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Smart Control and Energy Recovery of Pump-As-Turbines in Water Networks using Model Predictive Control

Aluthge Dona Nilki Weerawardana

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Supervisors: Prof. Aonghus McNabola and Prof. Biswajit Basu

Department of Civil, Structural & Environmental Engineering, University of Dublin, Trinity College, Dublin

Declaration

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Summary

The present-day, the conversion to electrical energy from renewable sources has gained the attention of many researchers. As the effects of climate change are evident, most countries in the world try to look for solutions to reduce their CO_2 footprint. In the European Union, two of the key targets in the climate and energy framework for 2030 are to improve up to at least 32% of the share of renewable energies and improve up to at least 32.5% of the share in energy efficiency (Commission, n.d.).

Hydropower is one such renewable resource that has a good balance between the energy output (electricity) and the energy input (needed for installation and operation of the plant for energy generation). Nevertheless, a hydropower system is a method of generating electricity from flowing water. Small-scale hydropower systems have been used as a dependable source of power for decades and decades. Small hydropower systems focus on installing turbines/pumps in rivers, streams, or in locations of existing water supply networks (WSN) where excess pressure exists. They can be used to exploit that excess pressure and in turn produce clean electricity. However, in the context of water supply networks, the sites where energy is otherwise dissipated, recovery potential is quite small (usually less than 100 kW). Therefore, it is not economically feasible to install the usual custom-made hydro-turbines.

For the reason above, researchers have investigated the possibility of installing low-cost micro-turbines within WSNs and it is called Pump-As-Turbines (PAT). PATs are water pumps in reverse mode which operates like a turbine. The main advantage of using it in WSNs when compared with other turbines is its low cost because it is mass-produced and has a low maintenance cost. As it requires the same skillset as maintaining a pump. On the other hand, they have some disadvantages as well. One of which is the absence of flow control devices. Therefore, a control valve needs to be installed in the location where a PAT is present. Over the years, researchers have studied the best way to install PATs within WSNs but very few focus on maximizing the potential recovered by exploiting the excess head in the PRV sites. However, some have performed experimental analysis on maximizing the power generated when a large variability in flow occurs, but it is often done for one PAT or multiple PATs, not in a simultaneous time frame.

Therefore, this master's thesis focuses on addressing the gaps in the literature in maximizing the potential of multiple PATs at the same time and addressing how to deal with the common constraints that are present within WSNs. The common constraints include keeping the actuators (valves) operating within their range, keeping tank levels within the minimum and maximum levels, and taking head loss constraints into account when water flows from one point to another. Apart from the main objective of this thesis, is to find a method to maximize the power produced by PATs in water distribution networks. It is also taking the common constraints into account. To keep the constraints satisfied a control strategy in the framework of Model Predictive Control was used. MPC is a control methodology used widely in the oil and chemical industries. MPC solves an optimization algorithm (consisting of a cost function and constraints) that is used to find the best control action that will drive the predicted output of a system to a certain reference point. Moreover, MPC can handle multi-input multi-output systems, it can also handle input and output constraints. Recently it is gaining attention in the water industry due to its advantages such as reducing pumping costs by operational management, reducing leakage by keeping pressure within certain limits, etc. Therefore, for this work, a control strategy is developed in the framework of model predictive control which is used to maximize the power generated by PATs and keep the common constraints of the network satisfied. A network in Ireland is chosen for the case study which has valves, tanks, a reservoir, and a critical node. To test if there is an improvement in the generated power, two different controllers in the MPC framework are compared. One controller is called the hybrid MPC, and the other is called the linear MPC. The difference between the two is that for hybrid MPC the PAT operation is included in the form of logic constraints whereas for linear MPC the PAT operation is included outside of the control algorithm. This work also introduces a new methodology to capture the head loss constraints. This is also included in the control algorithm. Finally, the results show that in using hybrid MPC an improvement is seen when compared with linear MPC. Also, the results show apart from the head loss constraints, tank levels are satisfied, and flow in the valves is within their range with a smooth operation. Additionally, the pressure at the critical node is also satisfied.

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List of abbreviations

BEP – Best Efficiency Point

PAT – Pump As Turbine

MPC – Model Predictive Control

DWNs – Drinking Water Networks

WSNs – Water Supply Networks

HR – Hydraulic regulation

ER – Electrical regulation

HER – Hydraulic Electrical regulation

GPV – General Purpose Valve

MILP – Mixed-Integer Linear Programming

MLD – Mixed Logical Dynamical

PRV – Pressure Reducing Valve

EU – European Union

GHG – Green House Gas

GA – Genetic Algorithm

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1. Introduction

1.1 Research context

Water and energy are interconnected with each other. Energy is needed to supply water to a system and water is needed to drive turbines for power generation. This relationship is given a name and it is called the Water-Energy-Nexus (Aster, 2012). In a water supply network, energy is consumed mostly in extraction, treatment, and distribution. It is estimated that about 6-7% of world energy is used up for drinking water production and distribution systems (Yang, et al., 2010; Coelho & Andrade-Campos, 2014). In countries like the United States, about ~4% of the electricity generated contributes to treating and distributing water to the public and private bodies (Copeland & Carter, 2017) Whereas, in the east, in countries like China, the energy required to supply and treat water doubled from 2002 to 2012 from 15 TWh to 34 TWh. Almost close enough to power Denmark which in 2013 consumed 34 TWh (Tan, et al., 2015). These values will only keep increasing in the coming years with the increase in population, urbanization, and wealth. Therefore, water companies around the world have agreed to look for more carbon-free sustainable solutions to reduce energy use in distributing and treating water (Young, 2015). Furthermore, The European green deal reveals targets set out to accomplish by 2050, one of which is to promote new renewable energy, and the target is set at 40% by 2030 (Quinn, 2021). This target is also reiterated in one of the COP26 goals "Secure global net zero by mid-century and keep 1.5 degrees within reach" (Anon., 2021).

Water distribution networks are complex systems that are designed to deliver water within the boundaries of a city or a designated region. A distribution system that delivers fresh water from point of supply to point of consumption consists of pipes, valves, pumps, tanks, reservoirs, etc, and supplies water to the end users with the required pressure will only get more difficult as the population keeps increasing (Karve, 2020). Nevertheless, when trying to achieve the objective of a WDN which is to deliver water to the consumers, certain challenges occur such as leakages, also known as non-revenue water from pipes and joints (Wagner, 2019). Leakage is a constant problem in Ireland, around 43% of the treated water is lost in leaks within the distribution system (Aodha, 2019). The amount of leakage depends on the water pressure, pipe age and quality of the fittings, etc. Apparently in water distribution networks leakage is mainly attributed to water pressure (Karve, 2020). The Fig 1.1. below shows the estimated percentage of losses in water networks in Europe.

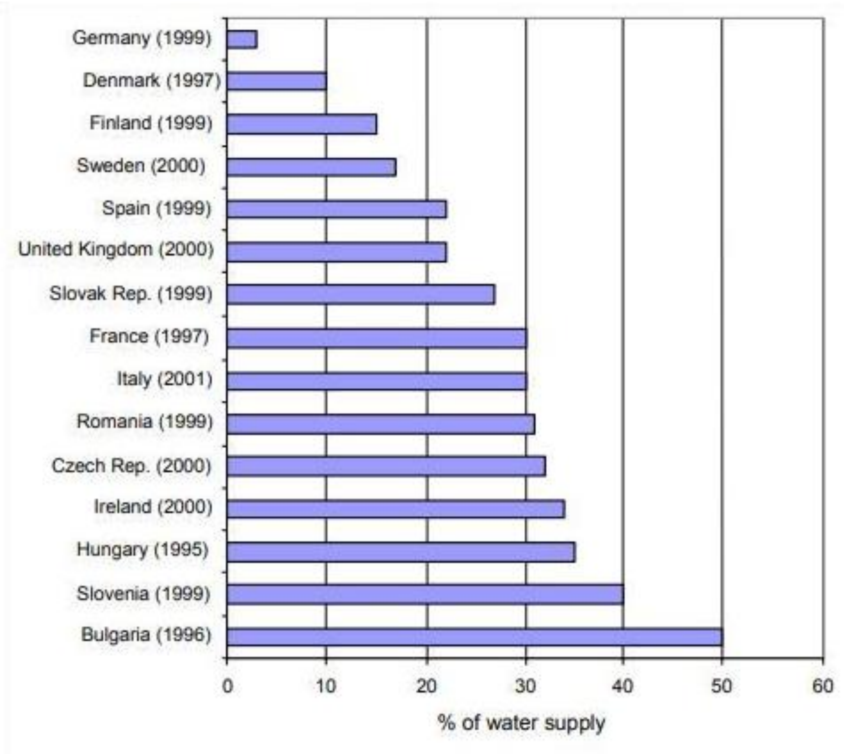


Fig 1.1. Estimated losses from water networks in Europe adapted from (Thyssen, 2017)

Additionally, high-pressure scenarios in water networks also occur due to their predefined topology and the requirement to deliver water with the necessary pressure. Due to this some parts of the network end up having excess pressure it is mainly for networks having a hilly topology, where there is a large difference between the source and the other parts of the network (McNabola, et al., 2014). The most common way to reduce the pressure in certain parts of the network is to install pressure-reducing valves (PRVs) or break pressure tanks (BPTs). However, the energy dissipated at PRVs is rather lost and not recovered. Therefore, researchers in the water sector have analyzed the scientific and economical potential of installing various hydro-turbines in the location of PRVs. Although the concept of energy recovery from water networks is not new, its interest for it gained attention at the beginning of the last few decades (McNabola, et al., 2011).

As the large hydropower energy recovery using large turbines is already explored and is currently still in practice the focus has shifted to small hydropower generation. One of the reasons for this shift is the advances in using the conventional pumps in reverse mode which are often called as Pump-As-Turbines (PATs) (Derakhshan & Nourbakhsh, 2008). Mainly due to their mass production and low cost in operation making it more feasible to be installed in small hydropower sites (Novara & McNabola, 2018) The definition of a small and micro-hydropower is defined following the power output from the plant. Usually, a plant is called pico-hydropower if it has a power output range < 5kW and it is called micro hydropower if it has a range between 200kW – 5kW. But globally it is acknowledged that if a plant produces less than 10MW it is called a small hydro-power plant (Anon., 2018). Moreover, it is estimated by ESHA (European Small Hydro Association) that an annual reduction of 29 million tonnes of CO_2 has occurred because of the 13 GW installed within the Europe Union (Eckert, et al., 2009). Even though, some drawbacks to PATs have been discussed before, such as lower part load efficiency and the absence of flow regulation devices in their operation in water networks where there is high variability in flow and head (Mitrovic, et al., 2021). However not many discuss how to maximize their energy conversion once it is installed in one of the sites. Also, not many discuss the bigger picture, which is after the installation of PATs, how to control water networks to keep the constraints in WDNs satisfied. Model Predictive Control was seen to control water networks and is used for control of pumps and to reduce the operational cost by minimizing certain KPIs related to pumping cost, maintenance cost, etc (Wang, et al., 2017; Wang , et al., 2016). Moreover, not many discuss how to maximize the potential of more than one PAT in multiple sites simultaneously. Therefore, this thesis aims to address the shortcomings in the literature on the maximization of PAT energy production during operation and show how to predict and determine the excess energy that can be converted in multiple locations in WDNs.

1.2 The Dŵr Uisce Project

This research is part of the multidisciplinary Dŵr-Uisce ("Distributing our Water Resources: Utilizing Integrated, Smart and low – Carbon Energy") project involving Trinity College Dublin and Bangor University. The main aim is to improve the long-term sustainability of water resources in Ireland and Wales through the development of innovative technological solutions, economic and environmental impact assessments and policies, and best practices. The main objectives involved are:

- Benchmark assessment of water sector in Wales and Ireland
- Developing new, innovative, energy-saving technologies for water supply systems focusing on micro-hydropower energy recovery and heat recovery.
- Development of a cross-border smart specialization cluster for knowledge exchange and innovation in the water sector
- Focusing on climate change implications in the water industry in Ireland and Wales

The Dŵr-Uisce project can be summarised by the following diagram in Fig 1.2.

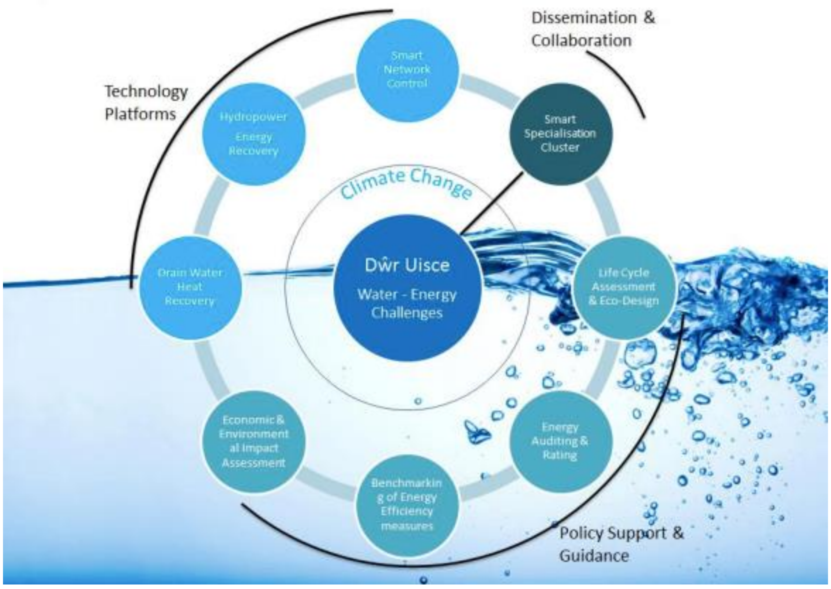


Fig 1.2. The main disciplines and project structure of Dŵr-Uisce

Smart networks control is included in work package 3 of the project and where its deliverables include:

- The multiscale controller in the MPC software framework for network energy and cost management
- Development of a control strategy using MPC to maximize the power generated by Pump As Turbines in real networks in Ireland and Wales.

1.3 Research Questions

The fundamental research question that needs to be addressed in the context of hydropower energy recovery in this thesis is: How to maximize the energy generation of PATs in WDNs using model predictive control? After the literature review to investigate the answer to the question above, several gaps are identified that have been formulated as sub-questions as the following.

