, transferring a massive amount of this data online is still not applicable or takes a long time. Fortunately, all necessary acquired data can be saved on a local storage medium; and an only particular piece of information needs to be transferred to a remote receiver via the internet network for analysis or monitoring purposes and a remote maintenance decision making. Moreover, SCA, as presented in Chapter 4, can provide a clear indication and sufficient information about the system condition during a continuous system health monitoring. For that, only SCA data, when it flags some unusual event, needs to be transferred online. This algorithm returns zero if the system shows a healthy behaviour and there is no change in the required demand in the absence of any disturbance. Once this value becomes +1 or -1, which indicates that something has occurred, a fault or the required demand has a human-made or accidentally changed or disturbance. This ill-behaviour according to SCA can be diagnosed using the time-based corresponding data of the controller and sensors signals. This amount of data has been already acquired and saved on a local medium for detailed analysis purposes.

When the SCA pointed there is a sign of a control signal change; the PID controller signal needs to be analysed. This analytical approach can be achieved by either data analyser algorithm integrated with the main monitoring LabVIEW programme or moving this piece of information to a separate data analyser software to estimate the controller signal trend to evaluate its best-fit equation. To evaluate the system EOL, the controller trend function needs to be extrapolated to a specific predefined threshold. This threshold was defined in Chapter 4.

A PID signal trend depends on, in addition to its parameters, the fault sources and the fault intensity. For CE105 apparatus, it may easily recognise two different features as follows:

- An incipient fault, which is starting and growing slowly with the time, at the drain part of the CE105, the tank, exit valve and the connection pipeline component gives a linear PID signal trend.
- Degradation of the pumping efficiency makes the PID controller showing a nonlinear behaviour (an exponential trend).

The trend of these faults is developed linearly with the time, and hence each of them was mimicked as a ramp function with an ability to set its slope to mimic different fault intensity. According to these two different PID signals, the proposed prognostics approach for this system, in particular, has two terms, linear and exponential to cover the above PID response features.

- ***Linear Term***

A power function can be used as a curve fitting formula to describe both linear and power function trend. If the power of Equation 5-1 is equal to one, the function becomes a linear function. Meanwhile, if it equals zero, in this case, the PID output signal is equal to the same value with the time, which means that the system is in excellent condition with no change in the process parameters.

$$V1_{PID} = AT^{B} + F_{1} \tag{5-1}$$

Where, *A, B* and F_1 are the function parameters, *T* is the time in *seconds,* and $V1_{PID}$ is the corresponding PID output voltage in *volt*.

- ***Exponential Term***

Equation 5-2, as an exponential equation, covers a range of a nonlinear PID signal trend according to its parameters, as shown below:

$$V2_{PID} = Ce^{DT^{E}} + F_{2} \tag{5-2}$$

Where*, C, D, E* and F_2 are the function parameters, *T* is a time in *seconds,* and $V2_{PID}$ is the corresponding PID output voltage in v*olt.*

These two terms need to be added to each other in one function to cover all the possible PID response,

$$V_{PID} = V1_{PID} + V2_{PID} \tag{5-3}$$

And hence,

$$V_{PID} = AT^{B} + Ce^{DT^{E}} + F \tag{5-4}$$

5.5.2 PID signal trend evaluation

At early stages of a fault age, the PID hastens to mask any deterioration in the system condition while its output signal is less than the maximum permissible value or a predefined threshold. As the fault grows with the time, the PID signal is interacting correspondingly with the fault degradation as described in Chapter 4. Hence, the incremental deviation pace and trend of the PID signal depend on the fault degradation speed and its severity, and the current condition of the system. As concluded in Chapter 4, the liquid free outflow rate depends directly on the liquid level if there is no change in the other system parameters, the setting of the exit valve for example. Either in the presence of a fault or no, the liquid level will not be changed because of faults if the PID signal is less than its saturation value. Accordingly, tracking this signal and estimating its trend equation is essentially needed to set an early alert of nearly predictive failure and by extrapolating this equation to a predefined threshold, the system EOL can be evaluated, as shown in Figure 5.4. The PID signal and its corresponding time, for the purposes of this PhD thesis, was transferred to Microsoft Excel programme. This transferred data should cover the period from that the fault was just appeared up to the current time. On this programme and for the series of time and the corresponding PID voltage during this fault period, the curve needs to be plotted, and the data trend has to be estimated according to Equation 5-4. This equation has six parameters, all of them need to be evaluated to build the trend equation. Data solver algorithm as one of Microsoft Excel numerical solving block can do this evaluation. Once these parameters have been evaluated, the data trend becomes known. By substituting the threshold value in this equation, the corresponding time can be estimated, and this is the end of the system useful life according to the current health condition. But solving this equation needs to use numerical methods and fortunately, there are many mathematical packages available online can be used.

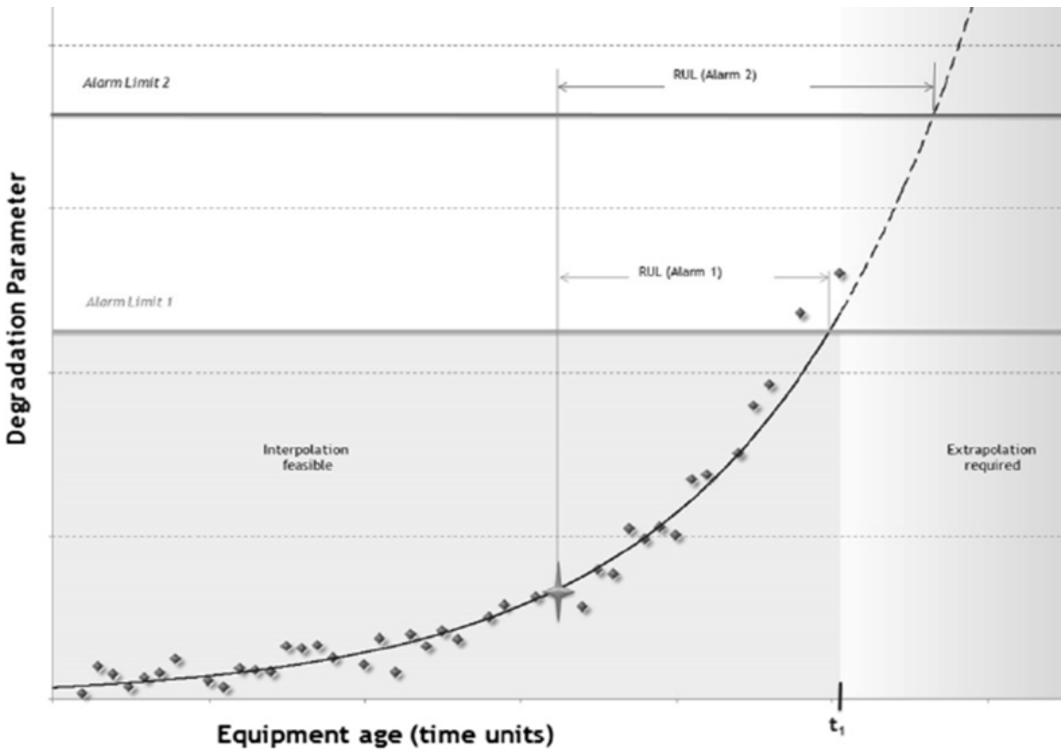
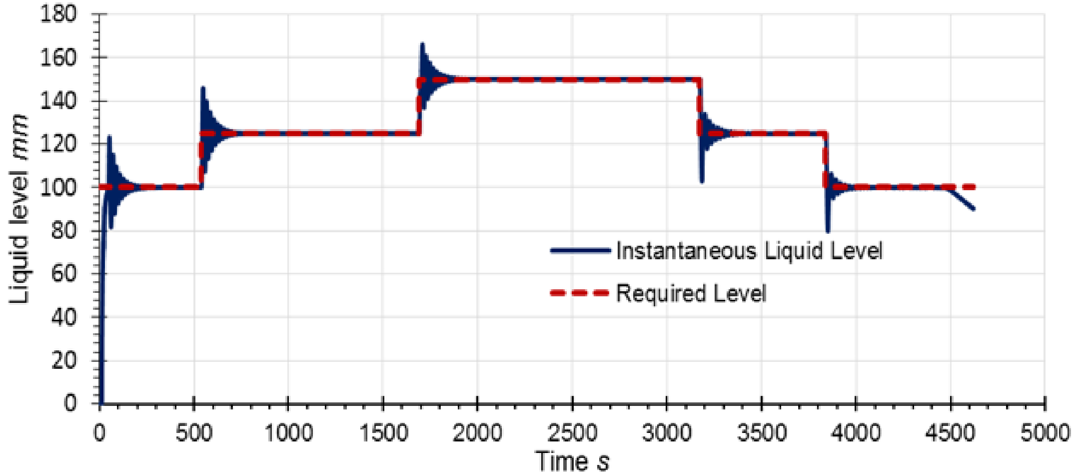


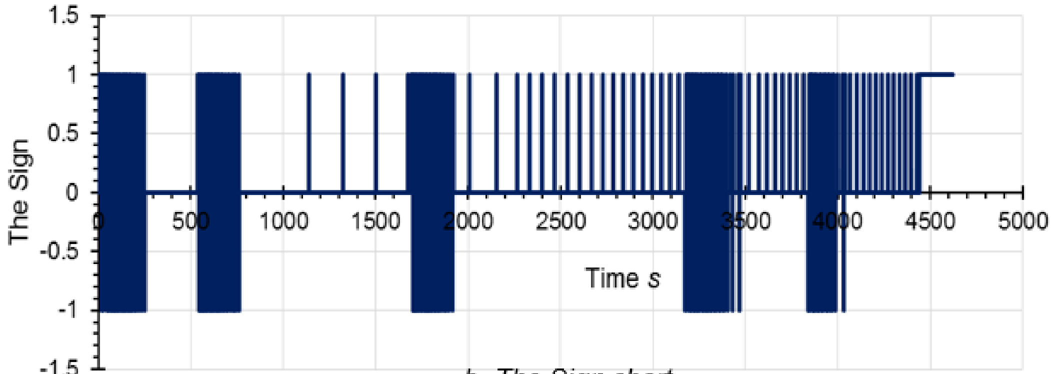
Figure 5.4 Trend evaluation of a degraded system (Sikorska, Hodkiewicz et al. 2011)

5.6 Case study

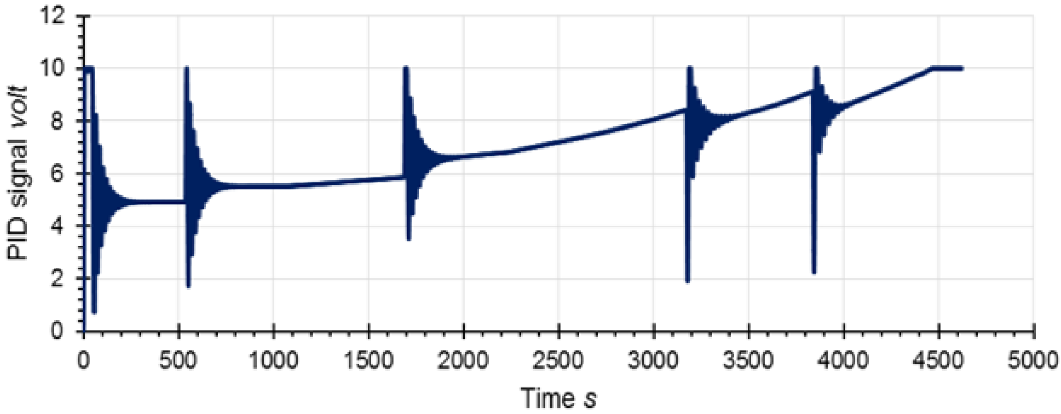
To study the proposed prognostic approach, simulation of the CE105 apparatus under LabVIEW environment that described in Chapter 4, was run. Data from different sources such as SCA; liquid level; the tank inflow and outflow rate; pump driving voltage; the required and instantaneous liquid level and the PID signal were presented on the simulation front panel and saved on the PC hard drive to deal with them later. By analysing these groups of data, it could be possible to track the system health condition; estimate the trend of the PID signal and evaluate the EOL according to Equation 5-4 by extrapolation, and/ or the RUL from the estimation point of time. An operation scenario with different activities was followed for the purpose of this case study, as can be seen in Figure 5.4. The total time taken for this run is 4621*s*, which is equal to one *hour* and 17 *minutes*. Such is an accelerated time for the purpose of this study in the absence of a practical data regarding the fault progression speed and operating scenarios. Steps of the proposed operation scenario will be presented in Section 5.8.