1) What technology can be used to maximize the potential of PATs in WDNs

2) While maximizing the potential can model predictive control to fulfill the common objectives in water networks such as pressure management.

3) Is there an improvement in maximizing the power of all PATs simultaneously between the controllers called Hybrid MPC and Linear MPC

4) Which controller performs better for it to be suitable for near real-time operation

The main aim of this thesis is to address the questions presented above.

1.4 Research Structure

- Chapter 1: focuses on the introduction, research question, and the funding information
- Chapter 2: focuses on the background study done related to the research questions.
- Chapter 3: shows the research approach and how the plan is set to answer the research questions.
- Chapter 4: focuses on the methodology and the step-by-step approach that was developed.
- Chapter 5: shows how the validation was performed.
- Chapter 6: shows the results.
- Chapter 7: is the conclusion and discussion
- Chapters 8 and 9 are the references and the appendix

2. Literature review

2.1 Introduction

This chapter focuses on the background study in the fields of conventional pressure management in water distribution networks and shows how PAT technology could be used as a way of coupling pressure management with hydro-power energy generation. Also, this chapter shows the basics of model predictive control and how it could be used in water networks to control hydro-turbines. The Fig 2.1. below shows how the gap in the existing literature was identified. The gap essentially relates to the limitations in the literature to date which does not focus on using MPC to control water networks with PAT technology. In the first section of the literature review, some basics of water networks are given with particular attention to GHG emissions associated with operating water networks. The next section starts with how pressure management can be introduced to keep pressure within the quality standard and reduce pipe breaks that occur due to high-pressure scenarios. The following section then points out how PRVs are used in pressure management and shows what control techniques are used presently in controlling PRVs in water networks. Then the focus shifts to model predictive control (MPC) as they are also used for control PRVs. Some basics of MPC are then shown in the next section followed by how MPC is used in hydropower to control turbines. The last section is about some basics of hydropower, how micro-hydropower is the trend these days, and points out why PATs are an attractive way to generate power in a micro hydropower setup. Additionally, this section also introduces PAT technology and shows how PATs can be installed within a water network. Water networks with pumps are not included in this review as this work focus on gravity networks. This chapter then ends with a summary of the review focusing on the research questions as an outline before.

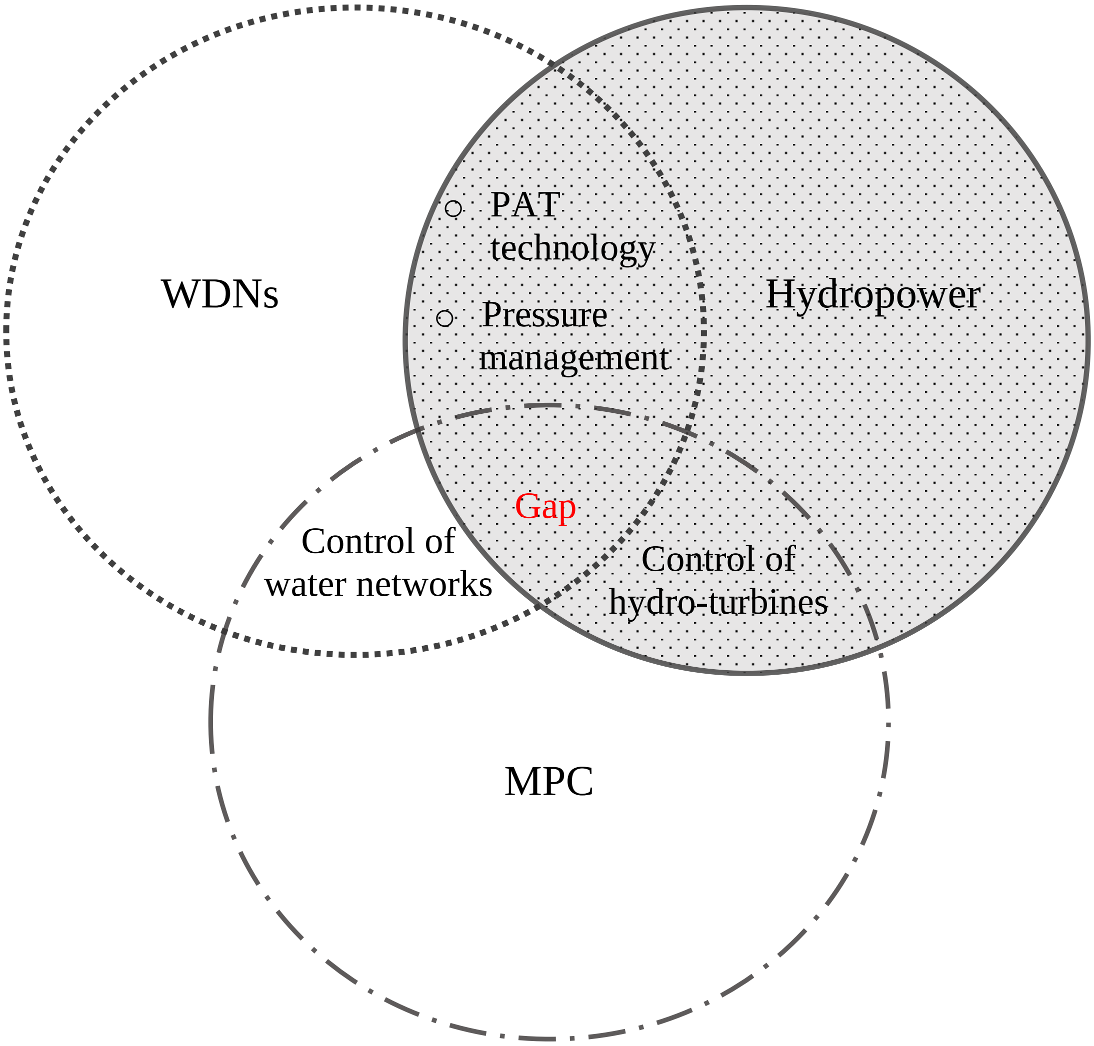


Fig 2.1. Approach to Literature review to identify the gap

2.2 WDN and energy consumption

2.2.1 WDN basics

Water networks have an interesting history dating back to the third millennium B.C. Soon after many advances occurred in the distribution system such as introducing devices to raise water to a height, water pumps, and methods to tackle unclean water (Mala-Jetmarova, et al., 2015). The history of urban water distribution networks goes before the Bronze Age (circa 3200 – 1100 B.C) with several staggering examples from (Angelakis, et al., 2012) including a well-thought-out system of hundreds of wells supplying water to domestic demands. Further going back in time in ancient Greece, around the second millennium B.C, a study done by (Crouch, 1993) reveals the first pipe layout supplying pressurized water to its consumers. Additionally, the Greeks constructed one of the first long-distance water supply systems with bridges and tunnels which were called “aqueducts” (Crouch, 1993) (see Fig 2.2.). Since then, as years passed on, in the modern era, many advances occurred with the advancement in human civilization. At present, the WDNs infrastructure is one of the most valuable developments that all humans depend on to get clean water.

(a)

(b)

Fig 2.2. Aqueducts: Clay pipes (a) and Terracotta pipes (b)
adopted from (Crouch, 1993)

Even though the infrastructure looks complex and new, the purpose of modern water networks is the same as the ancient ones, which is to deliver water from the source to the consumer. The source could be a lake, man-made reservoir, etc, the water from it is taken to a treatment plant known as Water Treatment Plants (WTPs) and their quality is assessed before the distribution process commence. The Fig 2.3. shows the basic distribution system from its source to different consumers adapted from an article in Canada. Usually, the treated water is pumped and stored in a water tank whose main purpose is to absorb the hourly variations in the demand, maintain pressure in the distribution mains, and supply water during emergencies.

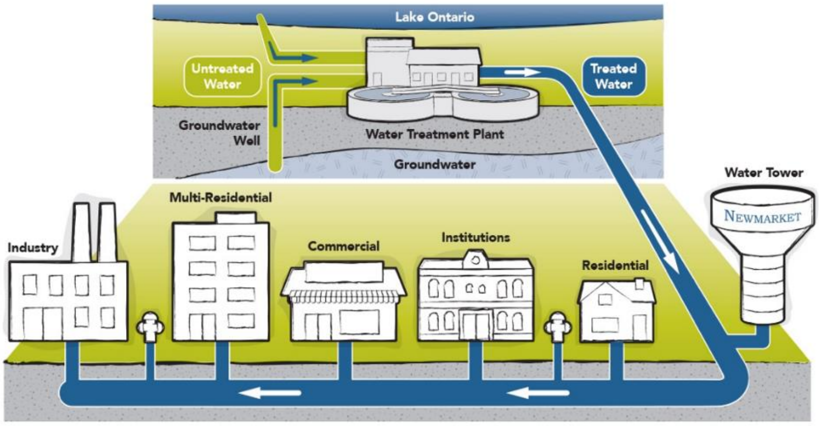


Fig 2.3. Drinking water distribution system adopted from (Newmarket, 2019)

There are four different layouts of distribution that are generally laid below the road. The layouts are called Dead end or Tree System, Grid Iron System, Ring System, and Radial System. The Fig 2.4. below shows the layouts in the order mentioned above.

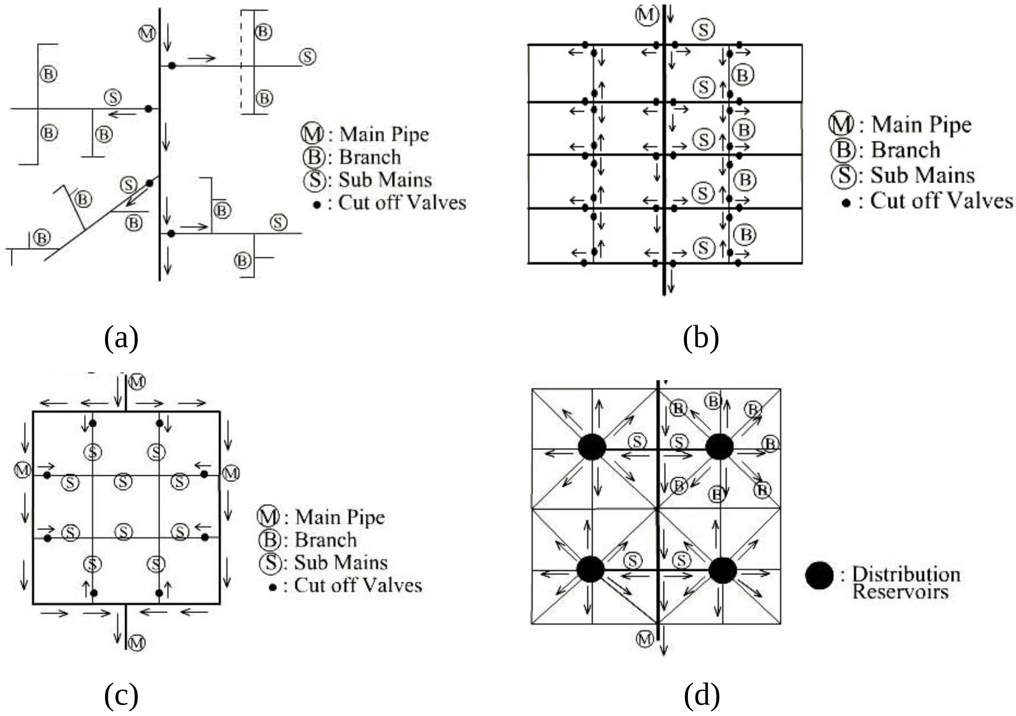


Fig 2.4. Layouts of water networks, (a) Dead end or Tree system, (b) Grid Iron system, (c) Ring system, (d) Radial system adopted from (Tiwari , 2019)

Additionally, for each layout there exist some benefits and disadvantages, table 2.1 mentions some of the most common advantages and disadvantages of each layout.

Layout	Advantages	Disadvantages
Dead end or Tree system	Cheaper to install, less complex	Stagnation of water can occur due to dead ends
Grid Iron system	Water is in good circulation	Need valve installation in all branches for pressure management
Ring system	Water may be supplied from two directions	Larger pipes and long lengths of pipes required
Radial system	Water can be distributed faster with high pressures	Costly, as need installation of individual reservoirs

Table 2.1. Advantages and disadvantages of different layouts of WDNs

Among the four, the most convenient layout to install is the tree or dead-end system, but if there is damage in one branch, it is not possible to supply water until the issue is resolved, whereas in the other three layouts (looped configuration) water may be supplied to consumers by more than one path. Moreover, the looped configuration is common in heavily populated areas and tree or dead-end systems (branched) are common in rural areas due to financial reasons (Nikhil & Damani, 2017). However looped configurations are more complex than branched networks due to their interconnectivity. Therefore, they can be costly to install and maintain. The complexity of a network can be determined by the beta-index of the network (Ducruet & Rodrigue, n.d.). A water network can be modeled using graph theory, using the number of pipes as edges *(E)* and the number of nodes (junctions) as vertices *(V)*, and the connectivity among the edges and vertices is called the beta-index

$$\beta = \frac{E}{V} \qquad (2.1),$$

If the calculated beta-index is < 1 that network is recognized to be a simple network and usually dead-end/tree-based networks are of that configuration, while more complex networks such as looped networks have a value >= 1. Nevertheless, a well-designed water network requires that it should be able to keep the water quality at the right standards, supply water to all parts with sufficient pressure, keep the extra volume in case of an emergency, and the network should be at least one meter away from the sewer lines, keep leakages at minimum (Adeosun, 2014).

Furthermore, pressurized water flowing in pipes possesses two main kinds of energy called potential and kinetic energy. Potential energy is the energy stored in the water and it is mainly due to the difference in the elevation and the pressure. Kinetic energy is that which is used in the execution of processes such as the movement of water (Miller, n.d.). In hydraulic engineering, the energy in a fluid is usually known as the hydraulic. It is the mechanical energy per unit of fluid, and it is often represented as the equation below (Evans, 2012).

$$E = \frac{v^2}{2g} + \frac{p}{\rho g} + Z = \frac{v^2}{2g} + \Pi \qquad (2.2),$$

Where E[m] represents the total energy of the fluid; v [m s^{-1}] is the average velocity at a cross-section of a pipe conduit; ρ [kg m^{-3}] is the density of water; g [m s^{-2}] is the gravitational acceleration; p [Pa] is the water pressure. Π [m] is known as the potential energy denoted as the piezometric head which is the sum of the pressure term and the elevation term in the equation.