a. The instantaneous and the required liquid level



b. The Sign chart

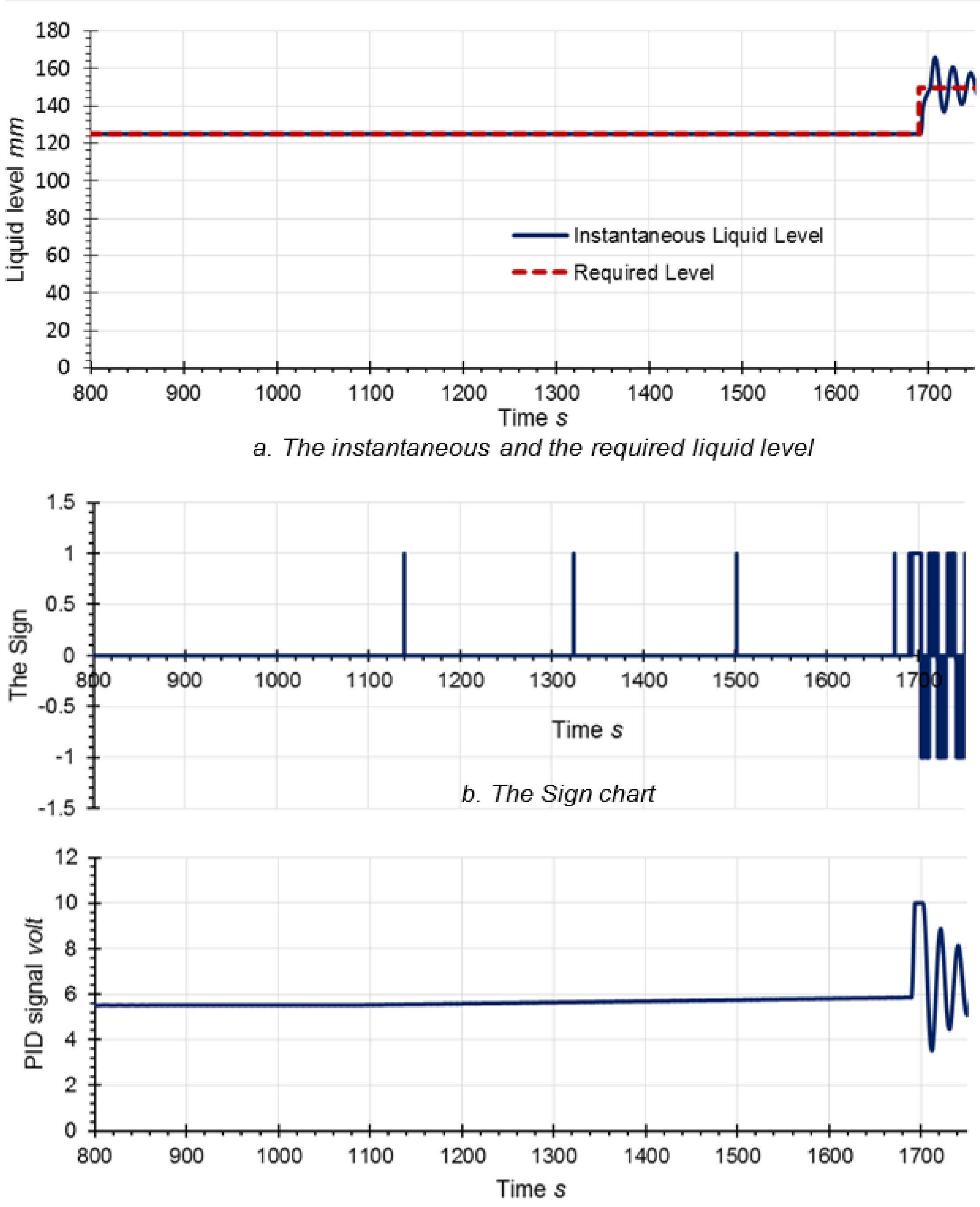


c. The PID signal

Figure 5.5 The proposed operation scenario

5.7 Results and discussions

1. The required liquid level was set to 100 *mm* at the starting point, where the absolute time is considered to be zero. Figure 5.5 shows that the liquid level reached its steady state and settled at its required demand after some fluctuation according to the controller parameters. This behaviour was repeated whenever the required liquid level was changed for the stated parameters.
2. At the time 538 *s* from the starting point, the liquid level was changed from its current height, 100 *mm* to a new demand of 125 *mm*. In the absence of any fault, the PID signal settled at its steady-state value (4.915 *volts*) corresponding to required liquid level. Theoretically, this health system has an endless useful life. During this period of time, the SCA returned zero continuously.
3. The system showed a healthy behaviour as the SCA returned zero continuously when it settled at its required demand, which it can be approved from the liquid level curve. At about 1139 *s* from the starting point, the pumping efficiency start being degraded gradually, which was mimicked in this simulation as a ramp function with a slope of $1*10^{-6}$. At that time, the SCA start pointing to the faulty system behaviour and sending the first fault indication. As the pumping efficiency degraded, the pumped liquid flow rate was decreased as a result, which led to having a liquid level drop. Even this drop was tiny and not visualised by an operator; the controller hastened to mask this deficiency through increasing the pump driving voltage continuously by an amount corresponding to what lost because of this fault to maintain the liquid level at its required demand, as can be seen in Figure 5.6.



a. The instantaneous and the required liquid level

b. The Sign chart

c. The PID signal

Figure 5.6 Degradation of the pumping efficiency at 125 mm liquid level

Now, it is time to analyse the PID signal of the period between point 1135 *s*, where the fault was started upward to the current time before having any unusual event, as shown in Figure 5.2, say the 1600 *s*. The PID signal trend needs to be evaluated, and from it, the EOL can be estimated, at which the PID signal will reach its maximum allowable value, i.e. 10 *volts*. As much data becomes available, the trend evaluation becomes more precise. The system will reach its EOL according to the current system conditions at 6400 *s* measured from the starting point.

4. After 550 *s* from the first sign of fault initiation, the required liquid level was increased to be 150 *mm*. From the SCA, as discussed in Chapter 4, it is easy to recognise that the demand has been changed to a new level. After a period of fluctuation and because of the fault has been still existing at the same intensity level, the SCA went back to its feature before this step, as can be seen in Figure 5.6. A new trend evaluation was done when the liquid level reached its demand, and consequently, the new EOL was estimated. According to the current system condition, the EOL will be reached at 6059 *s* from the starting point. The reduction of the predicted EOL is about 5.33%, if the liquid level, according to current health condition changed from 125 *mm* to 150 *mm*. This degradation is a result of increasing the required demand, which means the PID controller needs to work harder by increasing its output voltage.

During this period of time and at the 2200 *s*, a novel event occurred. The fault was duplicated to be $2*10^{-6}$ as a slope of the fault-mimicked ramp function. It is inapplicable to identify when the fault was changed by tracking only the liquid level curve. On the PID signal curve, it might not be easy to do this either. But on the Sign chart, it can be easily recognised when the change has occurred either in Figure 5.5 or Figure 5.7. The evaluation of the PID signal trend parameters for this period was done from the time the 2230 *s* forward to the current evaluation time according to Equation 5.4. From this equation, the evaluated EOL is 3915 *s*. There is a reduction in the EOL by about 38.83% in comparison with the previous time, which caused by the increasing of the fault strength.

In the presence of a fault, the SCA returns a series of positive ones with periods of zeros between them as the PID signal was increased, as shown in Figure 5.7. These periods became smaller and smaller with the time, which refers to the nonlinear controller response, such response was described in Chapter 4, is related to a fault at tank feeding side of the system. Meanwhile, these periods have a constant length; if the controller response is linear, such response is regarding a fault at the system drainage side. At this estimation time, the 2230 *s* the remaining useful life is 1685 *s*. The RUL of a system is the period between the current estimation time and the predicted EOL. It might be worth to decrease the liquid level to increase the remaining operation time, without having any maintenance activity.

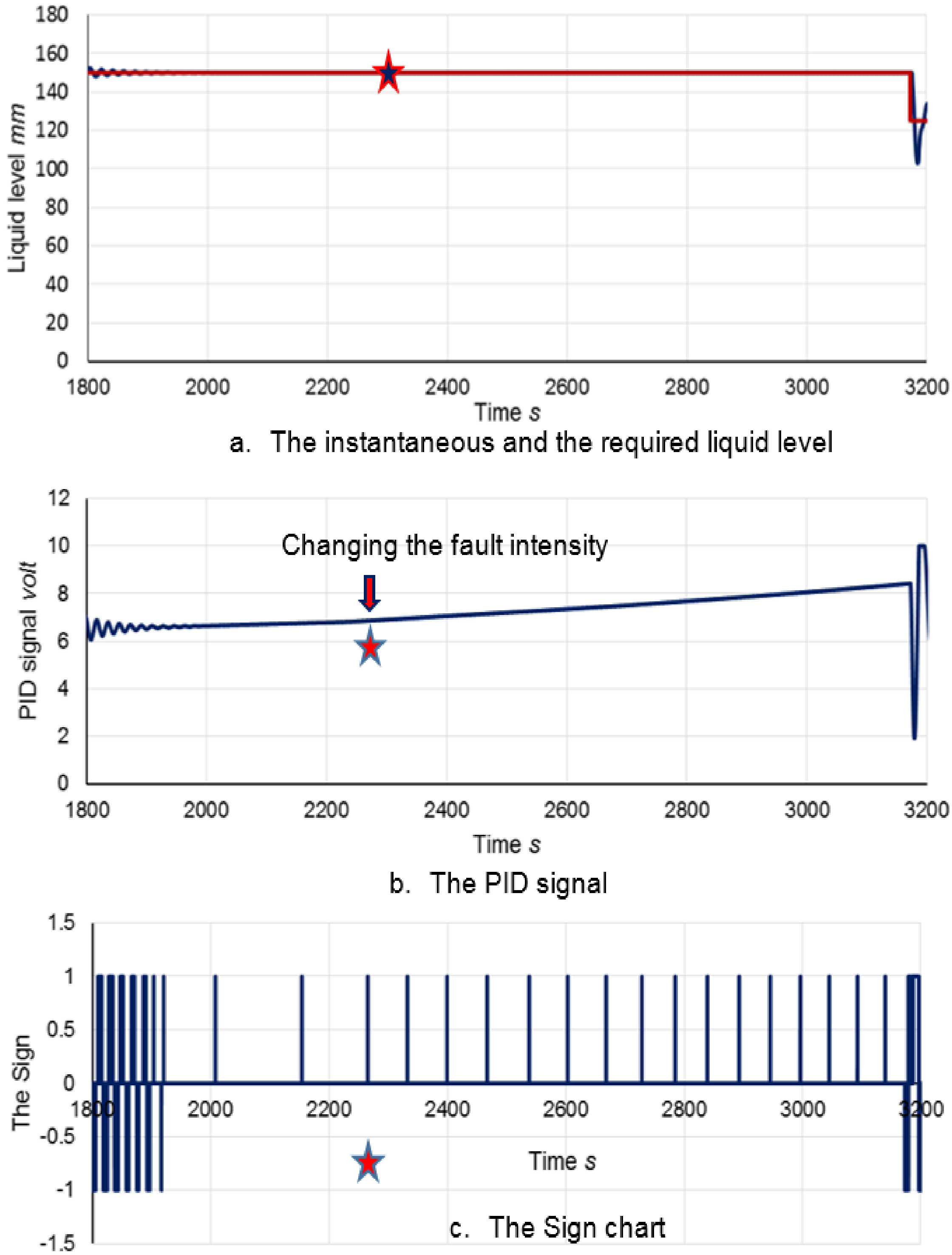
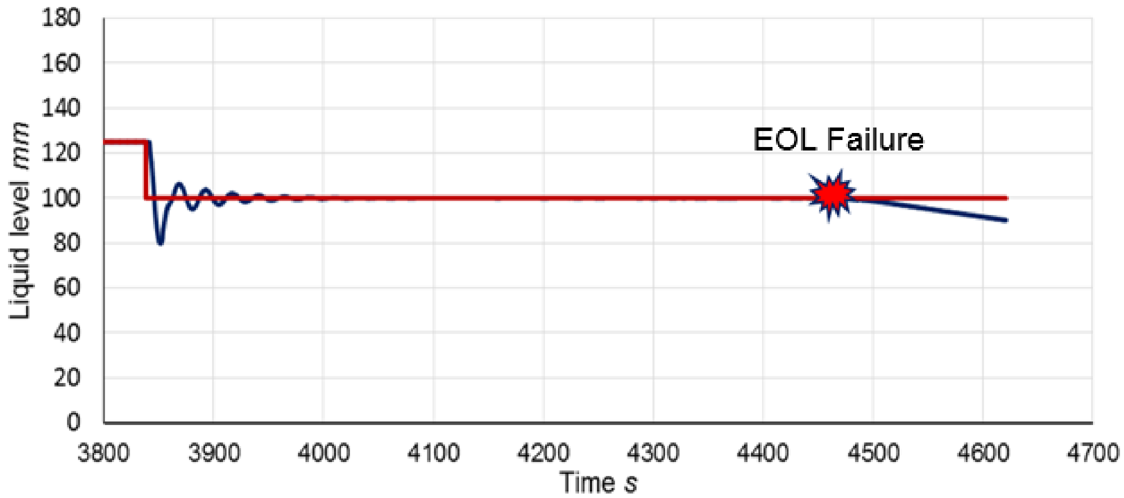


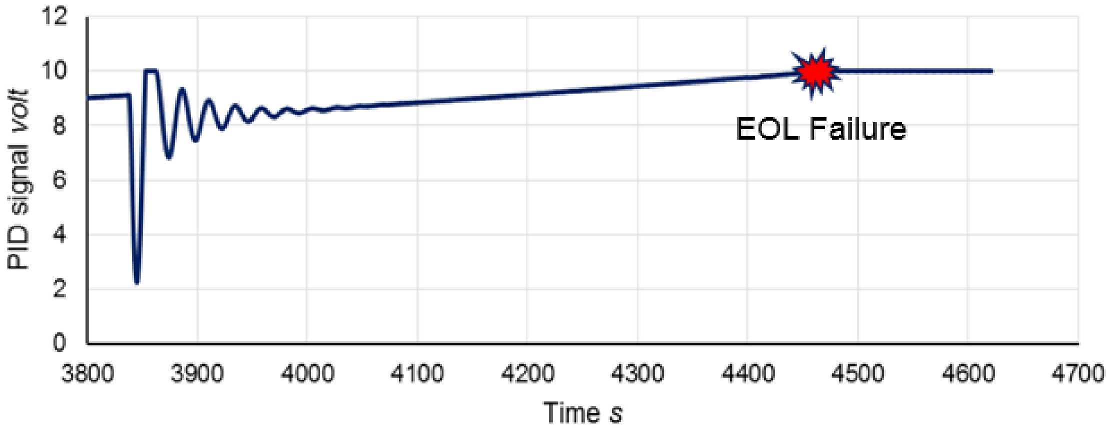
Figure 5.7 Changing the intensity of the pumping efficiency fault at 150 mm liquid level

5. At the time 3180 *s* from the starting point, the liquid level was decreased to be 125 *mm*. The new evaluation was started at time 3500 s, and accordingly the estimated EOL was 4140 *s*. Because of the benefit of the predicted EOL is only 3.52%, it might be worth to decrease the liquid level again to a new height in order to have an extra operating time.
6. The liquid level was reduced for the third times, and the new height was 100 *mm*. The estimation time started at 4100 *s* upward to 4325 *s,* and it showed that the EOL would be after only 368 *s*. In the simulation, the PID signal reached its maximum value, i.e. 10 *volts* at 4468 *s.*
7. When the system reached its EOL, the PID signal returned its maximum set value, i.e., 10 *volts* continuously, the SCA returned uninterrupted positive one. Because the system has developed a continually progressive fault and the PID reached its saturation maximum value, which means it cannot mask the fault anymore, the liquid level started dropping as a result, as can be seen in Figure 5.8.