When water flows in a pipe two main types of energy losses occur, the first one is called friction loss or major head loss. Friction losses are caused by the effects of the viscosity of the fluid, and they can be calculated using different formulas in hydraulic engineering. Two of which is called the Darcy-Weisbach and Hazen Williams formulas (see equation 2.3 and 2.4).

$$h_{loss} = f * \frac{l}{d} * \frac{v^2}{2g} \qquad (2.3),$$

$$h_{loss} = \frac{kl}{d^{1.16}} * (\frac{v}{c})^{1.85} \quad (2.4),$$

Equation 2.3 represents the Darcy-Weisbach formula, where, f [unitless] is the friction factor and it can be calculated from the Reynolds number depending on the state of the fluid (smooth, rough, turbulent, or transition flow) and relative roughness; l [m] is the length of the pipe; d[m] is the wetted diameter of the pipe; v [m s^{-1}] is the velocity of the fluid; g [m s^{-2}] is the gravitational acceleration of the fluid. Equation 2.4 represents the Hazen-Williams formula, where c is the c-factor that ranges between 0 – 150 depending on the material and the age of the pipe; and k=6.79 for velocity v in [m s^{-1}] of the fluid. Another energy loss that occurs in pipes is called minor head loss. It is the energy loss due to a fitting per unit weight of the fluid. This happens mainly at fittings, bends, and tees in a pipe network. Minor loss is calculated using the formula represented by equation 2.5 below.

$$h_{loss} = K\ \frac{v^2}{2g} \quad (2.5),$$

where K[unit less] represents a minor loss coefficient for valves, bends, and tees (Kudela, n.d.).

2.2.2 Energy consumption in WDNs

Presently water companies aim to operate WDNs for (1) providing clean water for their customers by maintaining the quality standards (2) finding methods to lower the operational cost by improving the energy efficiency of the network (3) minimizing the GHG emission throughout the process of operating the network (Sharif, et al., 2017; Haider, et al., 2014; Haider , et al., 2015; Bolognesi, et al., 2014). Energy savings for water networks mostly depend on improvements in the process, achieving efficiency targets, and lowering costs related to pumping (Cabrera, et al., 2010). Moreover, as energy prices continue to increase in the world and so do the GHG emissions associated with it, there is an increase in demand to minimize the energy requirements and develop more sustainable strategies for water use (Lopez & Jeter, 2006).

Energy use in water networks depends mainly on the energy source, the water quality, the pumping system (fixed speed or variable speed pumps), the size of the network, the age, and material of the network, and the topography of the area (Plappally & Lienhard, 2012; Lee, et al., 2017). For example, in the state of Virginia (USA) a small town called Louden, which has a hilly topography with a population of nearly 40,000 people used about 2.28 kWh/m^3 of energy for the distribution. whereas, in the same state a town called Alexandria which has a relatively flat landscape with a population of ~ 155,000 (in 2016) used 0.55 kWh/m^3 of energy (Alanis, 2009). This variation in the energy use which is three times less in the second town is mainly due to the topographic difference of the network. Moreover, water systems that use ground water as the source are more energy consuming than surface water systems. Even though ground water requires less treatment than surface water, pumping attributes to the main energy consumption due to the need of pumping raw water from aquifers. In total, only pumping, either surface or ground water systems, accounts for ~90% of the energy consumed in a water supply system (EPA, 2013). Fig 2.5. shows some information on the relative energy intensity for water systems using various water sources and it is obvious that groundwater requires more energy than surface water.

Utility water source	Mean	Minimum	Maximum
Groundwater	2,844	1,014	6,361
Lake Michigan	866	75	2,554
Surface	2,019	218	3,538

Fig 2.5. Energy intensity by water source (kWh/MG) adopted from (ISAWWA, 2012)

Additionally, for water networks, energy is consumed at each stage from extraction to distribution to consumer use. Therefore, Fig 2.6. shows the breakdown of energy consumed at each stage in a typical American water supply system adapted from (EPA, 2013).

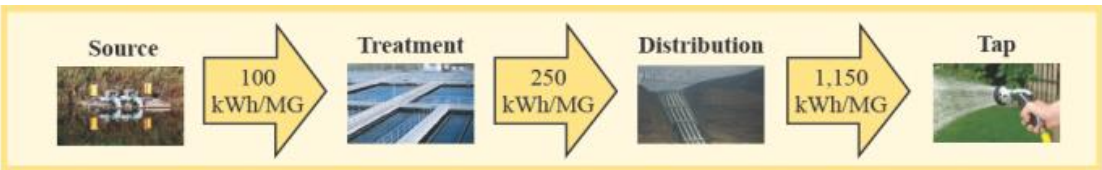


Fig 2.6. Average energy consumption at each stage in a drinking water system adopted from (EPA, 2013)

It is therefore important to make water networks energy efficient. It will not only save money for utility companies but also reduce GHG emissions. Water distribution is considered the main source of emissions in the supply process, typically if pumping is involved (Smith, et al., 2017). In Beijing (China), a study done by (Smith, et al., 2017) states that water distribution accounts for 63% of total emissions of centralized water supply mainly due to pumping to high-rise buildings. Additionally, in a case study done by (Cheng-Li, 2002) in Taipei, water networks contribute to 44% of emissions of GHG. Whereas, in the United Kingdom, the water industry alone accounts for 0.8% of the annual GHG emissions (Reffold, et al., 2008). Moreover, Fig 2.7. below shows opportunities to reduce carbon emissions at each stage in water/wastewater distribution networks.

Fig 2.7. Opportunities to reduce GHG emissions at each stage in water networks

2.3 Pressure management in Water networks

2.3.1 Importance of pressure management

A water distribution network is designed to deliver sufficient water to customers with the desired pressure throughout the operation, particularly during peak hours. During off-peak hours, mainly at night-time when the demand is low in the network, the nodal pressure can be higher than the acceptable pressure contributing to leakage (Monsef, et al., 2018). Pressure Management (PM) in water distribution networks plays an important role to reduce leakage and energy losses, this also helps to reduce GHG emissions associated with energy use in water networks.

In water networks, most pipe bursts occur at night not only due to high pressure but also because of the pressure fluctuations forcing the pipes to expand and contract frequently. Therefore, water utility companies try to keep a constant inlet pressure in zone/districts to ensure the consumers always have sufficient pressure (Borsting, n.d.) The pressure at the consumer's end depends on the friction in the supply line. To compensate for the friction, the inlet pressure is usually higher than the required minimum pressure. Nevertheless, friction depends on flow, and flow varies according to consumption. A constant inlet pressure means that the pressure varies during the day. That means the consumers will have high pressure when they use the water the least e.g., during late night or early mornings. The Fig 2.8. shows the variation of consumption and pressure at different times of the day adapted from (Borsting, n.d.).

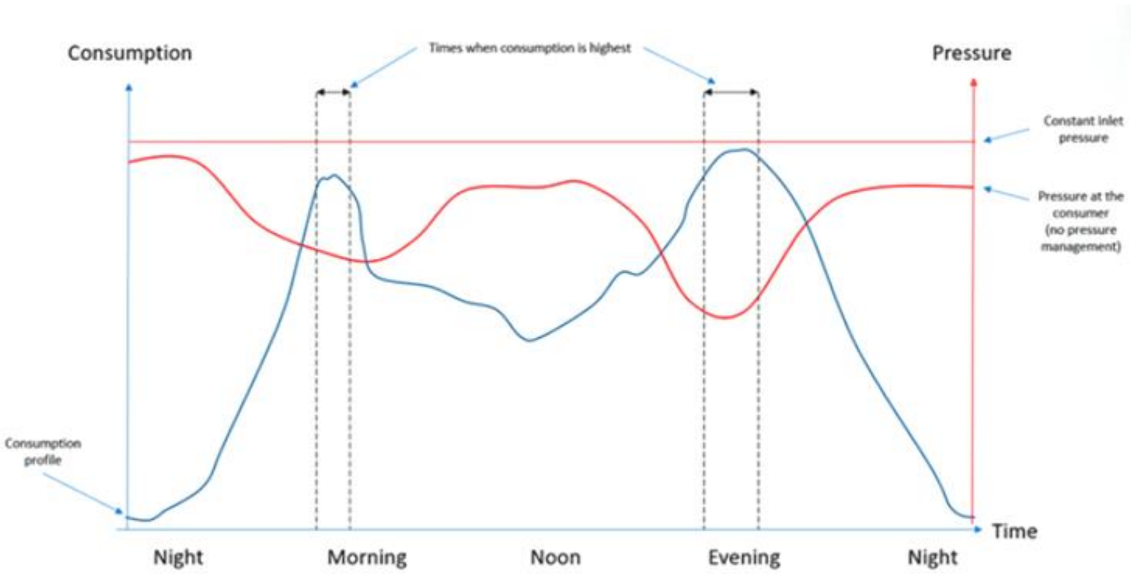


Fig 2.8. Variation of consumption and pressure on the consumer adopted from (Borsting, n.d.)

A study done by (Thornton & Lambert, 2006) has shown positive news on the implementation of pressure management by water utility companies. In the study, it can be seen the difference between the PM and after implementing PM from data in Gracanica (Bosnia and Herzegovina). It is shown in Fig 2.9. below.

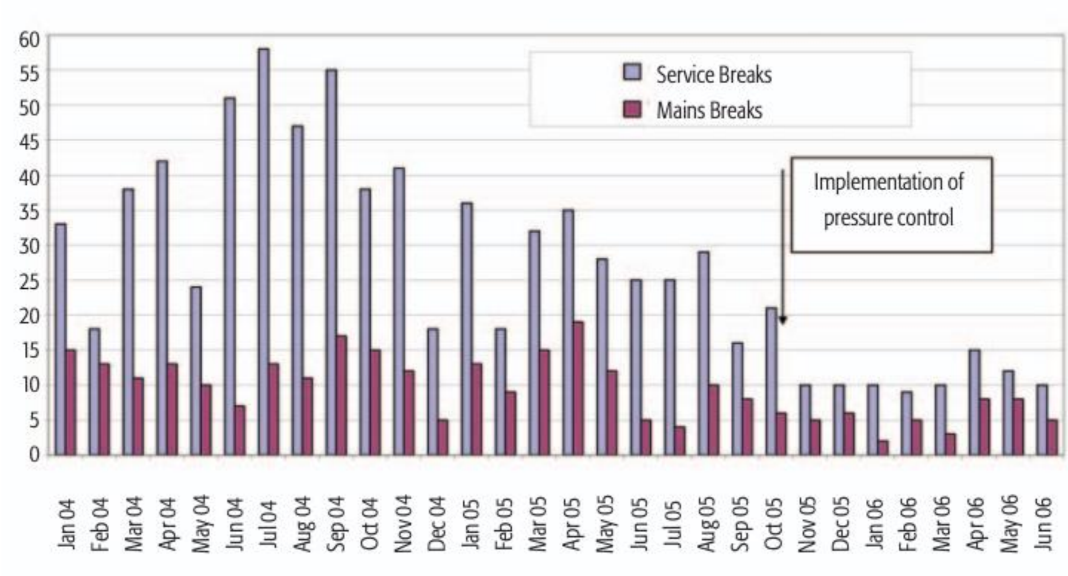


Fig 2.9. Pipe breaks each month before and after implementing PM adopted from (Thornton & Lambert, 2006)

After October 2006 after the introduction of pressure management, the breaks in service and main lines have drastically reduced.

2.3.2 Pressure management methods

2.3.2.1 Pressure Reducing Valves

Many different tools are currently in use for effective pressure management in WDNs. They include the implementation of valves such as Pressure Reducing Valves. PRVs are typically installed at parts in the network where there is excessive downstream pressure and these are often installed in pipes for leakage reduction (Araujo, et al., 2006). Pressure-reducing valves prevent the downstream head from exceeding a certain value by dissipating that excess head (Giugni, et al., 2014), as the excess head is reduced to the desired setpoint thus the water losses are indirectly minimized. Although there is no distinctive relationship between pressure and leakage frequency, the design of proper pressure control can attribute to a reduction in the recurrence of new leaks and bursts in pressurized pipes (Lambert, 2002). Nevertheless, PRVs lack the reliability to regulate pressure at various times of the day.

Therefore, researchers try to find methods for optimal control of PRVs and make sure their operation is sufficient in WDNs. The Fig 2.10. below shows an image of a PRV from the company Bermad.

Fig 2.10. BERMAD 700 Sigma en/es series PRV adopted from (BERMAD, n.d.)

2.3.2.2 Control techniques of existing PRVs in WDNs

There are different control techniques for controlling PRVs in water distribution networks, the first technique is called classical control which is mainly used in small networks and the next is called advanced control which can be used in a large network with high complexity. The third is using optimal control algorithms and they are mainly used in finding the optimal PRVs in a water network as such. The fourth one is called real-time control which uses SCADA for real-time measurements and taking appropriate actions based on it. The last is called model-free control, they use large data sets using simulators to get an accurate model. This often becomes very difficult as managing large datasets can become complex. The below section explains each technique in detail.

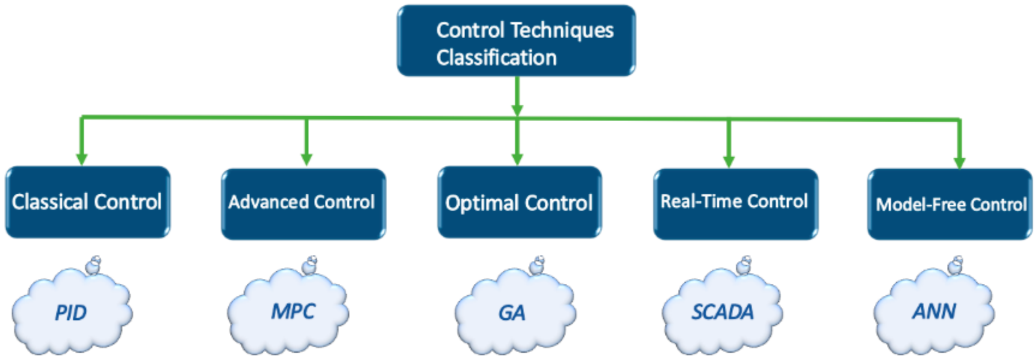


Fig 2.11. Various control techniques adapted from (Mosetlhe, et al., 2020)

Classical control such as a Proportional-Integral-Derivative (PID) uses a closed-loop feedback mechanism to control and drive a system to a setpoint/target. It can only be used in small-scale networks without considering any constraints. This is not suitable for WDNs as pressure and flow constraints are vital for an accurate representation of the network (Page, et al., 2016; Lei, et al., 2007). Whereas optimal control uses the principles of calculus to obtain the best operating parameters for reduction of leakage through optimal settings of PRVs (De Paola & Portolano, 2017) using various convex and non-convex algorithms. (Hindi & Haman, 2007) used a non-linear nonconvex optimization algorithm to address the pressure regulation problem by proposing a method to approximate non-linear pressure functions to linear representation, however, the computational burden to solve this is immense.