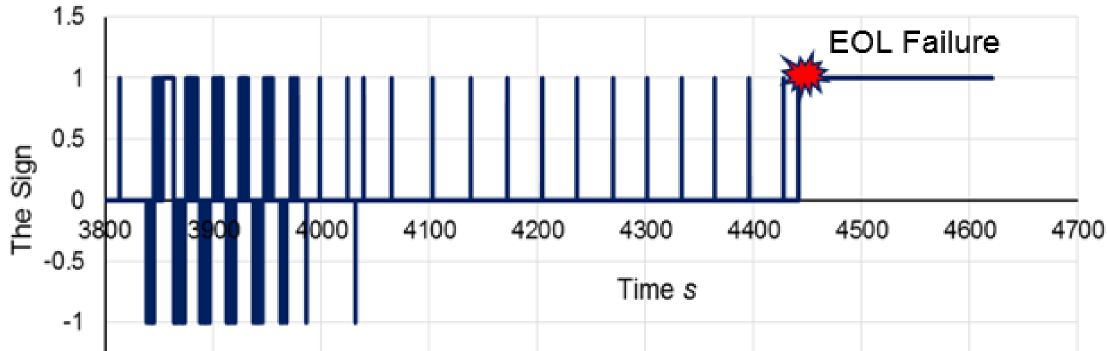
For the liquid level tank system, in particular, CE105 test rig, the proposed linear–exponential equation with a numerical method solver gives a precise estimation of the end of the system useful life and accordingly the remaining useful life.



a. The instantaneous and the required liquid



b. The PID signal



c. The Sign chart

Figure 5.8 The simulation result of the liquid level system at the end of its useful life

5.8 Summary

It is widely accepted for closed-loop control systems that the controller works to cover any fault and disturbance while the control signal is less than its maximum allowable value. This maximum limit can be pre-defined as a threshold. Accordingly, these closed-loop systems show healthy behaviour regardless of the presence of any hidden fault occurs as the controller manipulate its signal trend to achieve the system required demand. By tracking the controller signal trend and extrapolate it forward in the future to reach a specific threshold, the system end of life can be evaluated, and the remaining of its useful life can be calculated. As pre-discussed in Chapter 4, CE105 as a liquid level system shows linear and exponential PID signal trend due to leakage at the low-pressure side and a deterioration of the pumping efficiency respectively. For that, a couple of terms function, linear and exponential, was used to describe the PID signal trend. Form the current time and backward in the past, the function parameters were evaluated and then it was extrapolated to a specific threshold to estimate when this system will reach its end of life in future. This approach can be automated as a part of an integrated continuous monitoring system to evaluate the remaining useful life at any time where the system is in-service.

Tracking the PID signal trend to build its mathematical model followed by extrapolating it to a predefined threshold to evaluate when the under-monitoring system will reach its end of useful life is the main contribution presented in this chapter.

To verify the results of applying the approaches and algorithms that pre-discussed in previous chapters, a new design of a three individual-tank system (TTS) is designed and examined. Chapter 6 presents the TTS requirement design and its examination under different operating and faults scenarios.

Chapter Six

Three Individual Tank System

6.1 Introduction

This Chapter presents a review of the background and theory behind a new design of a three individual tank system (TTS). This system was designed to confirm the experimental results from CE105 and to overcome its limitations. CE105 was built with regulator drain valves that located away from the tank zero level, i.e., tank base. The layout of Chapter Six is as follows:

Section 6.2 describes the three individual-tank system (TTS), overall dimensions and its main components. The system's mathematical model is presented in Section 6.3. TTS as a closed-loop mechatronic system is controlled by using a PID controller under LabVIEW environment as presented in Section 6.4 to achieve the required demands and to apply a wide range of operating scenarios. Section 6.5 presents data acquisition (NI myRIO), which is used to interface between the LabVIEW programme on a PC and the TTS. Section 6.6 describes pulse width modulation DC motor control to drive the system water pump via L298N driver board. This dual H-Bridge motor driver is presented in Section 6.7. Section 6.8 presents the system controlling programme; LabVIEW programme front panel design and the design of the block diagram. Section 6.9 presents the estimation of characteristic equation of the TTS components, i.e., transducer and the drain orifice. The PID controller as a closed-loop control algorithm that uses to control this system is presented in Section 6.10. Section 6.11 and Section 6.12 present the simulation of the TTS under LabVIEW environment to build a virtual system in the former section and discusses the results of running the simulation for different requiring demands.

6.2 Description of three individual-tank system

This chapter presents a new mechanical design of a three individual-tank liquid system. It includes modelling, analysing and condition health monitoring of the system. A PID closed-loop controller was implemented in this system to obtain the desirable performances. Moreover, the controller-based health monitoring can be tracked of this system under different operating and fault scenarios. To implement a control algorithm for the liquid level concerning the inlet and outlet liquid flow rate of the tank, LabVIEW environment was used. Pulse

Width Modulation (PWM) was used to control a DC electric water-pump by receiving a specific signal from the control algorithm in range of 0 to 100%, for the drive voltage of 12 *volts*.

TTS is a typical liquid level system that consists of one or more of the following fundamental components:

1. Liquid tank.

2. Liquid feeder such as a liquid pump or prior tank system.

3. Discharge restriction such as circular diameter sharp-edged orifice or manual operated or solenoid valve.

4. Liquid level and flow rate sensors.

5. Liquid.

A Three Individual-Tank System (TTS) was designed to overtake the limitations of CE105, which shown in Table 6.1 and verify the results that were presented in Chapter 3, 4 and 5. Figure 6.1 presents the components of the three-individual-tank system. This apparatus consists of three separate liquid level systems in one compacted test rig. This overall system dimensions are 588 mm height, and its width and depth are 150 mm each.

Table 6-1 Differences between TTS and CE105 liquid level system

Item	CE105	TTS
1	It has coupled of interacted tanks	It has three individual tanks
2	It can be used as a single tank system.	It consists of three independent systems
3	One liquid pump to control the system input	Three submerged pumps, a pump for each tank
4	One flowrate sensor	Three flow rate sensors
5	The drain restriction is a regular valve, which can be analogous to an orifice in its mathematical model	The drain restriction of each tank is a real circular diameter sharp-edged orifice
6	Fibreglass tank with a transparent window	Circular clear Plexiglass tanks
7	By changing the drain valve setting, the liquid outflow rate can be changed, by changing the valve setting it is impractical to get back the same previous condition.	Each tank has its own changeable real fixed diameter orifice. It is capable to run three different tests condition at a time and easy to re-run any previous settings.
8	One operating scenario at a time	Three different operating scenarios at the same time.
9	There is an eccentric distance of about 46 mm between the tank base the drain restriction centre, as discussed in Section 3.5.5	The discharge orifice is mounted at the base of the tank to overtake the eccentric.
10	Accordingly, this test rig shows more linear than nonlinear behaviour as such all real systems do.	It behaves like a real nonlinear with a reasonable consistency to its mathematical model.

In particular, this nonlinear PID-controlled mechatronic system consists of three separate plexiglass cylinders, which are used as individual vertical-tanks *T1, T2* and *T3* with a cross-sectional area of $A=1257\ mm^2$ each. The liquid (coloured tap water) flows from each tank downward to the main common cylindrical reservoir from which submerged pumps 1, 2, and 3 supply tank *T1*, *T2* and *T3* respectively. Every single tank is equipped with piezoresistive pressure sensing transducer for measuring the liquid level. A digital PID controller can control the inflow rate Q_i such that the level in the tank T_1 can be pre-assigned independently. The liquid level in the tank is always related to the liquid properties, and its flow rate goes into the tank; and the discharge orifice diameter, which are considered to be constant during the process. The system connecting pipes and the tanks are not equipped with any adjustable valves neither manually nor electrically controlled.

The flow characteristics of the TTS can be controlled and changed to a wide range of physical characteristics by changing the cross-sectional area of the discharge orifice, which can be varied over a wide range of diameters up to 10 *mm* and shapes. The inlet channel is connected to a variable speed electrical pump which works with 12 v*olt* and varied according to pulse width modulation (PWM) in the range from 0 to 100%. Every single tank is considered as a Single Input Single Output (SISO) system where the inlet flow enters directly to the tank only as a single input to the system with a single drain for each tank via its outlet orifice. Other tanks have their own drain orifices with difference sharpness, shape and cross-sectional area to examine different outflow characteristics.

The pressure sensing liquid level sensors are located on the upper plate of the system, as shown in Figure 6.1. The liquid level sensor gives its output signals as a voltage proportional to the water level in its tank as it senses the differential pressure of the trapped air between the base of the tank and the sensor port in comparison with the atmospheric pressure. This sensor can be calibrated by comparing its measurement in *volt* on the system's operating programme under LabVIEW environment with the actual liquid level by using an available scale that mounted on the tank surface.

NI myRIO is used as an interface between the three individual-tank system and the LabVIEW programme on the PC.

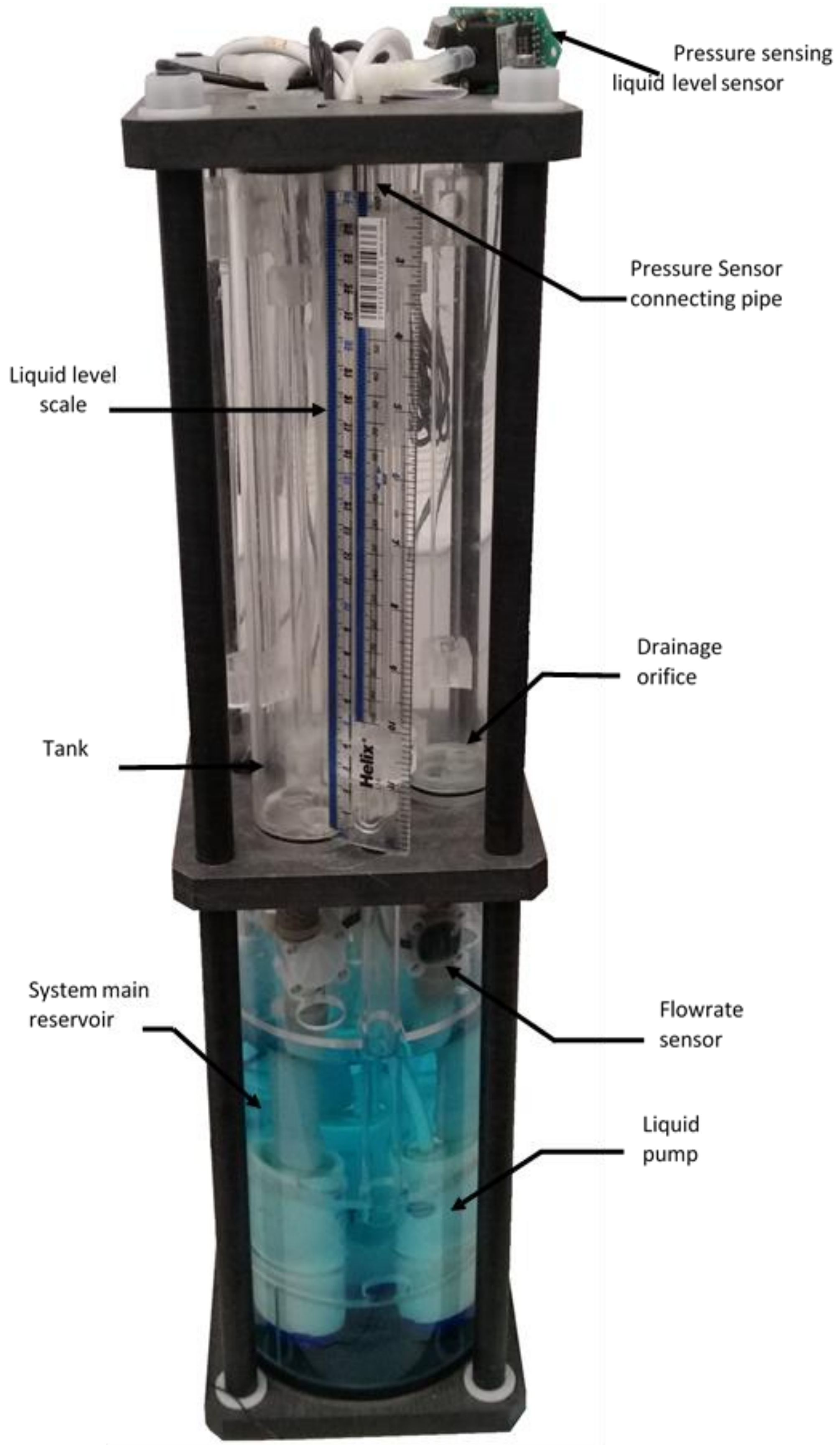


Figure 6.1 Three-individual tank liquid level system

A LabVIEW programme was prepared to manage the TTS, which on its graphical user interface (GUI), the PID parameters were set. Moreover, the system parameters such as the required liquid level and the input function, step or ramp function with a different slope, can be determined on the GUI. The graphical output can be tracked on the waveform chart on the front panel. The recorded data was sent to an Excel programme for analysis purposes.