Another (Eck & Mevissen, 2012) suggests solving the problem by quadratic approximation of the pipe friction using Hazen-Williams and Darcy Weisbach equations (two methods that are used to calculate pipe head loss) using a linearisation technique. Nevertheless, linearisation would reduce the accuracy of the solution. Some researchers have opted to use meta-heuristics like genetic algorithms to solve pressure control problems. These derivative-free algorithms can be used for example in finding the optimal number of PRVs while ensuring optimal operation. Another example would be using a multi-objective function to maximize the energy recovered and address the pressure reduction problem (Nicolini, August 2011; Saldarriaga & Salcedo, 2015). However, since these are heuristic-based approaches, global optimality is not guaranteed. Another technique in PM in water networks is model-free control-based concepts by the utilization of simulators to mimic the model using control optimization techniques. The drawback of this approach is that it requires a large data set to realize an accurate model (Haman & Hindi, 1992; Rao & Alvarruiz, 2007).

The final two control techniques are Real-time control and Advanced control. Both require a model-based representation of the system, and both can be used on large-scale water networks. The former use Supervisory Control and Data Acquisition Systems (SCADA) to obtain measurements in real-time and take necessary adjustments (Page, et al., 2017). The latter is using Model Predictive Control (MPC) which is an advanced control strategy used mainly in the chemical industries. It uses an explicit process model to predict and optimize the future behavior of the system (see Fig 2.13.). MPC can also be a part of real-time control when combined with SCADA systems. It can be placed as the global control law in determining the desired set-points for the local controllers to act on. The diagram adapted from (Wang, et al., 2017) gives an understanding of the hierarchical structure in Real Time control.

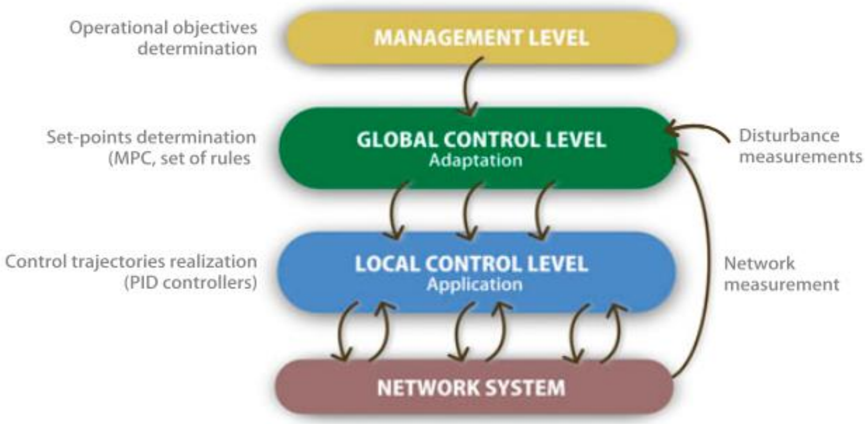


Fig 2.12. Structure of RTC adapted from (Wang, et al., 2017)

The data coming from sensors in SCADA systems provide information to determine the operational objectives to be included in the control design of MPC. Moreover, setpoints are determined after evaluating the objectives at the global control level. This will be sent to the local control layer where controllers such as PIDs will be placed to achieve the set point. For example, in the control of PRVs. The setpoints determined from MPC such as the optimal opening degrees to ensure the demand downstream could be sent to PIDs as reference points. These set-points help act as the reference value when minimizing the error between the actual opening degree value and the desired opening degree value.

2.4 Model Predictive Control in WDNs

Model predictive control is not a particular control strategy but rather a range of many control methods developed around three familiar ideas (Camacho, et al., 2003) : (i) the explicit use of a model to predict the process response at future time intervals (ii) the calculation of a control order by minimizing a particular cost function (iii) the use of a receding horizon strategy. Fig 2.13. shows the typical structure of Model Predictive Control.

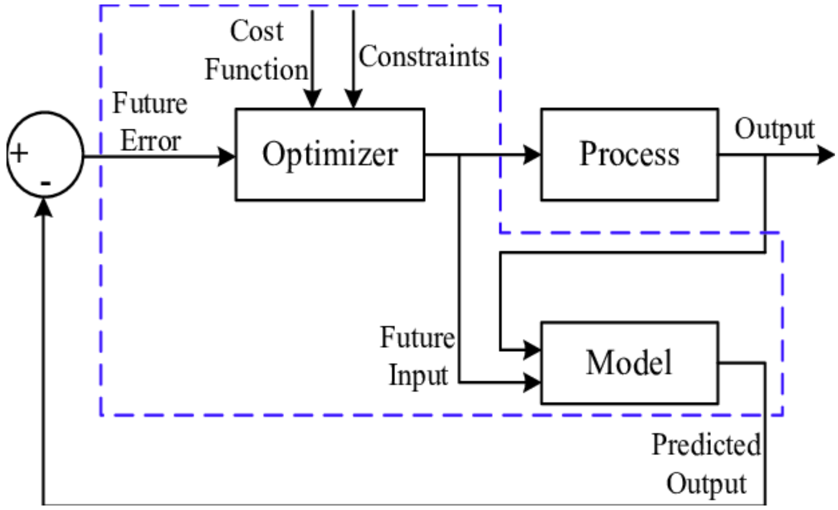


Fig 2.13. Structure of MPC adopted from (Rana & Pota, 2012)

Model predictive control uses the model of a system to predict its output based on the current and future values of its input. Using this information, the controller calculated the optimal value for the future control inputs concerning the predetermined cost function while taking constraints into account. (Rana & Pota, 2012).

In water distribution systems, model predictive is often used as a global control strategy. i.e., it is usually the control layer below the management layer from Fig 2.12 to derive setpoints for actuators to act on. As discussed before unlike other control techniques, MPC has the advantage of being able to add constraints to the control design. It can be imposed on either both manipulated or controlled variables (Hovd, 2004). MPC can also use a multi-objective function to handle more than one objective (Wojsznis, et al., 2007).

Multi-objective optimization can simultaneously satisfy hard and soft constraints while ensuring all the objectives are met. For the control of water networks, objectives can be formulated in a multi-objective context as the common goals are:

1) Pressure management – maintaining the pressure within an acceptable range.

2) Tank level management – keeping storage tanks from overflowing or falling below a minimum level.
3) Operational cost reduction – reducing pumping costs by introducing new methods such as pump scheduling algorithms (Wang, et al., 2017).

Moreover, hard constraints are the constraints that cannot be violated (for example: in water networks, tank levels can be a hard constraint). Soft constraints are constraints that can be relaxed within a small limit to allow the feasibility of the solution (for example: in water networks, the minimum and maximum flow value in a valve can be altered accordingly to guarantee feasibility in the objective function). Fig 2.13. below shows the structure of MPC. The control algorithm is fed with the cost function and constraints, while simultaneously using the prediction model. This prediction model is used to anticipate future outputs based on the past outputs from the system plant. The disturbances (see Fig 2.13.), for example; in a water network, demand is the most common disturbance. If the demand is not known forecasting algorithms such as Autoregressive (AR), Moving Average (MA) and Autoregressive Integrated Moving Average (ARIMA) can be used. The forecasting algorithms can predict both long-term and short-term demand depending on the data (Chen & Boccelli, 2014).

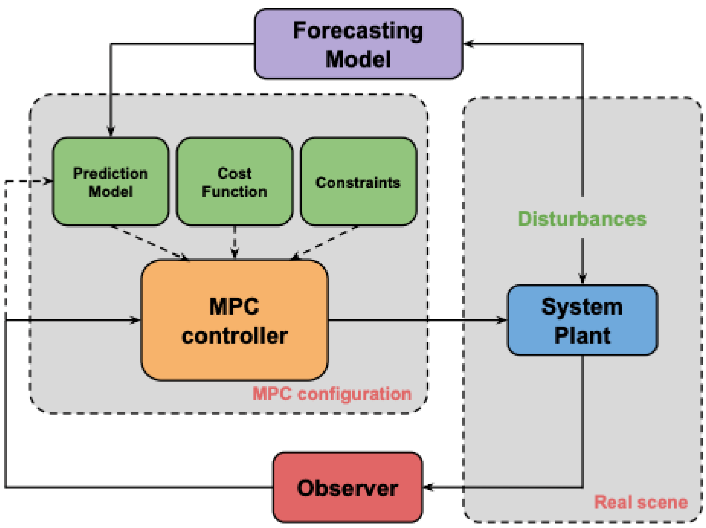


Fig 2.13. MPC control components adapted from (Wang, et al., 2016)

2.4.1 Control of Hydro Turbines using MPC

The operation of turbine governors is mainly done using classical control methods such as PIDs (Proportional-Integral-Derivative) (Culberg, et al., 2006). Even though they have advantages such as easy implementation, they have a slow response to system changes (not robust) as they are not designed to react to sudden system disturbances and uncertainties. Therefore, researchers have investigated studying model predictive control for controlling large hydro turbine governors. Even though model predictive control is new to hydropower, it has been extensively used in wind power generation and thermal power plants (Beus & Pandžić, 2018). The turbine governor is a system that regulates the inlet of water into the turbine, which then rotates to generate electricity. As per the guidelines provided by IEEE-75, a governor system consists of the following (Thapar, n.d.):

(i) Speed-sensing elements
(ii) Governor control actuators
(iii) Hydraulic pressure supply system
(iv) Turbine control servomotors

A turbine governor has two automatic controllers, (1) a speed controller and (2) a frequency/load controller (ABB, 2016). At the start-up sequence, the speed controller is used while the breaker is open. Once the generator is in synchronization with the power grid, the frequency/load controller is used. MPC is to be applied to the latter. Moreover, (Reigstad & Uhlen, 2021) used MPC for controlling a variable speed hydropower plant and the results suggest using MPC has improved the system performance and reduced water hammer effects in the penstock. This is primarily due to the accurate representation of the turbine model. The Fig 2.14. shows a hydraulic turbine governor for Francis and Kaplan turbines.

(a) (b)

Fig 2.14. Hydraulic turbine governor for a Francis turbine (a) and Kaplan turbine (b) adopted from (Kochendörfer, n.d.)

One of the reasons why MPC is not widely used for the control of Hydropower turbines is because hydropower plants have faster dynamic behavior (Beus & Pandžić, 2018). Although literature in the field of applying MPC for hydropower plants is limited, using MPC has a positive impact on plant performance and thus enhances power generation. However accurate representation of the system is critical as MPC relies heavily on an accurate model with many constraints.

2.4.2 Water Networks Modelling theory for using MPC

2.4.2.1 Modelling equations

To apply model predictive control in water networks, each element in the network needs to be modeled using its fundamental equations. Many modeling techniques have been identified in WDNs and this literature will elaborate on the techniques in a much more detailed manner (see, e.g.: - (Ocampo-Martinez, et al., 2009; Eker & Kara, 2001). A water network compromises tanks, pressurized pipes, pumping stations, and valves to manage flows and pressure to consumers.

1. **Tanks**

The head related to an n^{th} tank with a volume of water stored, v_n, can be shown as (Sun, et al., 2016):

$$h_n(k) = \frac{V_n(k)}{S_n} + E_n \qquad (2.6),$$

Where the volume V_n is the volume of the n^{th} tank and S_n is the cross-sectional area of the n^{th} tank and E_n relating to the n^{th} tank elevation and k is the time step. The mass balance expression of the tank relates to the stored volume V_n can be written as

$$V_n(k+1) = V_n(k) + \Delta t \left(\sum_i q_{in,i}(k) - \sum_j q_{out,j}(k) \right) \qquad (2.7),$$

Where, $q_{in,i}(k)$ and $q_{out,j}(k)$ corresponds to the i^{th} inflow and j^{th} outflow, respectively in (m^3s^{-1}). If $V_n(k)$ from (2.7) is substituted in (2.6), the equation re-arranges to.

$$h_n(k+1) = h_n(k) + \Delta t \left(\frac{\sum_i q_{in,i}(k) - \sum_j q_{out,j}(k)}{S_n} \right) \qquad (2.8),$$

The Δt is the sampling time

2. Pipes

Pipes transport water from one node to another node. During the transfer, the water pressure decreases because of friction, and there are many methods to calculate the friction loss in pipes. The most common one used is the Hazen-Williams since its friction coefficient is not a function of the flow or pipe diameter. However, Darcy-Weisbach is another method, and it is considered much more accurate than the latter as it considers a range of flow from laminar to turbulent (Ormsbee & Walski, 2016).

The Darcy-Weisbach equation has a variable called the friction factor, and this dimensionless value is used for calculating the friction loss in a pipe system. The friction factor relates to the pipe diameter, roughness, and Reynolds number.

$$H_u - H_d = \frac{f_p \cdot l_p}{DA_p{}^2 2g} Q_{ud}{}^2 \qquad (2.9),$$

Where H_u and H_d is the heads upstream and downstream of a node; f_p is the friction factor; l_p is the pipe length; A_p and Q_{ud} is the area and flow in the pipe.

3. Actuators

The flows across pumps and valves are the control variables for this work, as the flow across valves is manipulated to maximize the flow across PATs in Hydraulic regulation mode. These flows are considered continuous variables in a range of admissible values, although, certain head relation constraints apply.

For valves.

$$\Delta h_p = h_u - h_d \geq 0 \quad (2.10),$$
$$h_u \in \left[h_u^{min}, h_u^{max}\right],$$
$$h_d \in \left[h_d^{min}, h_d^{max}\right],$$

Where h_u and h_d denotes the heads of the valves upstream and downstream respectively, and h_u^{min}, h_d^{min} are the minima of the upstream and downstream heads and h_u^{max}, h_d^{max} denotes the maxima of the upstream and downstream heads.

2.4.2.2 Mathematical Modelling of a water network

By using the modeling methodology of each component in the water distribution network shown above, the model of WDNs can be represented by a set of differential-algebraic equations (DAEs). The derived discrete-time DAE model can be written as follows (Wang , et al., 2016):

$$x(k+1) = f\left(x(k), z(k), u(k), \delta\{k\}, w(k), d(k)\right) \quad (2.11),$$
$$0 = g\left(x(k), z(k), u(k), \delta\{k\}, w(k), d(k)\right) \quad (2.12),$$

Where *x* represents the vector of system states, *z* represents the algebraic states, *u* represents the vector of manipulated variables, *w* is the vector of non-manipulated variables, and the *d* vector denotes the system disturbances. In this work *d* is the demand of the nodes, while *k* denotes the time instantly, $f(\cdot)$ and $g(\cdot)$ are vectors of mapping functions. Furthermore, (2.11) represents the discrete-time differential equation illustrating the system dynamics, and (2.12) is the discrete-time algebraic equation describing the static relations of components in the water distribution network. Since tanks are the only elements with dynamical characteristics. The explicit form of (2.12) can be written as:

$$x(k+1) = Ax(k) + B_u u(k) + B_b\,\delta\{k\} + B_w w(k) + B_d d(k) \qquad (2.13),$$

Where *x(k)* represents the vector of hydraulic heads at the tanks as system states at time instant *k*. *u(k)* is the vector of manipulated flows across the valves and pumps at time instant *k*. It is the control input to the MPC problem, *w(k)* denotes the non-manipulated variables at time instant *k*, this is useful when the network has looped links, in the case of this work, even though there are loops, the flows are modeled in a way *w(k*) can be ignored. The vector *d(k)* corresponds to the water demands at time instant *k.* Furthermore $\delta\{k\}$ denotes the binary decision comprise of $\{0,1\}$. Also, A, B_u, B_b, B_w, B_d are system matrices of relevant dimensions.

Moreover, (2.12) static relationships between the elements can be explicitly explained below.

$$0 = \boldsymbol{E}_u u(k) + \boldsymbol{E}_w w(k) + \boldsymbol{E}_d d(k) \qquad (2.14),$$

Where (2.14) are the mass balance equations at nodes in the WDN. E_u, E_w, E_d are system matrices of appropriate dimensions.

2.5 Hydropower

Hydropower is one of the ancient and biggest sources of renewable energy. To generate electricity, hydro plants take moving water from lakes and rivers and through a penstock direct water to a turbine, which then turns to generated electricity. Fig 2.15. shows the setup of a hydropower plant.

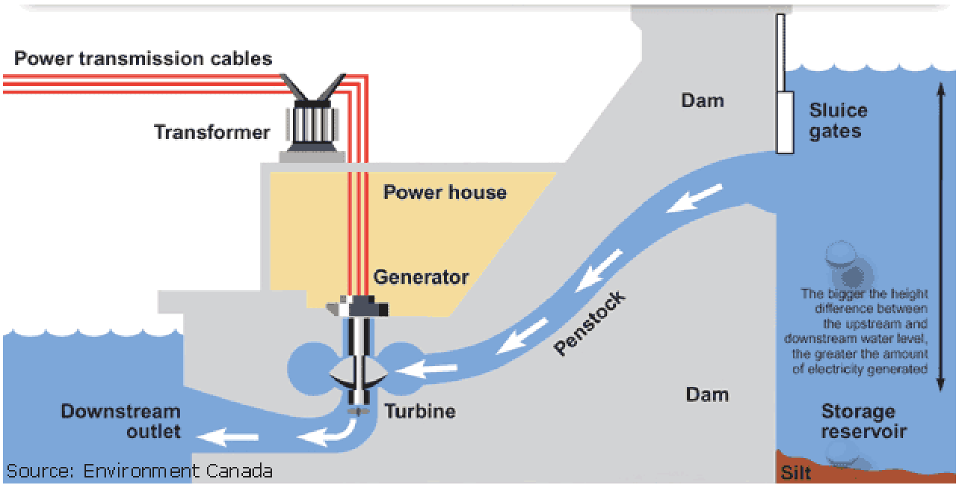


Fig 2.15. Hydroelectric power generation setup adopted from (Environment Canada, n.d.)

In the United States, hydropower contributes to 37% of the total renewable energy generated (US Department of Energy, n.d.). Hydropower became an energy source only in the later 19th century when the British-American engineer James Francis built the first modern water turbine (Nunez, 2019). At the present day, China has the world's largest hydropower power plant called the Three Gorges Dam, generating 22.5 GW (Kumar, 2017). The Fig 2.16. shows an image of the enormous Three Gorges Dam in China.

Fig 2.16. Three Gorges Dam, China adopted (Kumar, 2017)

As much as the benefits hydropower plants bring, they also have disadvantages. Big hydropower plants can damage river ecosystems and surroundings. For example, the Three Gorges Dam forced 1.5 million people out of their homes and flooded hundreds of villages (Lee, 2021). Additionally, hydropower plants can cause low oxygen levels in the water which can be harmful to the habitats (Union of Concerned Scientists, 2013). However, many say the environmental impacts of hydropower generation are low compared with the burning of fossil fuels (Nunez, 2019). In some places, small hydropower plants are established to have minimal impact on the environment (Rotilio, et al., 2017). The Fig 2.17. shows the classification of hydropower plants based on the power output.

Type	Power Output	Applicability
Large (described in this factsheet)	> 100 MW	Large urban population centres
Medium (described in this factsheet)	10 – 100 MW	Medium urban population centres
Small (see **small scale hydropower**)	1 – 10MW	Small communities with possibility to supply electricity to regional grid.
Mini (see **small scale hydropower**)	100 kW – 1MW	Small factory or isolated communities.
Micro (see **small scale hydropower**)	5 – 100kW	Small isolated communities.
Pico (see **small scale hydropower**)	<5kW	1 – 2 houses.

Fig 2.17. Hydropower classification adopted from (Carrasco & Pain, n.d.)

Small hydropower plants can be installed in several places in small rivers unlike large hydropower, which has less impact on the ecosystems (Mitsumori, 2016). For example, CO_2 emissions in 1 kWh of electricity are 11 g-CO_2 (Fujii, et al., 2017). Furthermore, mini/micro power plants have further advantages. Mostly it is not impacted by weather conditions and does not involve advanced systems to operate. Furthermore, it does not impact the livelihoods of people and they are mostly situated on hilly/mountainside where elevation difference occurs in the pipeline (Bildirici, 2019).

However, it is seen that the installation of conventional turbines in the sites for mini and micro hydropower generation is not economically viable (Ramos & Ramos, 2010). The Fig 2.18. show the relationship between the installation cost of the turbines vs their installation capacity.

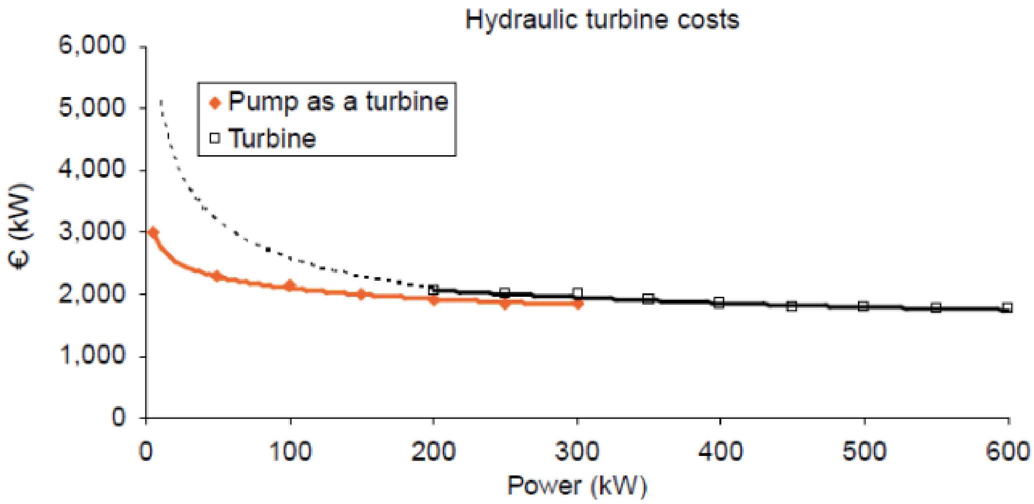
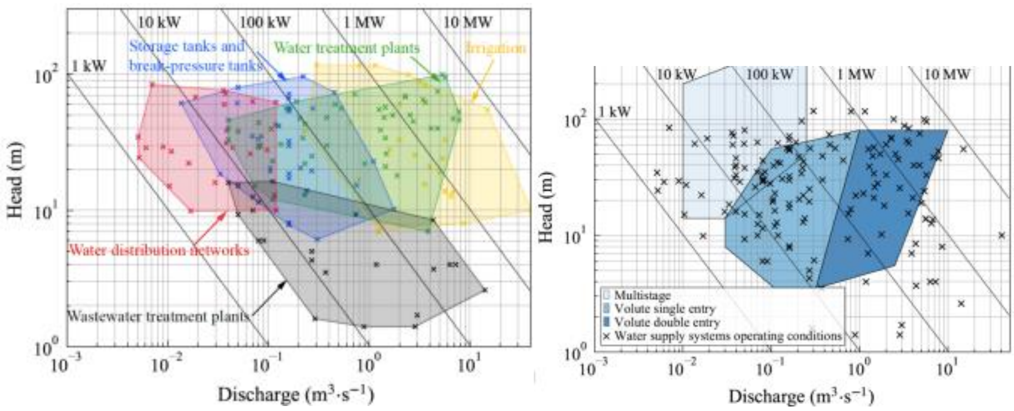


Fig 2.18. The trend for hydropower equipment initial cost adopted from (Ramos & Ramos, 2010)

Therefore, in the last few years, many have tried to explore other cheaper hydropower technologies to be used for smaller sites. Among the research, one technology gained attention. Pump As Turbines (PATs) (Carravetta, et al., 2012). (Delgado, et al., 2019) gathered average operating points from various literature in the context of WDNs, wastewater networks, and irrigation networks and compared their scale with the application of PATs that are available in the market. From Fig 2.19. the results from this study prove PAT technology is suitable for use in water networks.



(a) (b)

Fig 2.19. (a) average operating points of hydropower sites in water networks, (b) average operating points of the same sites with the application of PATs available on the market adopted (Delgado, et al., 2019).

2.5.1 Excess energy in water networks

In water networks, in any pipe with a steady flow, the total energy line can be shown as in Fig 2.20., if there are no minor head losses, connecting the head between each node (Samora, et al., 2016). The head in each node is usually higher than the required minimum pressure. It is typically set by utility companies to ensure sufficient pressure is reached on the consumer. However, if at any point the head is higher than the minimum pressure, there is excess energy. This excess energy usually varies with time as the demand of the network does not remain fixed.

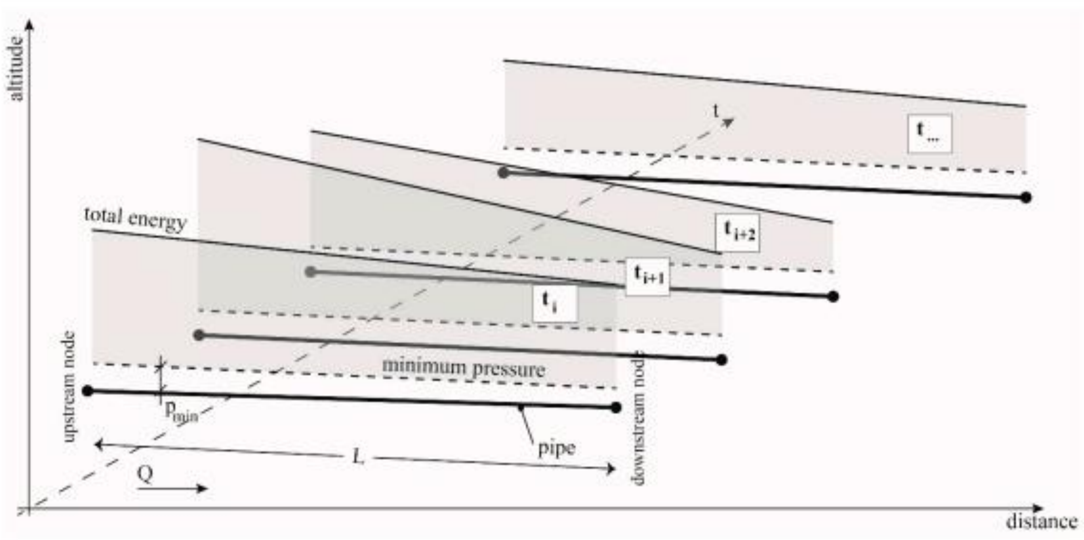


Fig 2.20. Excess energy at each point in a pipe adopted from (Samora, et al., 2016)

Nevertheless, this excess energy assuming its available to exploit is otherwise dissipated to the environment if no effort it's taken to recover it. Therefore, micro turbines such as PAT could be ideally installed at locations where excess energy occurs.

2.5.2 PAT technology

Pump As Turbines are pumps operating in reverse mode which can generate power when coupled with an asynchronous induction motor. Unlike in pump mode where energy is consumed, PATs can generate energy by exploiting the surplus head otherwise dissipated in the PRV (Corcoran, et al., 2012). The Fig 2.21. below shows a PAT installed in a group water scheme in Blackstairs, Ireland.

Fig 2.21. PAT installed by Dwr Uisce at Blackstairs GWS adopted from (EPS, 2019)

Pump As Turbines have been seen as an attractive way to couple power generation with pressure management due to many reasons one being having a low capital cost compared with other traditional turbines. Nevertheless, PAT efficiency reaches the best efficiency point (BEP) of around 0.6-0.7 in water networks due to flow variations (Carravetta , et al., 2014; Fecarotta, et al., 2018). But in other settings, it could be up to 0.8 (Mitrovic, et al., 2020).