The TTS qualifies for use in research projects in control and system prognostics and health monitoring research. It is nominated to be used at the department of measurement and control at Cardiff University to study and teach different methods of control and model-based diagnostic and health monitoring approaches. For such projects, the plant was equipped with facilities to connect to a PC via NI MyRIO data acquisition. An H-bridge card L298N was used to provide the required pulse width modulation signal to control the liquid pumping rate.

This chapter is focused on modelling of a three individual-tank system. It contains detailed description of a process of developing a computer model under LabVIEW environment. The model design process starts with measurement of characteristics, in real-time, of the three individual-tank system. An initial mathematical model based on first physical principles approach was derived and discussed in Chapter 3. The nonlinearities of the real-time system are identified and included in the final mathematical model and the simulation.

6.3 Mathematical model

This system can be assumed as a typical liquid level system with a typical circular diameter sharp-edged orifice as a drain restriction. The general block diagram of a liquid level system that presented in Figure 3.14 was followed to generate the three individual tank system model. The TTS mathematical analysis was build according to Section 3.2. But the TTS virtual system was built based on experimental characteristic equations of its transducer and mechanical elements. This experimental procedure will be discussed later in Section 6.9.

6.4 Controlling the TTS

The objective of many electrical or electronic control system is to measure, monitor and control process variable. It can be accurately controlled the process by tracking the output and feeding this signal back to compare the actual output with the desired output to reduce the error and if disturbed, bring the output of the system back to the original or desired response.

The quantity of the output being measured is called the feedback signal, and the type of control system which uses feedback signal to both controls and adjusts itself is called a closed loop system.

A closed loop control system also is known as a feedback control system is a control system which uses the concept of an open loop system as its forward path but has one or more feedback loops, hence its name, or paths between its output and its input. The reference to feedback means merely that the signal of the output is returned to the input to be a part of the excitation of the system.

Closed loop systems are designed to automatically achieved and maintain the required demand by comparing it with the actual condition. It does this by generating an error signal which is the difference between the output and the reference input. In other words, a closed loop system is a fully automatic control system in which its control action being dependent on the output in some way.

Most of the control algorithms are model-based of a controlled process. A plant model can also be used to study the system response and behaviour of the modelled plant without danger of a catastrophic deterioration (Chalupa, Novák et al. 2012). They classified the basic approaches of obtaining plant model into two types:

- A black box approach of modelling is based on the analysing of input and output signals of the system, and hence, it is possible to use the same identification algorithm for a wide range of different controlled applications. Also, there is no requirement to have a knowledge of physical principles of the controlled system.
- The first physical principles modelling (mathematical-physical analysis of the plant). The model obtained by black box approach is generally valid only for particular signals that it was built on.

Meanwhile, the first principle modelling provides a general model that is valid for a whole range of system inputs and condition.

The model is created by analysing the modelled plant and combining physical laws (Jeffrey and Jim 2013). In reality, there may be multiple unknown parameters and relations, when performing analysis of a plant. Accordingly, modelling a system based on its mathematical-physical analysis is usually suitable for simple controlled processes with a small number of parameters.

6.5 Computer interface board NI myRIO

A computer interface board, as shown in Figure 6.2, is available in the laboratory of the School of Engineering, Cardiff University as is to be used in the stated research and teaching activities. This board is used to interface between LabVIEW programme and the three individual-tank system and for many other purposes. The output port is used to send PWM to the pump according to the PID controller output signal via H-Bridge L298N, and the input ports are used to return the feedback signals about the water level of the tank and the flow rate of the pump. One of the available ground ports should connect to the ground port on the TTS. LabVIEW programme can distinguish all the signals easily, and the designed programme converts these signals to visible graphs and numeric data.

Figure 6.2 NI myRIO

6.6 Pulse width modulation DC motor control

Pulse Width Modulation (PWM) is a technique which allows adjusting the average value of the voltage that is going to the electronic device by turning ON and OFF the power at a fast rate. The average voltage depends on the duty cycle, or the amount of time the signal is ON versus the amount of time the signal is OFF in a single period of time, as shown in Figure 6.3.

Depending on the size of the motor, the LabVIEW software PWM output can simply connect to the L298N H-bridge, as shown in Figure 6.4

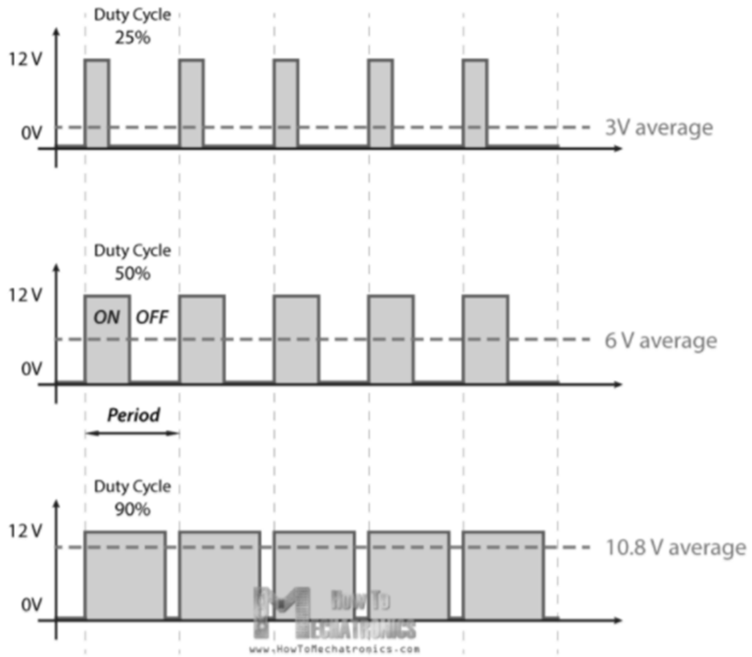


Figure 6.3 Pulse width modulation (Mechatronics 2017)

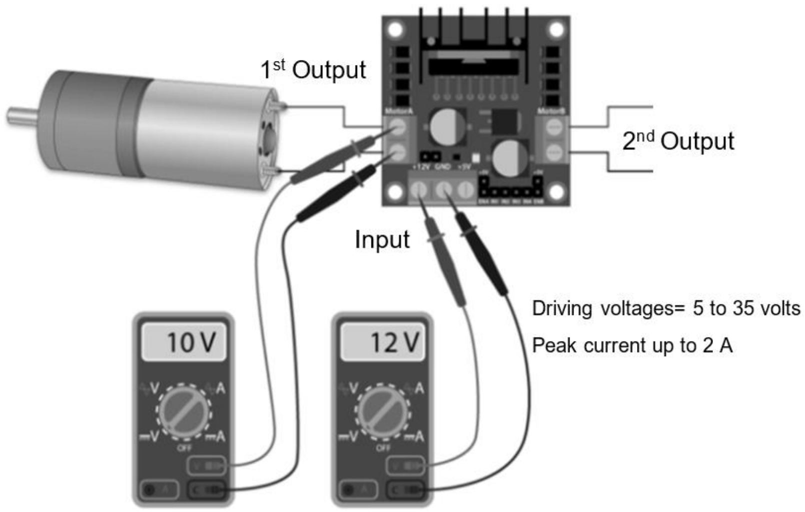


Figure 6.4 L298N driver PWM effect (Mechatronics 2017)

6.7 L298N driver

The L298N is a dual H-Bridge motor driver which allows speed and direction control of two DC motors at the same time, as shown in Figure 6.5. The module can drive DC motors that have driving voltages between 5 and 35 V, with a peak current up to 2 A.

This module has two screw terminal blocks for the motor *A* and *B*, and another screw terminal block for the Ground pin, the voltage common collector VCC for motor and a 5 V pin which can either be an input or output. A Velleman DC LAB POWER SUPPLY LABPS3020 was used as a DC regulator power supply to provide 12 *volts* to the H-bridge as an input while the output is PWM.

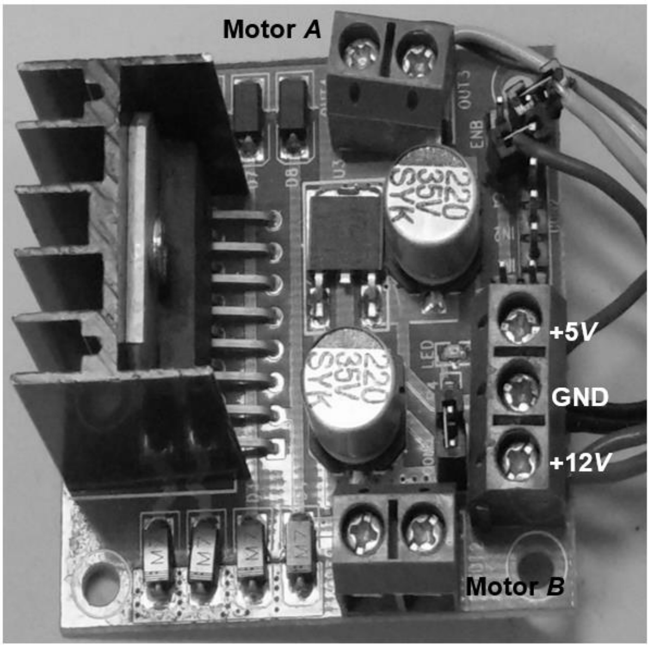


Figure 6.5 L298N DC motor drive

6.8 LabVIEW environment

According to National Instruments, “LabVIEW is a graphical programming platform that helps engineers scale from design to testing and from small to large systems”. It offers excellent integration with existing tradition software, Internet Protocol IP, and hardware while capitalising on the latest computing technologies. This programme offers different tools to solve today’s problems. It integrates all the tools that engineers and scientists need to build a wide range of applications in dramatically less time and has the capacity for continual future innovations faster and more effective. For these reasons, LabVIEW is considered as ideal software for any measurement or control system and is at the heart of the NI design platform. Moreover, it provides an ability to build a system simulation with a graphical user interface GUI. As shown in Figure 6.7, GUI contains all mimicked instruments to run the simulation or the real system as similar to real instruments.

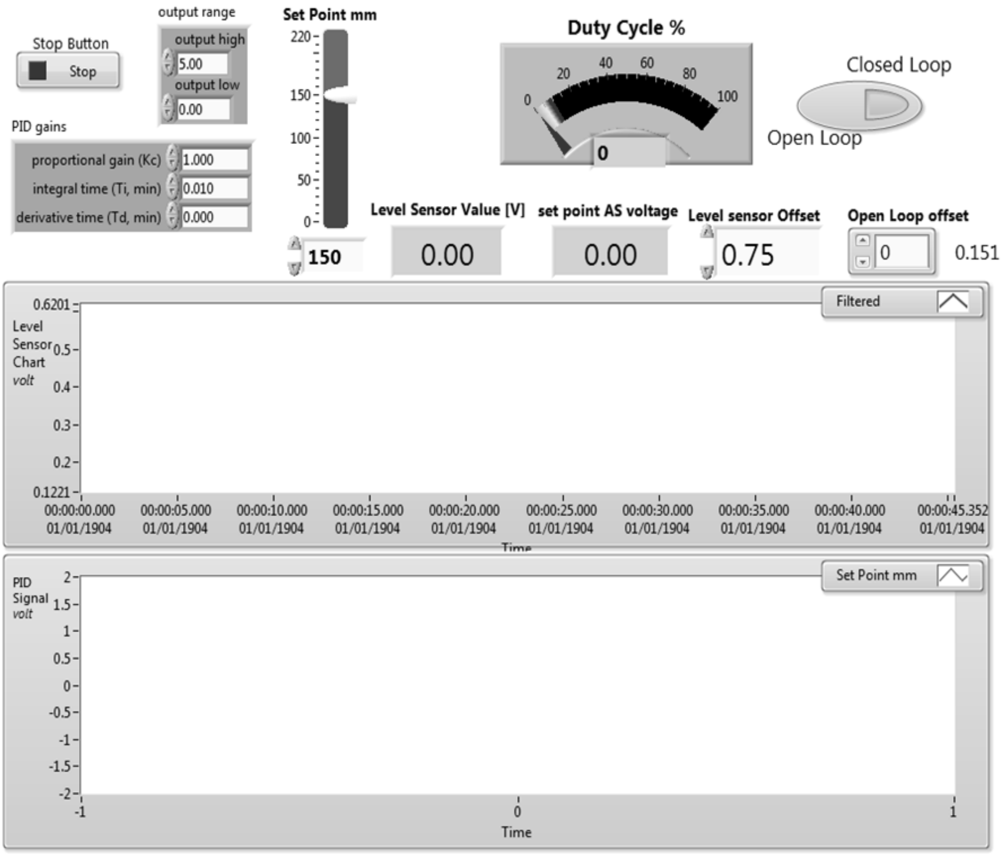


Figure 6.6 graphical user interface to drive the TTS

6.8.1 Front panel design

The front panel is considered as a control and feedback panel of the programme. Through this panel, the input parameters can be set and updated, and the output of the system can be displayed graphically and numerically. It needs to design the front panel to make the graphical user interface friendly and enables the inexperienced operator to use the system easily, as shown in Figure 6.7. The system is running in single tank system mode, in which the system behaves as a single tank, and the other tanks are totally neglected at this stage.

6.8.2 Block diagram design

The block diagram includes interfacing the level sensors to have the status of water level in the tank and interfacing the pump to send the proper driving voltage to run the system according to their characteristics equations. To design a system that meets the requirements, a PID controller is used but set as a PI controller. All calculations are wired together in a while loop to have an integrated system with fast response and high accuracy (Jeffrey and Jim 2013), (Essick 2016).

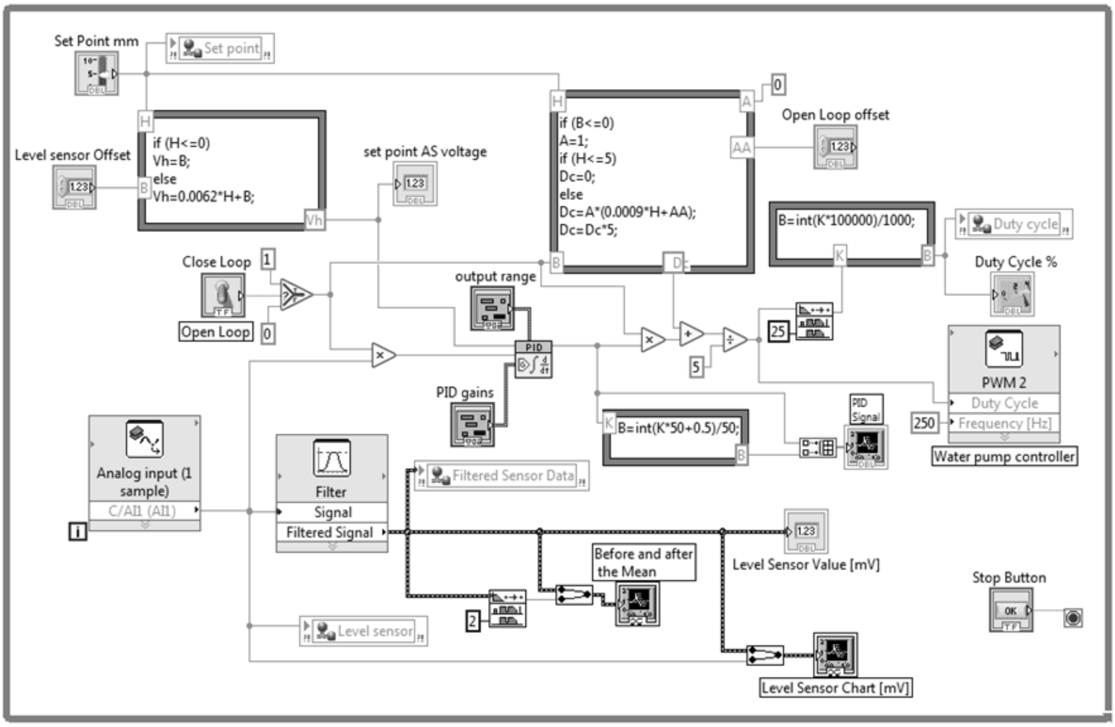


Figure 6.7 Block diagram to run the TTS

6.9 Characteristics equations of the TTS components

The pre-discussed procedure in Chapter 3, Section 3.6 was utilised to estimate the characteristics equations of the TTS components.

6.9.1 Liquid level sensor

A pressure sensing liquid level sensor (SensorTechnics 142SC01D-PCB D/C) was used to measure the pressure of the trapped air between the tank base and the sensor port *A* at the upper plate of the system, as shown in Figure 6.1.

Datasheet of this sensor, Appendix B, shows that it can be used to measure an absolute gauge or differential pressure through its two ports *A* and *B*, as shown in Figure 6.9, in range of 1 up to 150 psi which is equal to (0.0689 to $10.342*10^5$ *pascal*). As can be seen in Figure 6.10, shows a linearly proportional relationship between the real liquid level, measured on a ruler mounted on the transparent tank wall in *mm*, and the sensor reading in *volt*. The experimentally obtained calibration equation as the best curve fitting of the liquid level sensor is:

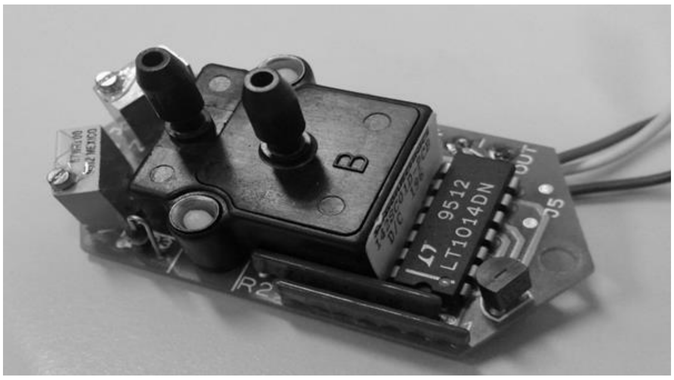


Figure 6.8 Pressure-sensing liquid level sensor

$$y = 0.0061x + 0.0531 \tag{6-1}$$

Where x is the liquid level in *mm*, and y is the sensor reading in *volt*.

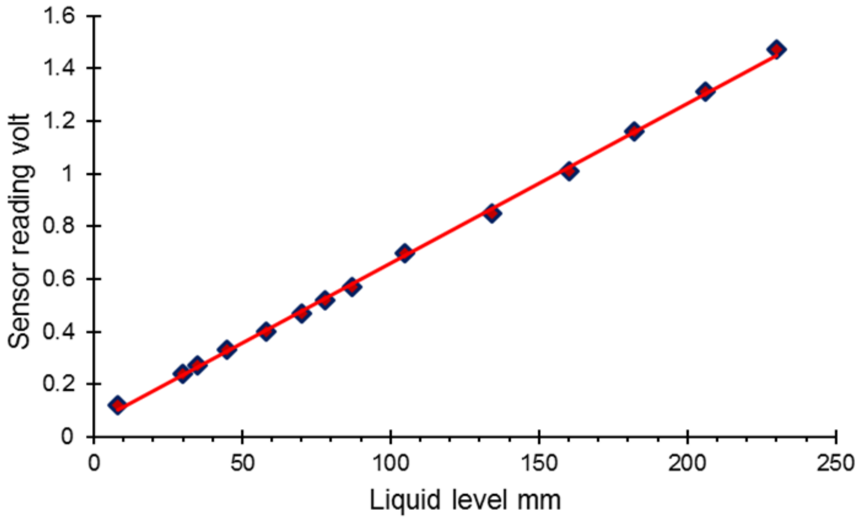


Figure 6.9 Calibration curve of the liquid level sensor mm to volt

6.9.2 Liquid flowrate sensor

Figure 6.11 shows a liquid level flowrate sensor (RS 508-2704), which was used to measure the liquid flowrate that went into the tank. It produces a pulse train output (frequency), which is proportional to the flow through the sensor. It covers a liquid flowrate range between 0.05 and 10 $l.min^{-1}$. An experimental test correlation between the readings of the inflow rate sensor in *Hz* and the corresponding liquid flow rate on the rotameter in $l.min^{-1}$ are shown in Figure 6.12. From this figure, it is apparent that the sensor output frequency is linearly proportion with the liquid flowrate passing through the sensor. From the curve fitting, the calibration equation of the inflow rate sensor is:

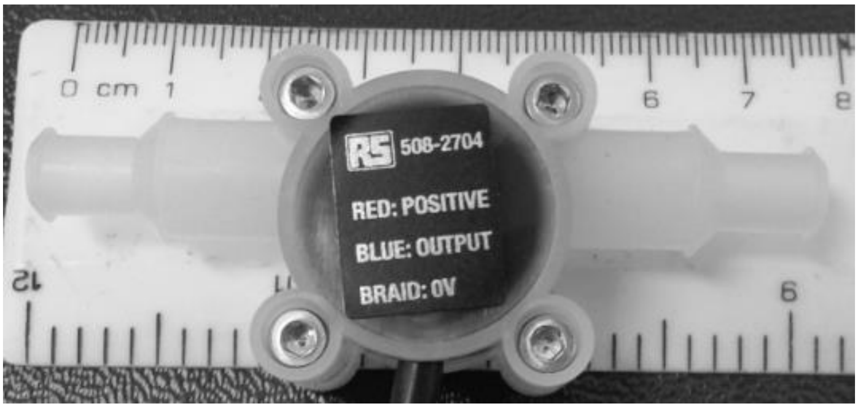


Figure 6.10 Liquid flowrate sensor

$$y = 21.934x - 0.8882 \tag{6-2}$$

Where x is the water flow rate in $l.min^{-1}$ through the flow rate sensor while y is the sensor reading in *Hz*.

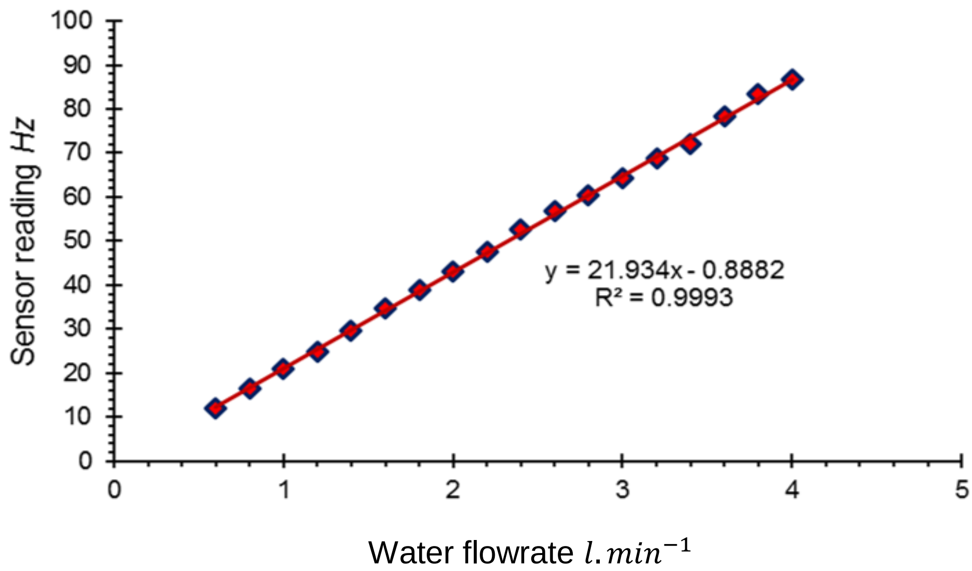
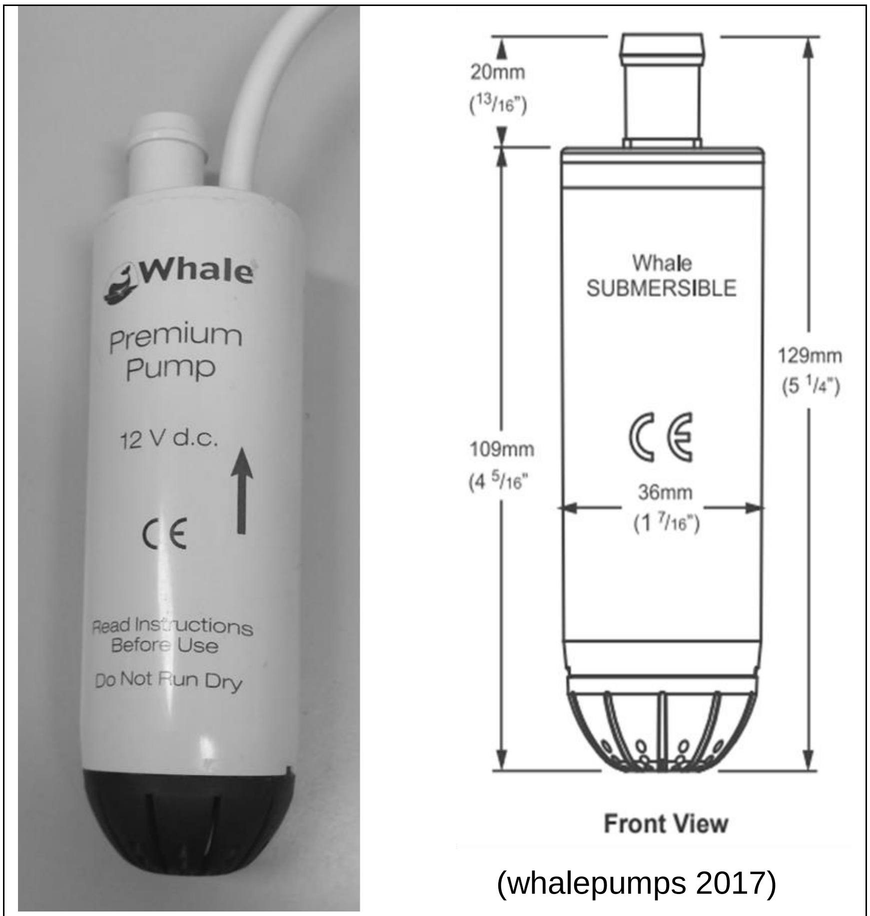


Figure 6.11 The calibration equation of the liquid flow sensor

6.9.3 The characteristic equation of the liquid pump

For each tank of the TTS, a Whale self-venting submersible water-pump GP1352 with a flow rate up to 13 $l.min^{-1}$, Figure 6.13, was used to pump water from the system main reservoir up to the tank. As stated on the datasheet of the Whale premium pump, Appendix C, is available in 12 *volts,* and it should install this pump to have its outlet be higher than the inlet. In the TTS, this pump was installed vertically and always fully submerged even the three tanks were fully filled.



(whalepumps 2017)

Figure 6.12 Whale premium submerged pump

6.9.4 Open loop calibration

There is a direct relationship between the liquid level in a tank and the drain flow rate when the outlet orifice diameter and the liquid characteristics are constant.