Although Pump as turbines is proven to be more attractive to couple with power generation and pressure regulation, there exists a lack of data, as manufacturers do not provide the performance curves along with the device, therefore researchers must opt to use affinity laws once both the performance curves of a prototype PAT are known. Affinity laws relate the performance of the prototype to the performance of a similar machine, i.e., having a different diameter and rotational speed, which can be used to predict the performance curves of similar machines (Morani, et al., 2018). The issue with using affinity laws is it assumes the efficiency of similar devices to be constant even though the rotational speed of the machine varies. This can contradict the actual behavior of the machines (Marchi & Simpson, 2013). The efficiency of a machine depends on the rotational speed; therefore, maximum efficiency is only achieved at an optimal speed setting, making the affinity laws only valid in a defined range of rotational speed, and the error in prediction increases as the rotational speed of the prototype and the other machine diverge. Although, (Fecarotta, et al., 2016; Carravetta, et al., 2018) developed a model that can predict the variation of the efficiency with the runner speed, nevertheless, there exist some limitations as it can be only true for machines with a specific range of speeds.

To test the real performance of PATs for different values of flow and head, laboratory experiments are required. In 2018, (Novara & McNabola, 2018), analyzed 113 PATs (with flows ranging from 1 to 320 l/s and pressure values from 3 to 353m, and determined a two-degree polynomial to calculate the head across the PAT and a two-degree polynomial to determine the instantaneous power. This proved to be more accurate compared with the other polynomials derived by (Derakhshan & Nourbakhsh, 2008) and (Fecarotta, et al., 2016). Additionally, a significant problem in water distribution networks is represented by the need of ensuring a required head drop, under variable operating conditions; that is, of head and discharge.

As a solution to this, (Carravetta, et al., 2012) and (Carravetta, et al., 2013) proposed two configurations called Hydraulic Regulation (HR) and Electrical Regulation (ER) schemes for hydropower generation and pressure regulation, which are explained below.

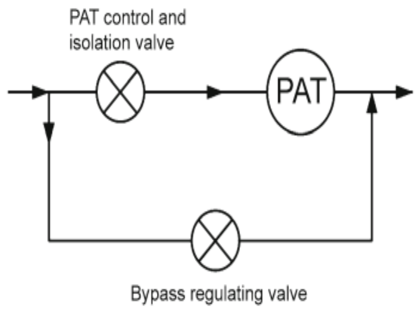


Fig 2.22. HR scheme adapted from (Carravetta, et al., 2012)

This is a series-parallel hydraulic circuit in which a PRV is in series and in parallel with a pump as a turbine (refer to Fig 2.22.). When the available head in the system is higher than the head-drop deliverable by the PAT, the excess head is dissipated by the valve in series. In the case when the flow is large, the PAT would produce a head-drop higher than the available, therefore, the bypass valve will be opened to allow the excess flow to pass through. This configuration is preferred over the Electrical Regulation (ER) scheme, which consists of a similar setup, but an inverter is introduced to vary the frequency of the PAT (changing the rotational speed) thereby varying the performance curve. In other words, the PAT characteristic curve is modified to match the available head. When both the schemes are compared (Carravetta, et al., 2013), the HR mode showed a larger efficiency when the working conditions vary from the design values due to any demand pattern variation.

Moreover, in terms of economics, the HR mode showed shorter payback periods than the ER scheme. Nevertheless, to improve the global efficiency of the plant the first two regulation schemes (HR) and (ER) can be coupled (with HER) to represent the third scheme. A study by (Fecarotta, et al., 2018) showed insignificant improvements in energy production using HER when compared with HR schemes. A diagram of the HER scheme is provided for clarity (refer to Fig 2.23.).

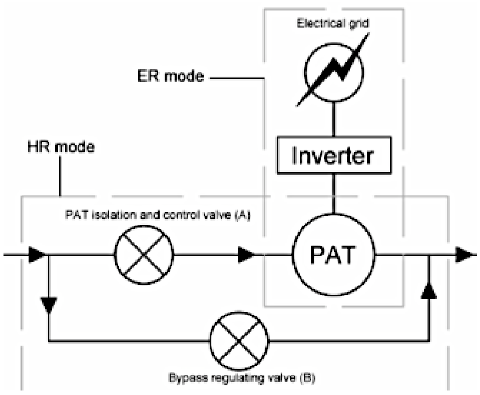


Fig 2.23. HER scheme adapted from (Carravetta, et al., 2013)

2.5.3 PAT installation in a water network

In gravity water networks, PATs can be installed in two potential sites (Voltz & Grischek, 2019), also see Fig 2.24.

1) The location where flowrate is separated from the demand downstream through a storage facility (tank) – which is also known as a “buffered-site”
2) Or at the location where flowrate is determined by the demand use in the downstream supply area – which is also known as the “non-buffered site”

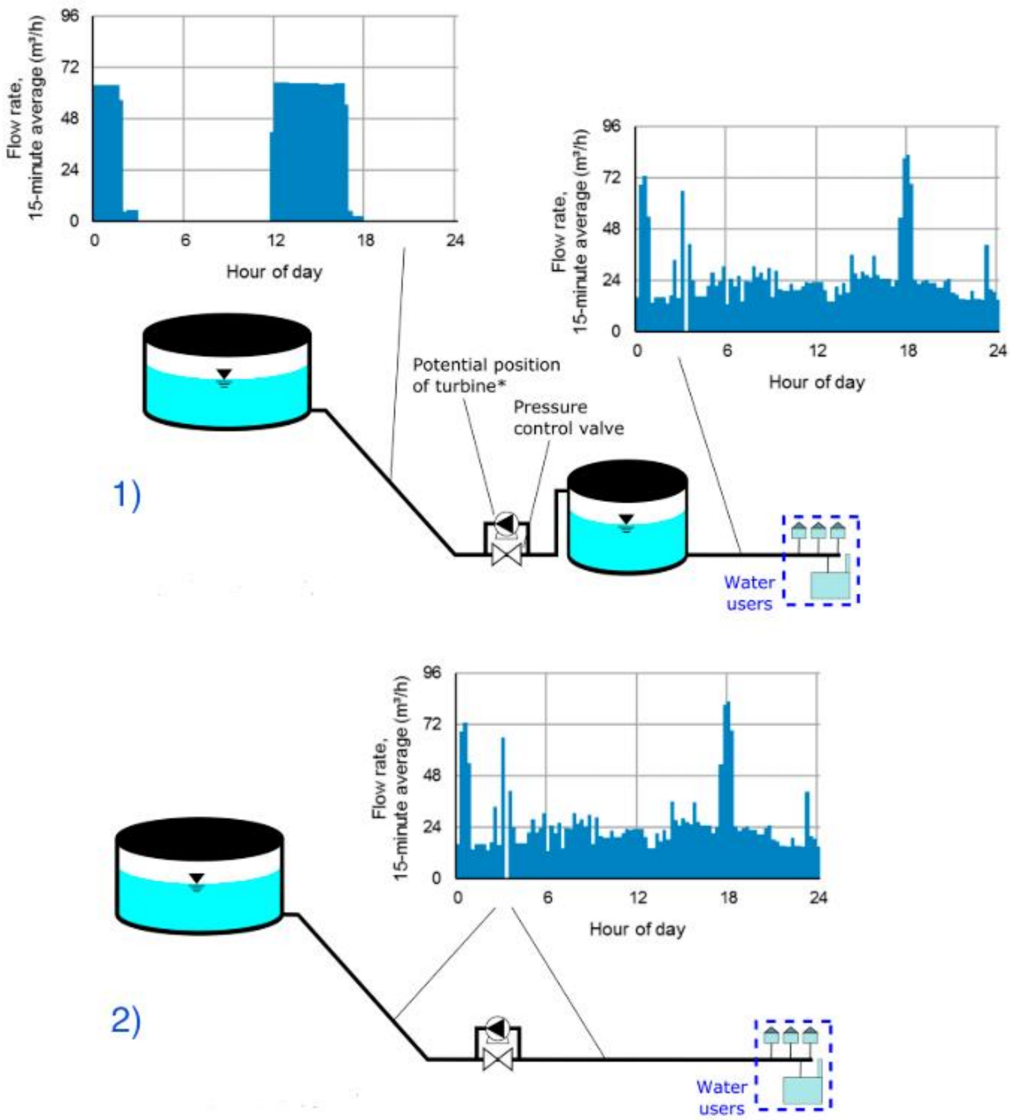


Fig 2.24. The difference between buffered and non-buffered sites adapted from (Voltz & Grischek, 2019)

For sites that have the configuration like 1), flexibility is possible for the in-flow to the PAT site such that it can maximize the energy production. But in 2) the turbine needs to be designed systematically such that it can operate in a wide range of flow and available heads. Therefore, it needs more information and complex methods (Pérez-Sánchez, et al., 2018; Ramos, et al., 2010; Carravetta, et al., 2018). Nevertheless, (Voltz & Grischek, 2019) mentions that sites in configuration 1) are more frequent and serve as a profitable opportunity for generating renewable energy. Also, they allow the water supplier the resilience in calculating the rate, and time of the tank filling which indirectly correspond to turbine operation (with the assumption that the inflow rate is not constrained – e.g.: varying inflow from a mountain spring). Therefore, the inflow rate can be modified to maximize the energy generation through the PAT despite how it was influenced in the past few years

(Voltz & Grischek, 2019). However, while comparing literature, there are also studies that treat sites in configuration 1) as sites in configuration 2). For example, (Ramos, et al., 2010; Vilanova & Balestieri, 2014; Novara, 2016; Monteiro, et al., 2018) all present case studies which focus on the configurations like in 1) but most of them treat the sites as if they were sites in configuration 2). That means they assume the inflow remains consistent and perform experiments to design PATs to suit that inflow, other than trying to adjust the flow rate to allow a single, optimized PAT. The term optimized PAT means that the flow rate and available head for it to exploit and generate the maximum power for a period have been optimized. Furthermore, authors such as (Fecarotta, et al., 2018; Carravetta, et al., 2018; Corcoran, et al., 2012; Voltz & Grischek, 2019) all show different methods numerically or experimentally in using a PAT in a water network, but they all show only offline methods and also they only summarise on controlling one PAT and does not include in the results where more than one PAT could be installed within a water network.

2.6 Summary

After conducting the literature review on WDNs, hydropower technology, and model predictive control, with particular attention to pressure management using PRVs, PAT technology, and control of WDNs and Hydro-turbines using model predictive control the following are identified as the main findings:

- Water networks are energy intensive, and each process requires energy, for example, to extract, treating and distribution. Additionally, each process is associated with a considerable amount of GHG emissions and more sustainable solutions are needed.
- Excessive pressure can have negative impacts on water networks, such as pipe breaks can occur when pressure management is absent. The typical way to tackle high pressure is through the installation of PRVs, but unlike automatic PRVs, typical hydraulically operated ones do not have the ability to regulate variations that occur with pressure at different times of the day
- There exist various control techniques to control PRVs in water networks but Model predictive control is seen as the most attractive due to its ability to take many constraints into consideration and provide the optimal output based on a cost function and constraints.

- Research into the control of hydropower turbines using MPC is limited due to the reason dynamics involved in hydropower generation change much more frequently than in other renewable energy generation plants.
- Mini/micro hydropower plants are less damaging to the environment and conventional turbines are not economically viable to install at locations where their excess energy is present.
- Excessive energy exists in pipe networks and PATs are deemed more suitable for power generation in those sites
- PAT coupled with PRVs can be installed in three configurations, (i) HR scheme where a PRV is in parallel and series with the PAT (ii) ER scheme which coupling the PAT with an inverter introduced to vary the frequency of the PAT (iii) Having HR and ER combined to make HER scheme as ER alone cannot maximize the energy production.
- PATs installed in gravity water networks can have two configurations (i)The location where flowrate is separated from the demand downstream through a storage facility (tank) – which is also known as a “buffered-site” and (ii) Or at the location where flowrate is determined by the demand use in the downstream supply area – which is also known as “non-buffered site”. However, configuration (i) is preferred as PAT flow can only be optimized if installed in that setup.
- Besides, all of the above-mentioned literature focuses only on the optimisation of one PAT site and does not show how more than one PAT in water networks can be optimized together for maximum power generation.

3. Methodology

3.1 Research Approach

To answer the research question and sub-questions defined in section 1.3 the research work that will be presented in the following sections of this thesis consists of a background study that points out that WDNs are energy intensive along with GHG emissions associated with each process. One of the methods to make WDNs energy efficient would be to introduce Pressure Management, which is also part of the background study. One of the ways to reduce pressure in a network would be to introduce PRVs to nodes that have high downstream pressure, therefore some control techniques on how to control PRVs in existing WDNs are also part of the literature review. A review on model predictive control is also done as part of the background study as it is seen as a better option to control PRVs in WDNs. Additionally, it is also shown how PRVs are replaced at the sites where excess pressure occurs with PATs. As PATs lack flow regulation, PRVs are installed in a series-parallel configuration (HR scheme) in WDNs. Finally, the background study also shows how PATs are installed in gravity networks. Following that, the question to be answered which is, "What technology can be used to maximize the potential of PATs in WDNs" is done in the methodology section which shows the steps involved in deriving how MPC can be used to maximize the power generation. This will also answer the sub-question, "While maximizing the potential can model predictive control fulfill the common objectives in water networks such as pressure management". The results for that are shown in the results section and the validation section which show how the algorithm considers head loss constraints and pressure constraints in the WDN under study.