To study this relationship, a series of power supplied in percentage as duty cycle to the pump and investigated the stable liquid level in the absence of a controller effect (open-loop test). The result is as shown in Figure 6.14. The best fit for this relationship is as shown in Equation 6.3.

$$y = 0.0009x + 0.1503 \quad (6\text{-}3)$$

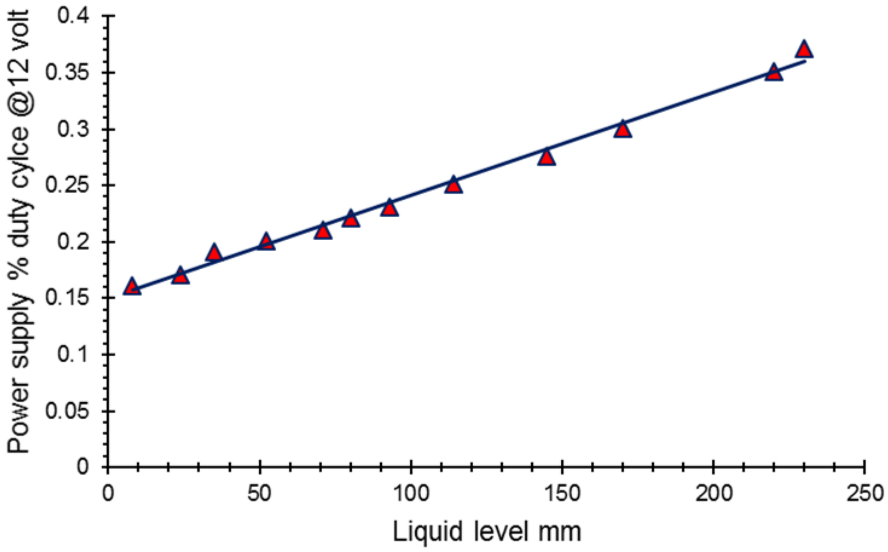


Figure 6.13 System open loop behaviour

6.9.5 Drainage orifice behaviour

The behaviour of the outlet restriction as a circular sharp-edged orifice, Figure 6.15, is presented in Figure 6.16, for 6 *mm* diameter of the orifice, the best fit for his relationship is as shown in Equation 6-4 at steady-state where the inflow rate equal to the outflow rate.

$$y = 5.376x^{0.5031} \quad (6\text{-}4)$$

Where x is liquid level in the tank and y is the free outflow rate measured in *Hz* by using the flow sensor at steady-state where the inflow rate equal to the outflow rate.

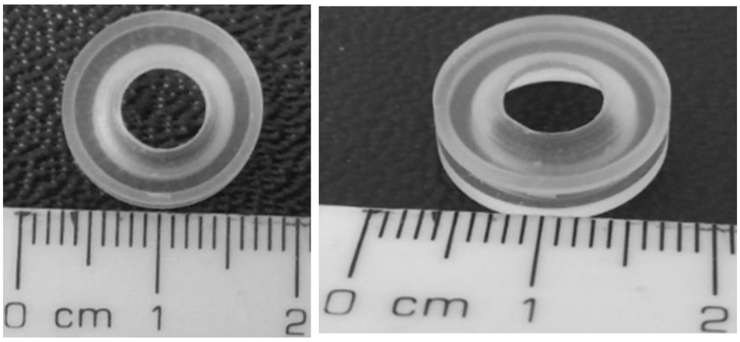


Figure 6.14 A circular sharp-edged orifice

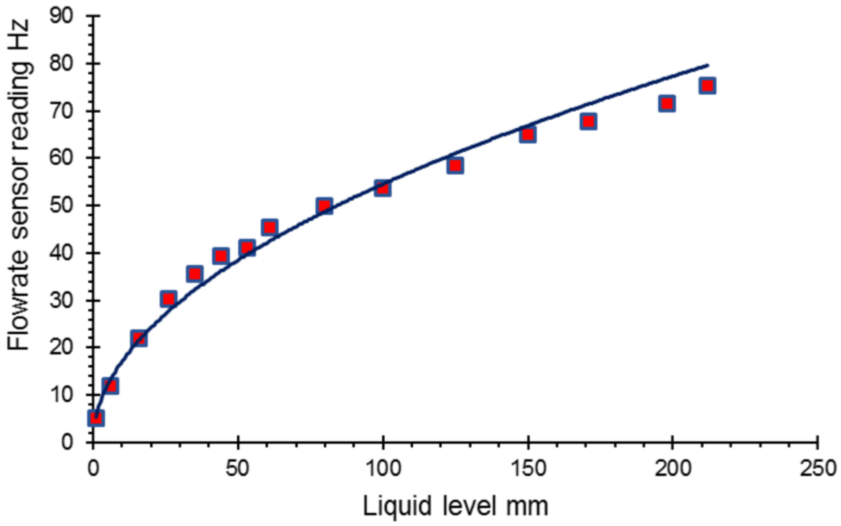


Figure 6.15 A 6 mm diameter orifice calibration equation

6.10 PID controller

Proportional- Integral- Derivative (PID) controller is widely recognisable sorts of feedback controllers. Currently, a PID controller is one of the most common control algorithms utilising to control processes. It is used in domestic and industrial applications, for example, heating and cooling systems, liquid level monitoring, flow and pressure control application. In a PID feedback control system, it needs to specify a process variable and a set – point. The output of this feedback controller is a control signal, and it is generally, based on the error between some user-defined set-point and some measured process variable. Liquid level systems are commonly controlled by using a conventional PID controller because of its simple structure and application. Such a feedback controller minimises the error between the required demand and the related plant measured variable through regulating the process-controlled inputs. Furthermore, every single element of a PID controller refers to a particular action taken on the error value to achieve the required demand (Kumar and Dhiman 2011).

(Kumar and Dhiman 2011) argued that the liquid level system has some limitations and it is hard to have optimal control using only PID controller because the parameters of the system are varying continually. Accordingly, they took the liquid level of three water tank for an object, and utilise MATLAB to design Genetic Algorithm and Particle Swarm Optimisation control. (Almutairi and Zribi

2006) suggested a static and dynamic sliding mode control scheme for a coupled tank system. From their simulation and experimental results, they illustrated the effectiveness of the proposed controllers. These controllers provided an advantageous sensitivity to the variations in the parameters and external noises of the system. On the other hand, Fuzzy Logic Controller (FLC) is also commonly implemented in many pragmatic industrial applications. (Gaurav 2012) analysed the performance of the system by using a conventional PID controller and fuzzy logic controller through MATLAB and Simulink. Gaurav made a comparison among various time domain parameters to confirm that the FLC has a small overshoot and fast response as compared to a conventional PID controller.

6.11 Simulation of TTS under LabVIEW environment

The differential pressure sensing liquid level sensor generates an analogue electronic signal that is proportional to the liquid height in the tank. A controller in a closed loop liquid level system receives signals from the liquid level sensor, and by comparing them with a pre-defined set point, the controller sends a proper signal to drive the water pump. The latter, which in turn, pumps an amount of water proportional to the voltage supplied. This water goes into the tank to achieve the desired liquid level and consequently the liquid outflow rate from it. Even a closed loop or automatically controlled tank system needs to have a readable scale to track the liquid level, at least for the calibration purpose of the level sensor.

Applying the Sign chart algorithm on a real system needs to deal with high level of noise that the PID signal has. This noise comes from several internal and external sources. It could be worth to have an extra study to eliminate this noise before using SCA to monitor a real system. Two main fault sources were added to build a comprehensive virtual system of the TTS under LabVIEW environment. This virtual system could cover several proposed fault and operating scenarios. Degradation of the pumping efficiency and leakage or blockage at the low-pressure side are the main two categories of fault simulated to monitor the health condition of the TTS. Each category is caused by several reasons as summarised in Table 4.1. This simulation was built based on the experimental characteristic equations, as shown in Figure 3.23 and Figure 3.26.

The pre-discussed characteristic equations were used to build a closed loop simulation under LabVIEW environment to study the system behaviour when some proposed faults occur.

6.12 Results and discussions

6.12.1 TTS response

When the three individual-tank system run under closed loop controller of the GUI that discussed above, the result was as presented in Figure 6.17. PID controller parameters were at their default values set by the LabVIEW programme. Liquid level was changed from 0 to 150 *mm* as a step function, and the response was as shown in Figure 6.17. The continuous dark blue line refers to the instantaneous liquid level measured by using the liquid level sensor. The dashed red curve refers to the smoothing data by evaluating the mean value of each 25 points. Due to this smoothing algorithm, it could be easy to recognise an offset between the raw, and its smoothing data. For that, the controller feedback signal is the raw data, not the smoothed.

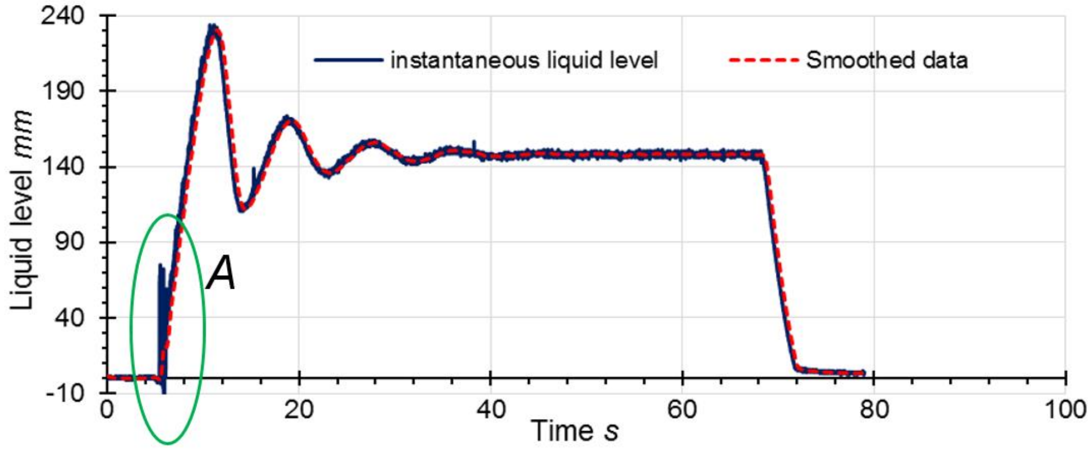


Figure 6.16 The TTS response when the required demand is 150 mm

In Figure 6.17 the mentioned area A refers to a water jet inside the tank when it was empty at the beginning of applying the driving voltage. The reason for this turbulent is due to the variation between the tank cross-sectional area (1256 mm^2, where the diameter is 40 *mm*) and the pump discharge (13 $l.min^{-1}$).

When the tank is empty as in Figure 6.17, the water goes from the pump as a vertical water jet into the empty tank, but after a while, when the accumulated water in the tank reaches about 60 *mm* it works as a damper. Controller signal, sensor and system response will be affected because of this temporary tumultuous behaviour.

6.12.2 Simulation response

Similarly, when the liquid level was changed from 0 to 150 *mm* on the simulation, all other parameters at their default values. The response of the simulation of TTS is as shown in Figure 6.18.

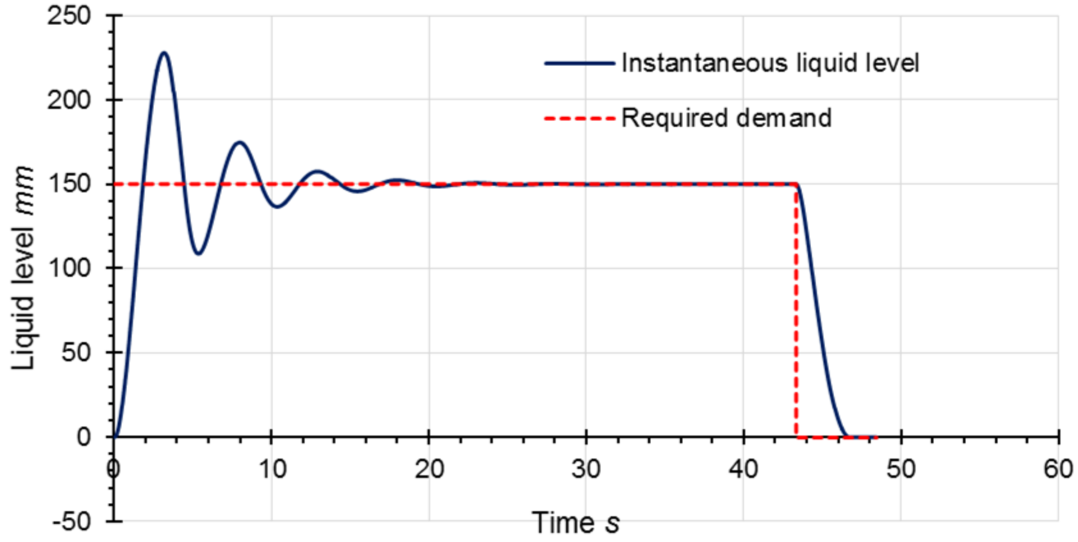


Figure 6.17 The response of the TTS simulation under LabVIEW environment

By comparing Figure 6.17 with Figure 6.18, there is a significant similarity between them. In both, the liquid level settled at its required demand after the same overshoot and fluctuation response. On simulation, the TTS health condition can be studied to diagnose a different kind of fault sources and intensity. It can be confirmed that the three individual-tank system is a robust mechatronic design with a robust simulation to monitor the system health condition using this system and its simulation as future work.

6.13 Summary

In order to confirm the results of the CE105 liquid level system, a new three individual-tank system was designed and fabricated. Each tank can be assumed as a complete standalone system. It can be run, controlled, and health monitored separately. There are two important limitations of CE105 that the new system dealt with. The regulator drain valve of CE105 was replaced by a real sharp-edged circular orifice, and the eccentric of the valve position was eliminated by locating the orifice at level zero, i.e., directly at the bottom of the tank. The same procedure to build a virtual system that pre-discussed in Chapter 3 was followed to express the new system transducers and components characteristic equations and used them later to build the virtual system. Moreover, fault sources were added to the simulation to monitor the system behaviour for a wide range of operating scenarios and fault sources and different strength. The Sign chart algorithm was added to the simulation to monitor the system health condition. The examination of the virtual system under different operating conditions showed an effective and high efficiency of the SCA to monitor the health condition of the system for any change of the required demand in the presence of hidden faults. The result shows a reasonable similarity to that presented in Chapter 4 for diagnostic and monitoring and Chapter 5 for prognostics and evaluation of the system remaining useful life.

Chapter 7 conclude this PhD research and presents some recommendations for extending this study in the future.

Chapter Seven

Conclusions and Recommendations

7.1 Conclusions

This thesis has investigated prognostics and health monitoring, and maintenance strategies of feedback controlled mechatronic systems. As presented in Chapter 2, while maintenance has a significant impact on final product costs, monitoring the whole system health and predicting when it will reach its end of useful life as a contribution to reducing the costs is not an easy task. Developing health monitoring approaches of critical equipment in industrial activities is of major interest to manufacturers and operators. The benefits of these approaches include maintenance costs reduction, reducing in-service failure, reduction of ongoing scheduled maintenance activities, time and costs and increasing the system useful life.

Key to enabling such benefits to be realised are via robust algorithms capable of operating within the real-world system. In this thesis, the demonstrated algorithms were developed using acquired data from test rigs as pragmatic systems operated in a real-time environment. This data was used to build nonlinear virtual systems that can be run with the variety of operating and fault scenarios faster than real time to evaluate how good faults detection is going to be. Thus, these developed approaches have shown the applicability to be used for virtual systems for which they were developed and provided future opportunity to be used with real systems in future health monitoring technologies. Robust monitoring algorithm that returns clear with sufficient details and small in size output signal, which can be transferred via internet facilities to abroad monitoring and analysis centre, makes a significant contribution.

Chapter 3 presented a nonlinear mathematical model of the liquid level system and incorporated with the characteristic equation of each member of CE105 coupled tank system; its virtual system was built. This detailed virtual system was run in a real-time environment for a variety of operating scenarios. It can be concluded that there is reasonable consistency between a pragmatic system and its virtual for different operating requirements as presented in Chapter 3.

In Chapter 4, the development of a new approach based on the required demand and the control signal to monitor the behaviour and health condition of entire feedback controlled mechatronic systems was presented. The presented conclusion in this chapter is a novel approach that was built to track the controller signal is efficient and capable to assigning any change in the required demand, and any abrupt or slowly progressed deteriorating faults. This health monitoring approach deals with the earliest possible, yet reliable, detection of deteriorating faults, in particular slowly progressed faults which are often hard to be detected especially in their early stages. Moreover, this approach provides an ability to diagnose the sort, location and intensity of different kinds of faults. While the Sign chart algorithm returns a digital signal with only (-1, 0, +1) values, it can be integrated with the control system to have an automated comprehensive operating and health monitoring system.

In Chapter 5, the development of remaining useful life estimation that based on the controller signal was presented. This estimation approach uses a mathematical model of two terms, linear and exponential, to describe the trend of the control signal at any stage of the operating scenario in the presence of faults. It can be concluded that this approach provides a continuous and updated estimation of the remaining useful life while the system is in-service regardless faults deterioration model, intensity, number of presence faults and their progression speed. This approach can be implemented with the operating and monitoring system to have an integrated prognostic, and health monitoring of feedback controlled mechatronic systems.

In Chapter 6, a new design of three individual-tank system was presented. This liquid level system, in comparison with CE105, has different tank size, discharge restriction, water pumps and sensors. This new system was designed to overtake the limitations of CE105 regarding its discharge restriction location and shape, which discussed amply in Chapter 3. The key conclusions of Chapter 6 are the applicability of both SCA health monitoring algorithm and the estimation procedure of the remaining useful life for new feedback controlled mechatronic system.

The novelty of this PhD thesis is to bring controller-based health monitoring of an entire system together with on-going monitoring of operational conditions and thus to enable more informed prognostic projections.

7.2 Future Works

- Building a system model by using singular or multiple perturbation techniques of control theory. Increasing the noise level, power supply fluctuation from the source and changing the liquid properties, i.e. density and viscosity are some examples of this disturbance.
- The Sign chart algorithm has been applied in virtual system level successfully. Now, it needs to apply it for a real system after having an efficient noise-removal filter.
- In developing a prognostic algorithm, there is a benefit of using real-world data. Such data captures and illustrates how different sources of uncertainty affect how a fault progresses over time. For that, it may need to use real-world data to develop the proposed prognostic algorithm.
- It needs to verify the ability to diagnose a closed loop controlled mechatronic system by estimating the number of the vertical lines per unit time in the SCA and their distribution. Through this proposed study, type of fault and its intensity may be recognised without installing any extra measuring instruments or approach.

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Appendices

APPENDIX A

RV PRODUCT DATA SHEET

OEM: 2088-403-144 (Aqua-King)

AFTERMARKET: N/A

APPLICATION

Multi-fixture RV fresh water installations. Other uses may include 12V DC pressurized water systems in cabins. This pump may be used for general fresh water transfer.

PUMP:

Type:	3 Chamber Diaphragm
Ports:	1/2"-14 NPSM-Male.
Liquid:	130 ℉ [54 ℃] Max
Dry-Prime:	9 feet [2.7 M]
Inlet PSI:	30 PSI [2.1 Bar] Max
Run Dry:	Yes

ELECTRICAL:

Motor:	12VDC Permanent Magnet, Intermittent Duty
Protection:	Thermal Overload, Automatic Restart
Leads:	16 AWG, 16" [40 cm] Red +, 13" [33 cm] Black -
Fuse:	10 Amp Recommended
Control:	Adjustable Switch. Shut-Off 45 PSI [3.1 Bar] ± 5 PSI [0.4Bar] Restart 25 PSI [1.8 Bar] ± 5 PSI [0.4 Bar]

These legendary pumps have set the standard for the RV Industry. SHURflo 2088 pumps are equipped to deliver high performance and reliability every time they are used. SHURflo potable water pumps operate three independent pumping chambers which allow the pump to self-prime and lift water up to 12 feet. With smooth flow and uninterrupted operation, the Classic™ Series pumps include a built-in check valve to prevent back flow into the tank. Each pump features an adjustable switch and the capacity to run dry without damage to the pump or motor.

MATERIALS:

Housing:	Polypro
Valves:	EPDM
Diaphragm:	Santoprene
Hardware:	Zink Plated Steel

APPROVALS:

c-UL

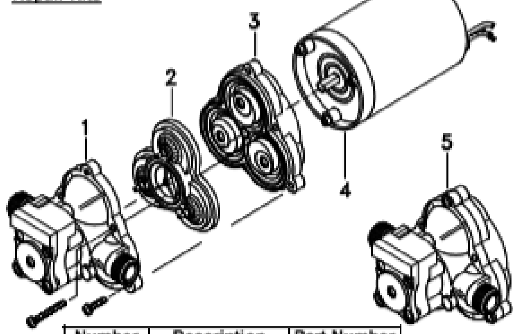
SHIPPING:

Net Weight:	5 Lb [2.3 Kg] each
Carton Quantity:	6
Carton Weight:	30 Lb [13.6 Kg]
Carton Size:	24"L x 18"W x 5"H [60.9cm x 45.7cm x 12.7cm]

RELATED DOCUMENTS:

Catalog:	MS-030-138
Installation Manual:	911-352
Applications Spec Guide:	MS-020-005

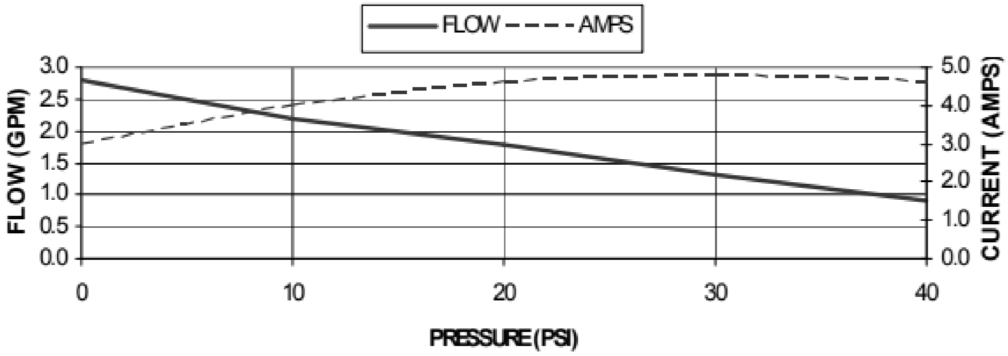
Repair Kits



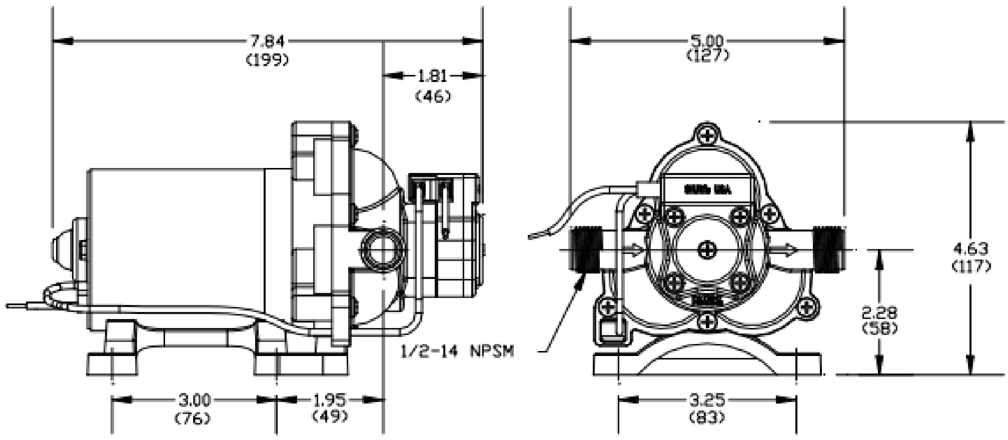
Number	Description	Part Number
1	Housing / Switch	94-231-20
2	Valve Assembly	94-232-06
3	Drive Assembly	94-238-04
4	Motor	94-11-148-04
5	Pump Head	94-236-08
Not Shown	Check Valve	94-237-00

TYPICAL PERFORMANCE

PRESSURE		FLOW		CURRENT
BAR	PSI	GPM	LPM	AMPS
0.0	0	2.8	10.5	3.0
0.7	10	2.2	8.3	4.0
1.4	20	1.8	6.8	4.6
2.1	30	1.3	4.9	4.8
2.8	40	0.9	3.4	4.6



DIMENSIONS [mm]



SHURflo reserves the right to update specifications, prices or make substitutions without notice.

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Visit our Website at www.shurflo.com

2088-403-144 Rev. July 2011

140SC...-PCB / 420SC...-PCB Series

Signal conditioned precision pressure transducers

FEATURES

- 1 to 150 psi
  absolute, gage or differential pressure
  (custom calibrations available)
- 1...6 V or 4...20 mA output
- Internal supply regulation
- Precision temperature compensated and calibrated
- Special calibrations for small volumes on request

Scale: 1 cm
1 inch

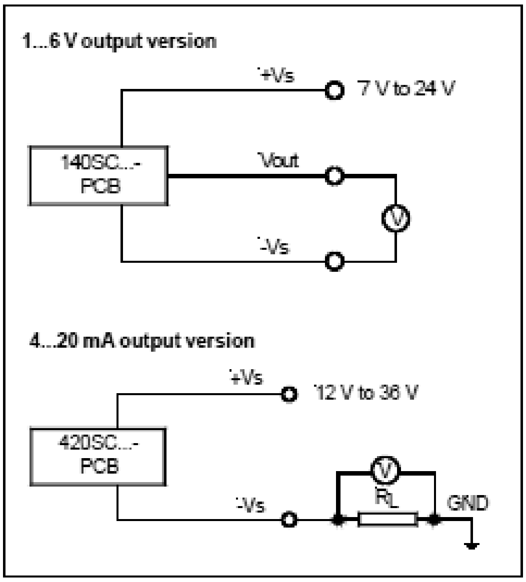
SERVICE

Non-corrosive, non-ionic working fluids, such as dry air and dry gases

SPECIFICATIONS

Maximum ratings	
Supply voltage	
140SC...-PCB	7...24 V
420SC...-PCB[1]	12...36 V
Maximum load current	
140SC...-PCB only	
Source	20 mA
Sink	10 mA
Temperature limits	
Storage	-55 to 100°C
Operating	-40 to 85°C
Compensated	0 to 70°C
Lead temperature	
(10 sec. soldering)	300°C
Humidity limits	
Pressure inlets only	0 - 100 %RH
Proof pressure[2]	
All 1 psi, 3 psi, 5 psi devices	20 psi
All 15 psi devices	30 psi
All 30 psi devices	60 psi
All 100 psi devices	150 psi
All 150 psi devices	200 psi

ELECTRICAL CONNECTION



PERFORMANCE CHARACTERISTICS

1 - 6 V output version (unless otherwise noted V_S = 8 V, R_L > 100 kΩ, t_{amb} = 25°C)

Characteristics		Min.	Typ.	Max.	Unit
Operating pressure					
vacuum gage devices[3]	141SC01G-PCB	-1		0	psig
	141SC05G-PCB	-5		0	psig
	141SC15G-PCB	-15		0	psig
	141SC30G-PCB	-30		0	psig
	141SC100G-PCB	-100		0	psig
differential devices[4]	142SC01D-PCB	0		1	psid(g)
	142SC05D-PCB	0		5	psid(g)
	142SC15D-PCB	0		15	psid(g)
	142SC30D-PCB	0		30	psid(g)
	142SC100D-PCB	0		100	psid(g)
	142SC150D-PCB	0		150	psid(g)
absolute devices[5]	142SC15A-PCB	0		15	psia
	142SC30A-PCB	0		30	psia
	142SC100A-PCB	0		100	psia
pressure/vacuum devices[4]	143SC01D-PCB	-1		1	psid(g)
	143SC03D-PCB	-2.5		2.5	psid(g)
	143SC05D-PCB	-5		5	psid(g)
	143SC15D-PCB	-15		15	psid(g)
Zero pressure offset	141SC.../142SC...-PCB	0.95	1.00	1.05	V
	143SC...-PCB	3.45	3.50	3.55	V
Full scale span[6]	141SC.../142SC...-PCB	4.95	5.00	5.05	V
	143SC...-PCB	2.45	2.50	2.55	V
Full scale output		5.90	6.00	6.10	V
Output at lowest specified pressure	143SC...-PCB		1.00		V
Non-linearity and hysteresis (BSL)[7]			0.1	0.5	%FSO
Thermal effects[8] Combined offset and span (0 to 70°C)	all 1 psi devices		±1.5	±3.0	%FSO
	all others		±0.5	±1.0	%FSO
Long term stability[9]			±0.1		%FSO
Response time (10 to 90%)			0.1		ms
Power supply rejection rate	Offset		0.05		%FSO/V
	Span		0.03		%FSO/V