To further challenge the answer, two different controllers are compared. Both controllers' objective is to maximize power production but is designed in two ways. This will answer one of the sub-questions "Is there an improvement in maximizing the power of all PATs simultaneously between the controllers called Hybrid MPC and Linear MPC" and the final sub-question to be answered is "Which controller performs better for it to be suitable for near real-time operation". This is also answered in the results section as the response times are shown on which performs better and why. The research approach can be broadly viewed in Fig 3.1., 3.2. below, which shows the flow in this thesis starting from the research question

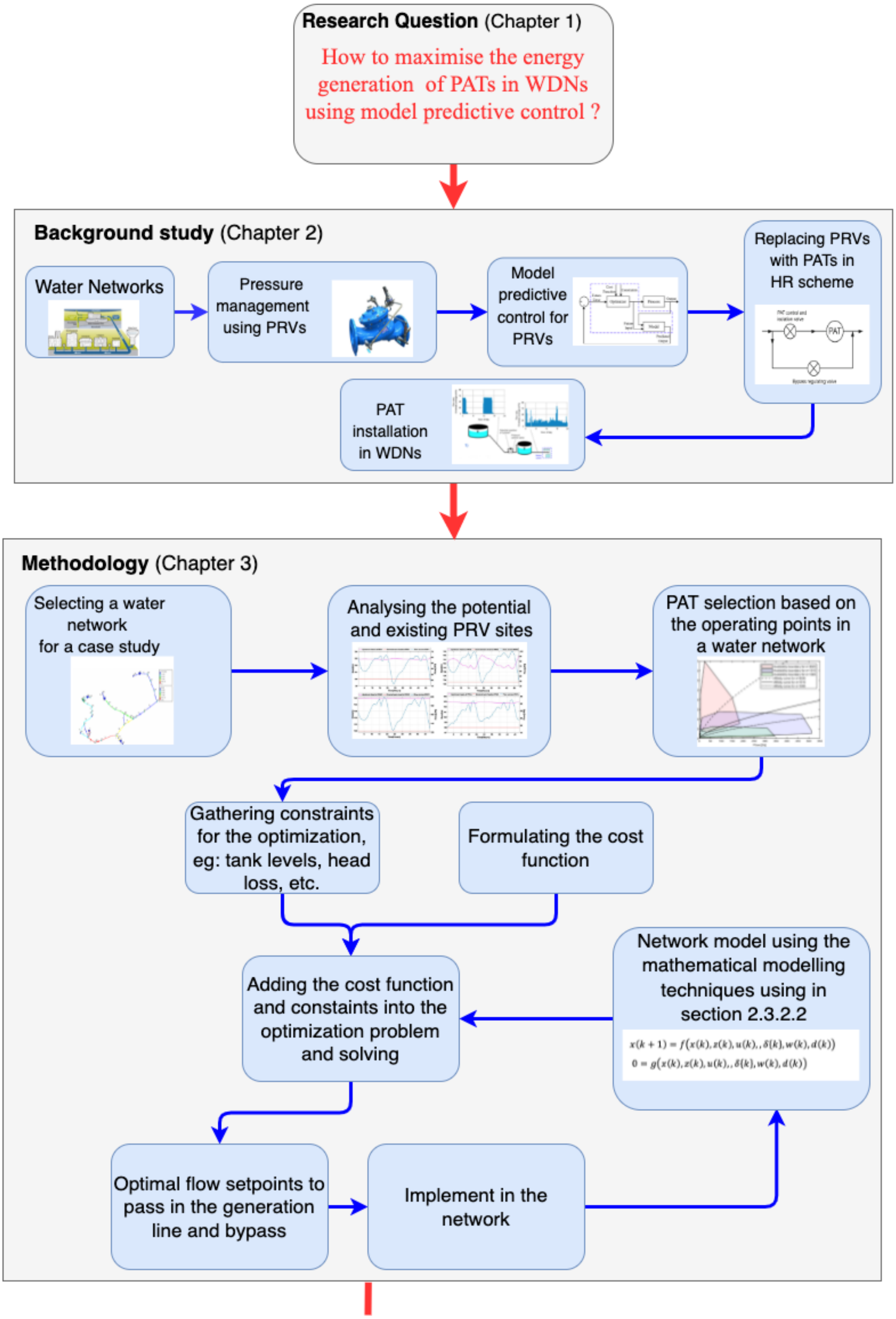


Fig 3.1. Research approach

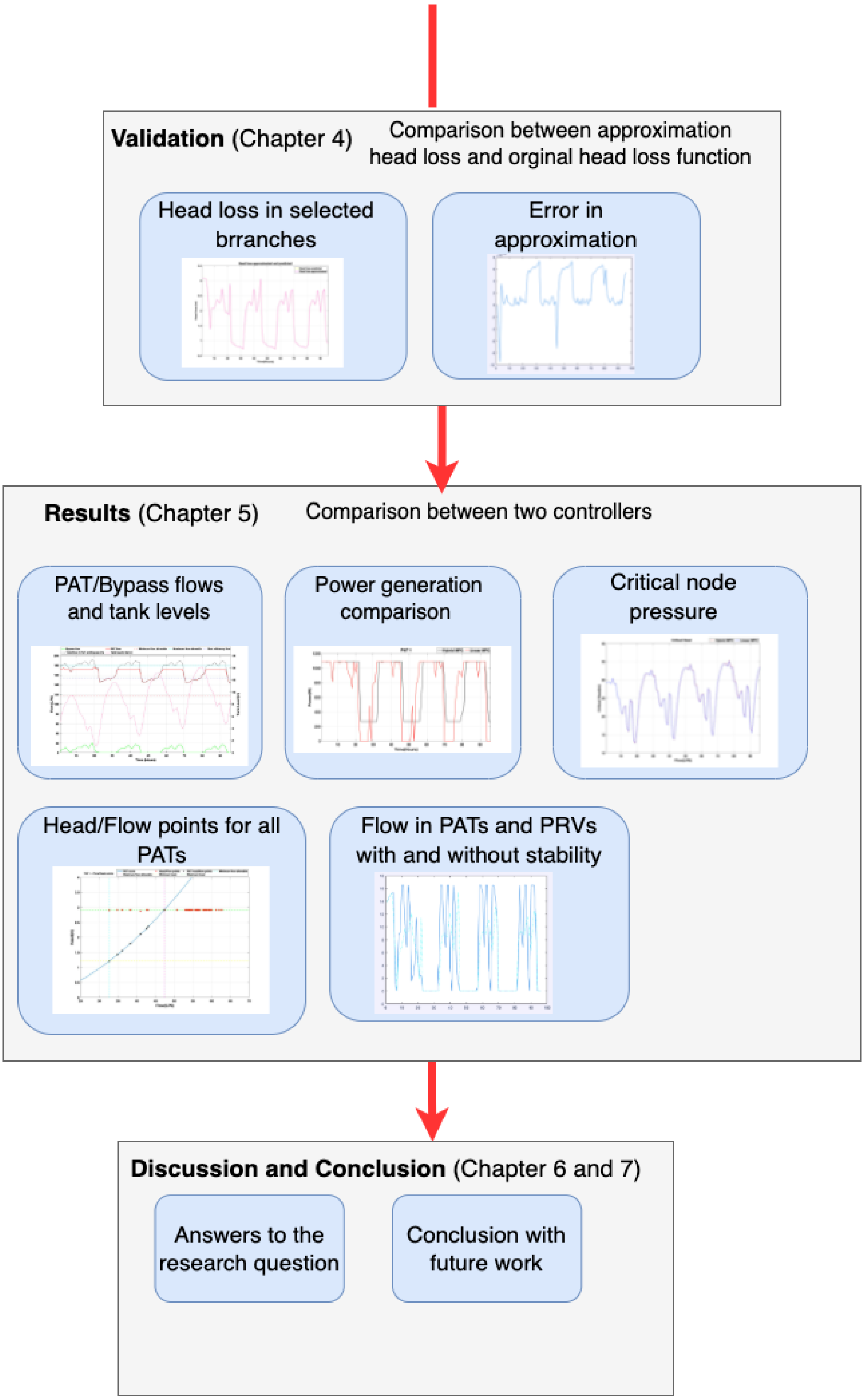


Fig 3.2. Research approach continuation

3.2 Introduction

This work presents a methodology for optimization of more than one PAT like configuration 1) in section 2.4.2 for a drinking water network using an optimization algorithm. There are four potential locations for the installation of PATs within the part of the network. Besides, the methodology determines the optimal flow that should be passed through the PAT based on a prediction model that considers the dynamics and demand of the network. The prediction model is designed based on Model Predictive Control. MPC is a control technique used for decades to control a plant or a system by predicting the behavior based on the current state. MPC uses an explicit representation of the system and in this work, the system represents the water network. Furthermore, like any other optimization algorithm, MPC also has the typical structure of having an objective function and constraints. The advantage of MPC is that the constraints do not need to be static. It can be updated inside the algorithm for every time step if needed. Also, it can consider more than one objective, thus allowing for multiple objective formulations (Wojsznis, et al., 2007).

In most drinking water networks, there are equality and equality constraints to be included in the optimization method. Equality constraints would be for example: -mass balance equations in nodes and if tanks are present, then the tank dynamics relating volume with tank inflow and outflow. Moreover, inequality constraints would be on tank levels (minimum and maximum levels). Additionally, there would another set of actuators, as most networks have pumps or valves present to increase the head or control the flow through the pipes. Pumps have a head-flow curve that is provided by the manufacturer which needs to be considered and valves also have maximum and minimum flow values which need to be included (Sun, et al., 2016).

Moreover, apart from equality and in-equality constraints, head loss constraints also need to be considered. The issue with head-loss constraints is that it is highly non-linear because if Hazen-Williams or Darcy-Weisbach formulae are used to describe their relationship they would have either an exponential or a quadratic trend (Ormsbee & Walski, 2016). Therefore, to accurately model a water network, this non-linear nature has to be taken care of inside the prediction model. For this work, a novel method is presented which is added to the algorithm. This method will estimate the head loss values using a function based on yalmip (Lofberg, 2004). This is an alternative method for linearisation or including non-linear constraints in the algorithm as previous works have done. The advantage of using the proposed method apart from easing the computational burden of using non-linear constraints is that it can accurately represent the head/flow relationship and it gives the freedom to choose between formulas

Additionally, it is also important to keep a secure volume in the tank for any emergency reasons. Also, valves need to be operated smoothly avoiding a potential unsteady state in the water network if made to close and open suddenly. However, some of the previous work consider the emergency volume and valve safety operation as part of the objective function (Grosso, et al., 2014; Wang , et al., 2016; Sun, et al., 2016; Wang, et al., 2017). This increases the computational burden on the solver to find the optimal solution to satisfy all the objectives in the multi-objective scenario. Therefore, in this work, the emergency volume aspect and the valve smoothness are considered as part of the constraints.

Additionally, another set of constraints needs to be considered for optimizing PATs. PATs are usually installed in a water network in a series-parallel configuration as suggested by (Carravetta, et al., 2012). The reason behind that is to effectively regulate the operation of the PATs. PATs are installed with a combination of PRVs in both series and parallel branches to regulate the head and with the PAT in series with one PRV to exploit the surplus head. Therefore, this also is considered in the prediction model. To accommodate the operation of the PAT, the algorithm is modified in a way to include logic in the constraints.

3.2 Objective of this work

A case study from Ireland is used to test the control algorithm developed in this work. The network is summarised under the case study section, this network has five PRVs present and one pump present. For this work, only the locations of four PRVs are considered, and the pump operation is not included in the objective function. Moreover, two different layouts of the network were tested. The first arrangement is called the one-tank model, which has only one tank and one PAT proposed to be installed. The other arrangement is called the three-tank model, which has four potential locations for PAT installation in a tree-based network. It also has three tanks to be monitored along with one critical node where the pressure is always kept at more than 12m (minimum standard pressure).

This work aims to maximize the hydropower generation of multiple PATs in a WDN for five days. As an initial step, the algorithm developed is tested on the one-tank model and later tried on the three-tank model. To fulfill the objectives for this work, a linear multi-objective function is formed which will determine the optimal flow to pass through the PATs to maximize power over five days of simulation. Once the optimal flow setpoints for the PATs are derived from the control algorithm it is implemented in the network. For both arrangements, the demand of the network is considered as a measured disturbance to the network, i.e., the controller does not know in advance what the demand is. Furthermore, to test the controller performance the measured disturbance is set to change randomly every hour and the controller performance is tested.

Apart from the above, another aspect of this work is to keep the pressure on all nodes always including the critical nodes between 12m – 48m. This is done to avoid leakage or avoid low-pressure scenarios. Also, as the network has storage tanks, their level is monitored and kept within the minimum and maximum values. In addition, a security volume is established which can be used in case of an emergency. The other objectives include considering head loss constraints. An approximation technique is performed using Darcy-Weisbach formulas.

To summarize, the objectives of this algorithm are:

- Implementing MPC to multiple PATs for:
    - Power maximization for all four PATs
    - Integrating a logic for the operation of the PATs
    - Considering the demand as a measured disturbance
    - Predicting the tank level for 36 hours ahead (choice of 30 hours of prediction horizon is justified later in the thesis) and simulating for five days
- Changing the demand to test the performance of the control algorithm
- Keeping the pressure at nodes satisfied
- Keeping the tank levels within the minimum and maximum range
- Always keeping a safe volume in all three tanks
- Keeping the actuators functioning smoothly
- Validating the head loss approximation technique

3.3 Case study and Model set up

The case study used for this work is from a rural water supply network in Ireland, located in County Laois about 100 km from the capital city. The case study is adapted from (Morani, et al., 2018) and it is a tree-based network. This network configuration was chosen because apart from the simplicity, in a practical scenario pipe laying is easy and cost-effective compared with other layouts. Additionally, for hydraulic analysis of networks, the preferable configuration is tree networks when compared with other types (Hafsi, et al., 2018). The reason is due to no closed loops in the network and only node equations are required directing it to a linear system of equations (Hafsi, et al., 2018).

The original network consists of 58 nodes and 55 links, and this was reduced to 29 nodes and 29 links by aggregation of the demand nodes not connected to any control element/tanks. This means any downstream demand nodes (with no control elements) in any branch expanding from the main line are added to the upstream node. This ensured that the branch always gets the required demand. Moreover, it also reduced the complexity of the network, making it simple to model accurately.

To move into the detailed information on the network, this is a gravity-fed network with a reservoir at 160 m. A pressure-reducing valve (PRV5) is present, and it is located downstream of the reservoir for managing the pressure at desired levels throughout. Apart from that valve, there are four other pressure-reducing valves distributed in the network (PRVs referred to as PRV1, PRV2, PRV3, and PRV4). PRV5 is not considered for this work as the flow line from PRV5 splits into two parts at N8 (see Fig 3.4.). Pipe 6 and 10 which flows towards T4 are not captured in the results of this work as the pump is not considered in the algorithm. Fig 3.3 shows the original network and Fig 3.4 shows the modified network.