PERFORMANCE CHARACTERISTICS

4 - 20 mA output version (unless otherwise noted V_s = 15 V, R_L = 100 Ω, t_{amb} = 25°C)

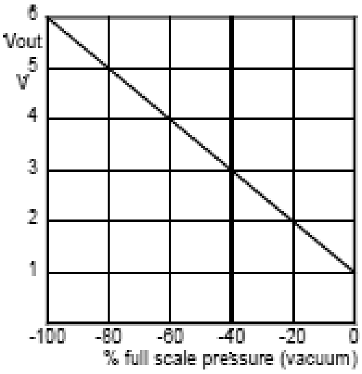
Characteristics		Min.	Typ.	Max.	Unit
Operating pressure					
differential devices[4]	420SC01D-PCB	0		1	psid(g)
	420SC05D-PCB	0		5	psid(g)
	420SC15D-PCB	0		15	psid(g)
	420SC30D-PCB	0		30	psid(g)
	420SC100D-PCB	0		100	psid(g)
	420SC150D-PCB	0		150	psid(g)
absolute devices[5]	420SC15A-PCB	0		15	psia
	420SC30A-PCB	0		30	psia
	420SC100A-PCB	0		100	psia
pressure/vacuum devices[4]	423SC01D-PCB	-1		1	psid
	423SC03D-PCB	-2.5		2.5	psid
	423SC05D-PCB	-5		5	psid
	423SC15D-PCB	-15		15	psid
Zero pressure offset	420SC...-PCB	3.9	4.0	4.1	mA
	423SC...-PCB	11.9	12.0	12.1	mA
Full scale span[6]	420SC...-PCB	15.8	16.0	16.2	mA
	423SC...-PCB	7.9	8.0	8.1	mA
Full scale output			20.0		mA
Output at lowest specified pressure	423SC...-PCB		4.0		mA
Non-linearity and hysteresis (BSL)[7]			±0.1	±0.5	%FSO
Thermal effects[8] Combined offset and span (0 to 70°C)	all 1 psi devices		±1.5	±3.0	%FSO
	all others		±0.5	±1.5	%FSO
(-40 to 0°C, 70 to 100°C)			±2.0		%FSO
Repeatability			±0.1		%FSO
Long term stability[9]			±0.1		%FSO
Output noise			±0.04		%FSO
Response time (10 to 90%)			0.1		ms
Power supply rejection rate	Offset		0.05		%FSO/V
	Span		0.03		%FSO/V

Specification notes:

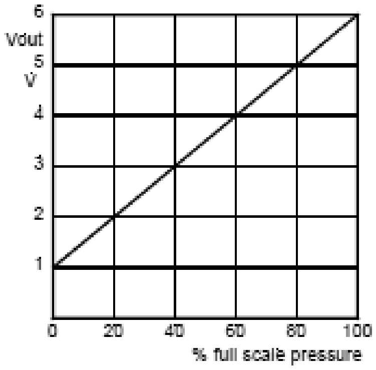
1. The minimum supply voltage is directly proportional to the load resistance seen by the transmitter. For more details see the load limitation diagram.
2. Proof pressure is the maximum pressure which may be applied without causing damage to the sensing element.
3. The output signal of all 141SC...-PCB devices is proportional to the vacuum applied to port B, relative to port A, e. g. the output signal increases when pressure is applied to port A relative to port B.
4. The output signal of all 142SC...D-PCB and 143SC...D-PCB devices is proportional to the pressure applied to port B, relative to port A, e.g. the output signal increases when vacuum is applied to port A relative to port B.
5. The output signal of all 142SC...A-PCB is proportional to the pressure applied to port A.
6. Full scale span is the algebraic difference between the positive full scale output and the zero pressure offset.
7. Non-linearity refers to the Best Straight Line fit measured for offset pressure, full scale pressure and 1/2 full scale pressure.
8. Thermal effects tested and guaranteed from 0 - 70°C relative to 25°C. All specifications shown are relative to 25°C.
9. Change in output after one year or 1 million pressure cycles.

OUTPUT CHARACTERISTICS

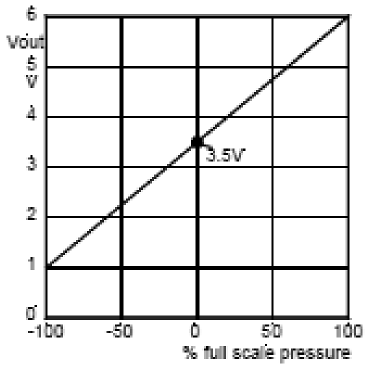
1 - 6 V output versions
Vacuum gage devices
141SC...-PCB



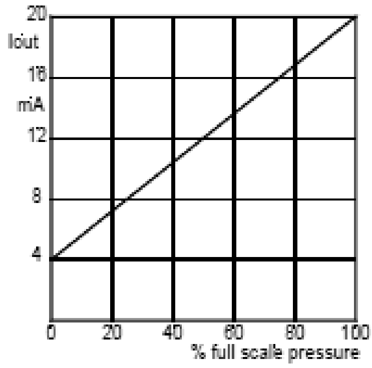
1 - 6 V output versions
Differential devices
142SC...-PCB



1 - 6 V output versions
Pressure/vacuum devices
143SC...-PCB

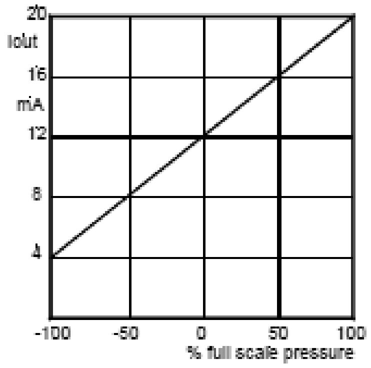


4 - 20 mA output versions
Differential devices
420SC...-PCB



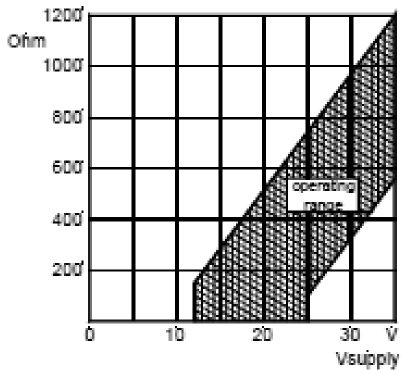
OUTPUT CHARACTERISTICS

4 - 20 mA output versions
Pressure/vacuum devices
423SC...-PCB

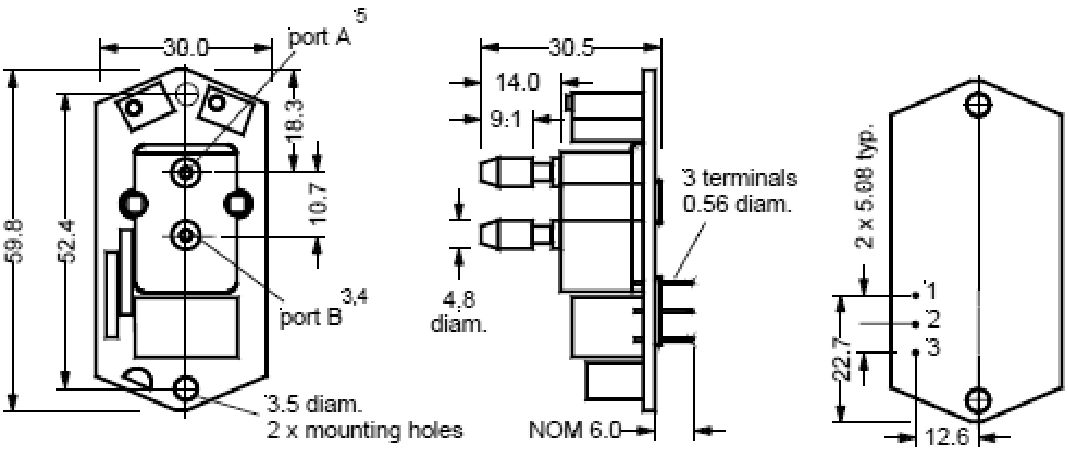


LOAD LIMITATION

4 - 20 mA output versions



OUTLINE DRAWING



mass: 20 g

Pin connection

Pin	Connection 1 - 6 V version	4 - 20 mA version
1	+Vs	NC
2	-Vs	-Vs
3	Vout	+Vs

dimensions in mm

ORDERING INFORMATION

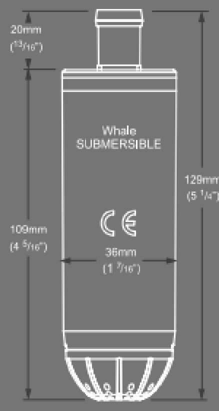
Operating pressure		Part number	
		1...6 V output	4...20 mA output
Vacuum gage devices	0 to -1 psig	141SC01G-PCB	---
	0 to -5 psig	141SC05G-PCB	---
	0 to -15 psig	141SC15G-PCB	---
	0 to -30 psig	141SC30G-PCB	---
	0 to -100 psig	141SC100G-PCB	---
Differential/gage devices	0 to 1 psid(g)	142SC01D-PCB	420SC01D-PCB
	0 to 5 psid(g)	142SC05D-PCB	420SC05D-PCB
	0 to 15 psid(g)	142SC15D-PCB	420SC15D-PCB
	0 to 30 psid(g)	142SC30D-PCB	420SC30D-PCB
	0 to 100 psid(g)	142SC100D-PCB	420SC100D-PCB
	0 to 150 psid(g)	142SC150D-PCB	420SC150D-PCB
Absolute devices	0 to 15 psia	142SC15A-PCB	420SC15A-PCB
	0 to 30 psia	142SC30A-PCB	420SC30A-PCB
	0 to 100 psia	142SC100A-PCB	420SC100A-PCB
Pressure/vacuum devices	0 to ±1 psid(g)	143SC01D-PCB	423SC01D-PCB
	0 to ±2.5 psid(g)	143SC03D-PCB	423SC03D-PCB
	0 to ±5 psid(g)	143SC05D-PCB	423SC05D-PCB
	0 to ±15 psid(g)	143SC15D-PCB	423SC15D-PCB

Custom calibrations available

Recreational Vehicles

Submersible Pumps

High Flow/Premium Submersible Pump
1 Year Warranty



Front View

18 Electric Pumps

Submersible Freshwater Pump Range

Higher Flow Rates and Greater Life

Compact, quiet, lightweight design suitable for use with pressure switch and microswitch systems. Ideal for use pumping from external water containers.

Standard Pump 10 ltrs/min - GP1002

- Simple, compact and an economical solution
- Ideal for basic, one outlet applications

Premium Pump 13 ltrs/min - GP1352

- Reliable, general purpose and suitable for multiple outlets
- Long life, very quiet with low power consumption
- An inexpensive way to update a manual to an electric system

HighFlow Pump 16 ltrs/min - GP1652

- Market leading submersible pump for flow performance suitable for showering

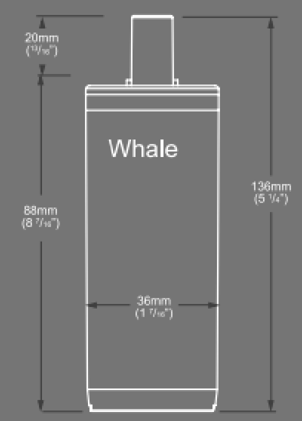
Model Specifications

Model	Standard	Premium		High Flow
Voltage	12V d.c.	12V d.c.	24V d.c.	12V d.c.
Pump	Sub	Sub	Sub	Sub
Submersible Pump Old Model	GP8015	GP8815	GP8825	GP1652
Submersible Pump New Model	**GP1002**	**GP1352**	**GP1354**	**GO1652**
Fuse Size	5 amp automotive		5 amp automotive	3 amp automotive
Weight	0.15kg (0.3 lbs)			
Connection to Flexible Hose	10 mm bore hose	Suits 10 mm or 13 mm Bore Hose		
Connection to 12 mm Quick Connect Plumbing	WU1211 (Stem Adaptor 11mm - 12 mm) see page 26			
Materials in Contact with Liquid	Pump Body: ABS, Seals: Nitrile, Strainer: Polypropylene, Impeller: Stainless Steel / PBT , Cable: PVC			

Note: New model codes are direct replacements for old model codes

Submersible Pumps

Standard Submersible Pump
1 Year Warranty



Performance Data — Flow Rate Per Minute / Current Draw

Model / Discharge Head	Standard 12V d.c.	Premium 12V d.c.	Premium 24V d.c.	High Flow 12V d.c.
0 m (0ft)	10.3 ltrs 2.4 amps	13.2 ltrs 3.6 amps	13.2 ltrs 1.8 amps	15.8 ltrs 3.8 amps
1 m (3ft)	8.75 ltrs 2.2 amps	11.75 ltrs 3.3 amps	11.75 ltrs 1.6 amps	14.8 ltrs 3.7 amps
3 m (9ft)	5.75 ltrs 2.0 amps	9.75 ltrs 2.9 amps	9.75 ltrs 1.45 amps	12.8 ltrs 3.5 amps

Note: Pump's performance may vary depending on the plumbing system and restrictions on outlets in your caravan/motorhome.

User Tips

For best performance:

- *Maximum continuous operation should not exceed 15 minutes*
- *Do not run pump dry as it will cause pump damage*
- *Do not use to pump water that is over 60°c*
- *We recommend the pump stands vertically in the tank*
- *Before switching on, place the pump in water and shake for a few seconds to release trapped air. This will ensure successful priming and should be repeated after refilling the water tank*
- *Add an in-line pump into a system to boost water flow (see page 20)*