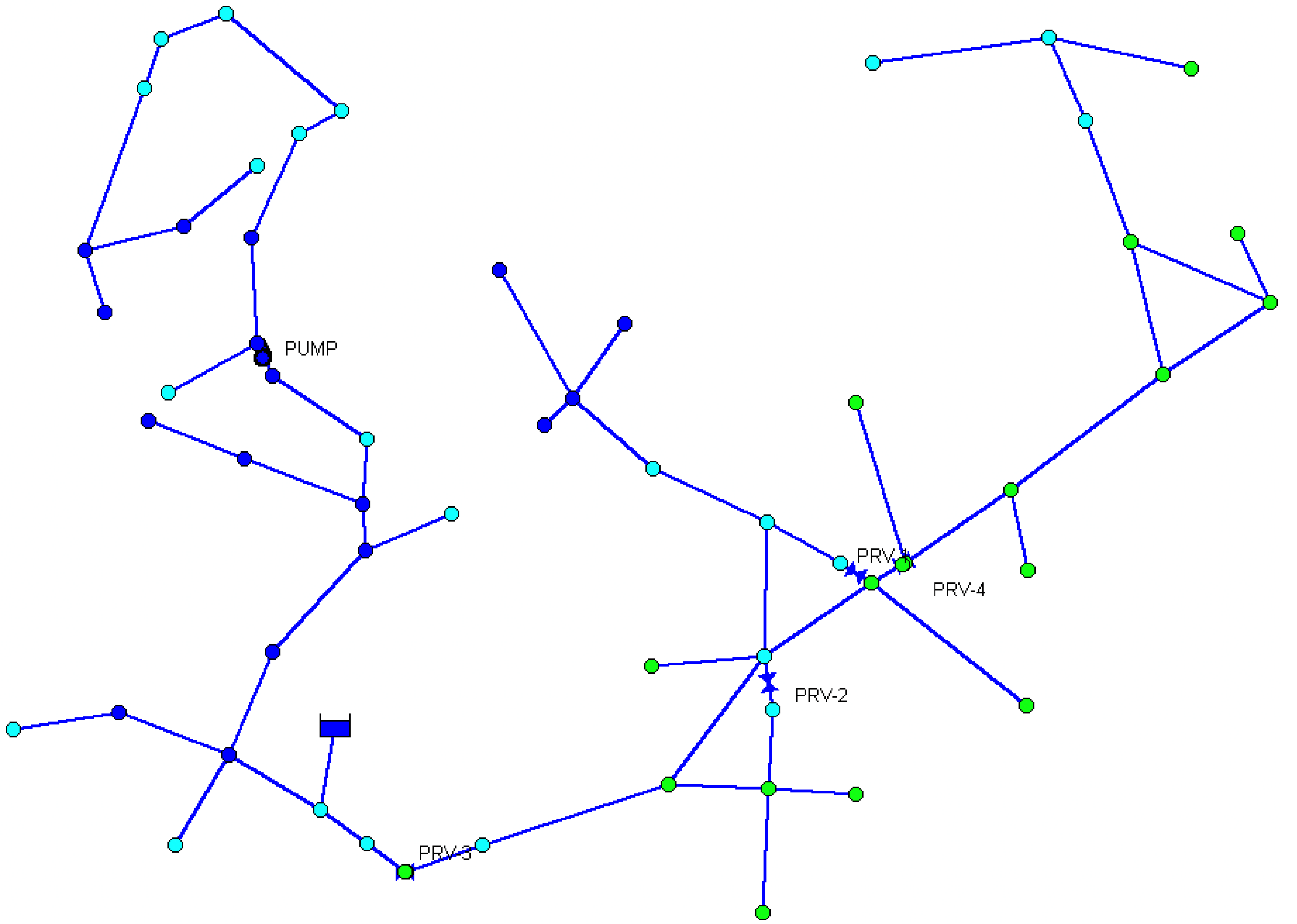


Fig 3.3. Original Ballacolla Network

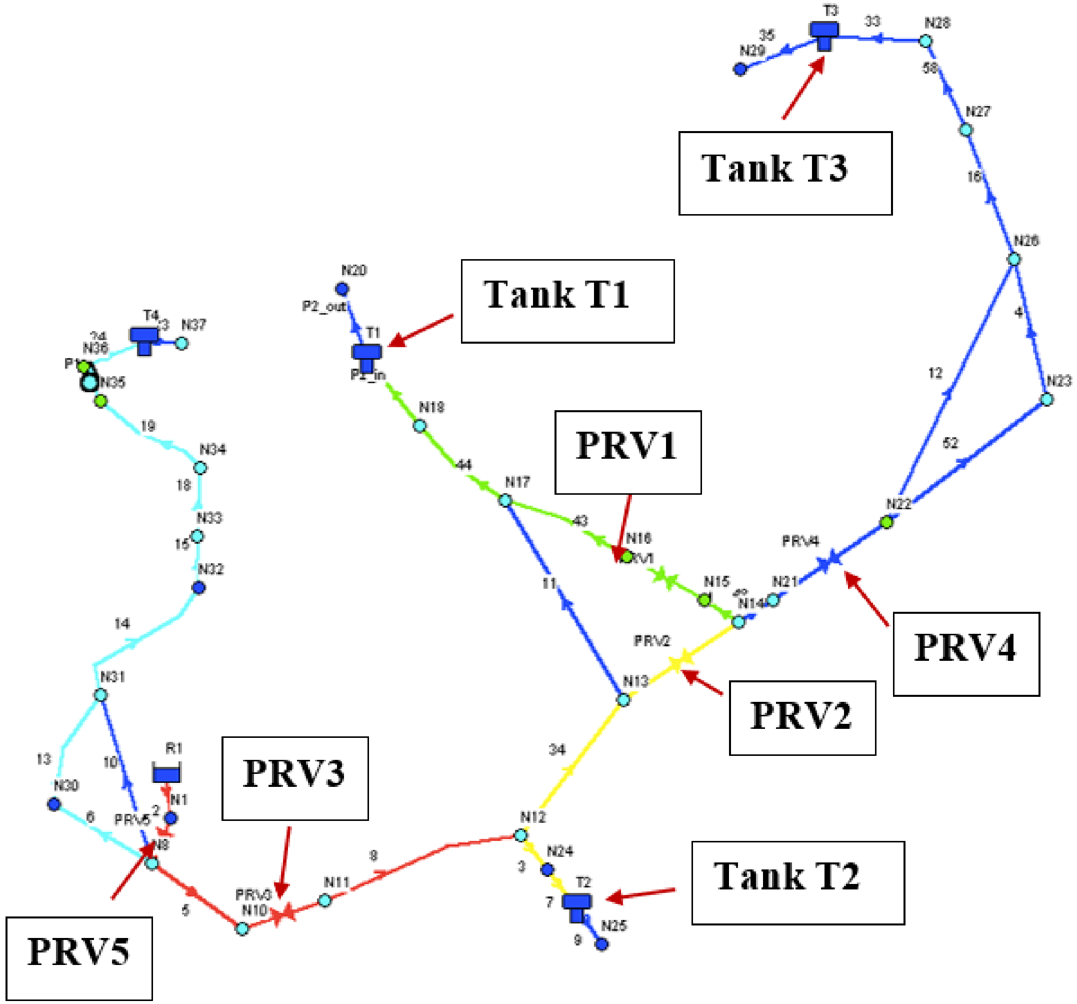


Fig 3.4. Modified Ballacolla network

To address the potential for the head that can be recovered by replacing it with PATs, a head-flow diagram is shown for all four PRVs in Fig 3.5.

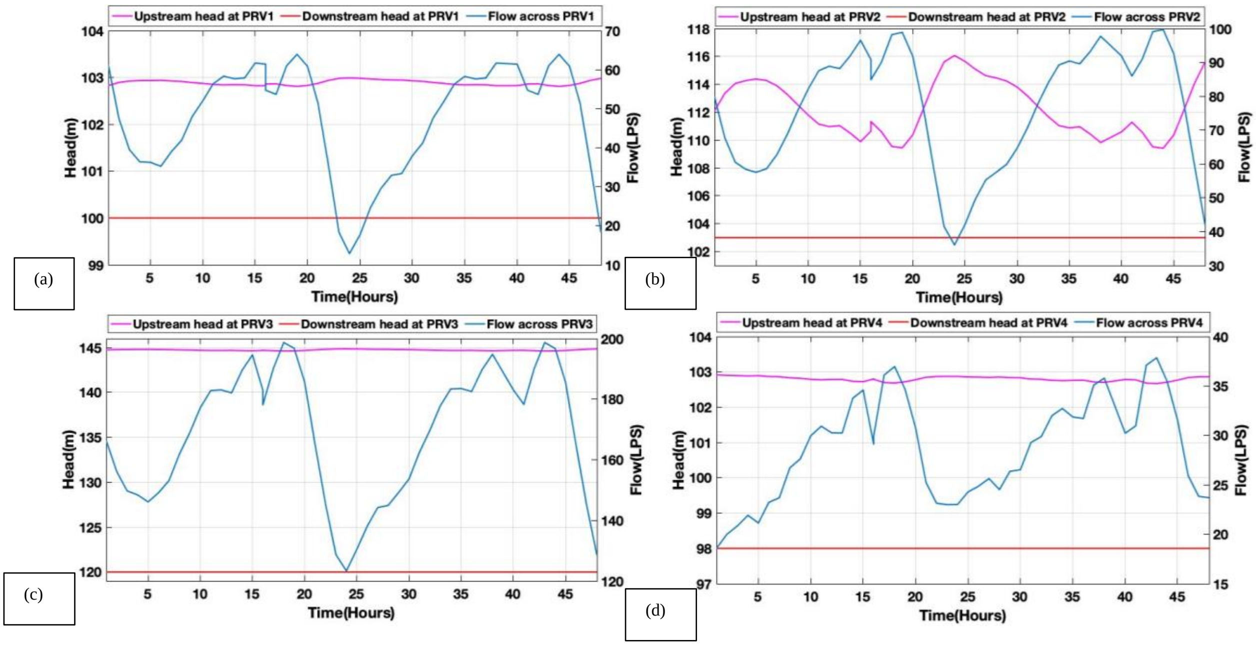


Fig 3.5. Head/Flow at PRV sites a) surplus mean head at PRV1 = 2.88m, b) surplus mean head at PRV2 = 9.27m c) surplus mean head at PRV3 = 24.72m d) surplus mean head at PRV4 = 4.80m

The network is modified by adding four storage tanks (T1, T2, T3, and T4). T1 is installed upstream of node N20 (a critical node). T2 is located between nodes N24 and N25, and T3 is added between N28 and N29. Moreover, another tank T4 is added between N36 (where a pump is present) and N37. The tanks are added to see the variation of the demand in the downstream nodes

Additionally, to increase the level of network complexity at least closer to a beta index of one, two pipes are added in a looped configuration (Ducruet & Rodrigue, n.d.). Apart from the extra links added, a new branch was created which is located between valves N11 and N13 (see Fig 3.4.), this branch has a tank (T2) and demand nodes like other branches. The reason to add another branch was to include an extra tank to model three tanks instead of two. Another reason for modifying the original network by adding tanks and branches is to create a configuration like class 1 sites as proposed (Voltz & Grischek, 2019). This is because a new inflow regime to the PAT site can only be introduced for maximum hydropower generation if storage tanks are present. Furthermore, for this work only three tanks T1, T2, T3, and four PRVs, PRV1, PRV2, PRV3, and PRV4 are considered.

There are two demand patterns defined, one is the original pattern which was inherited from the original Ballacolla network and that pattern is adjusted to match the reservoir outflow discharge which is shown below in Fig 3.6.

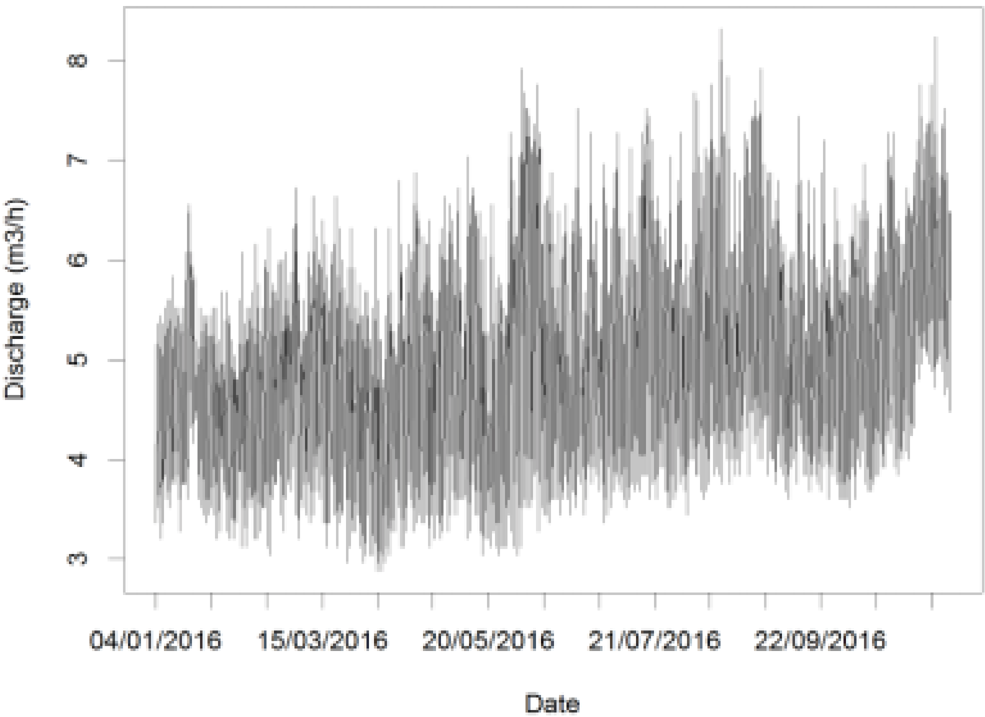


Fig 3.6. Outflow discharge from the reservoir in the Ballacolla network between 4/1/2016 and 13/12/2016

The other pattern is adapted from the D-town network (artificial network) (Salomons, et al., 2012) which is a modeled demand pattern based on demand nodes connected. The demand patterns used for this work are shown below in Fig 3.7. and Fig 3.8.

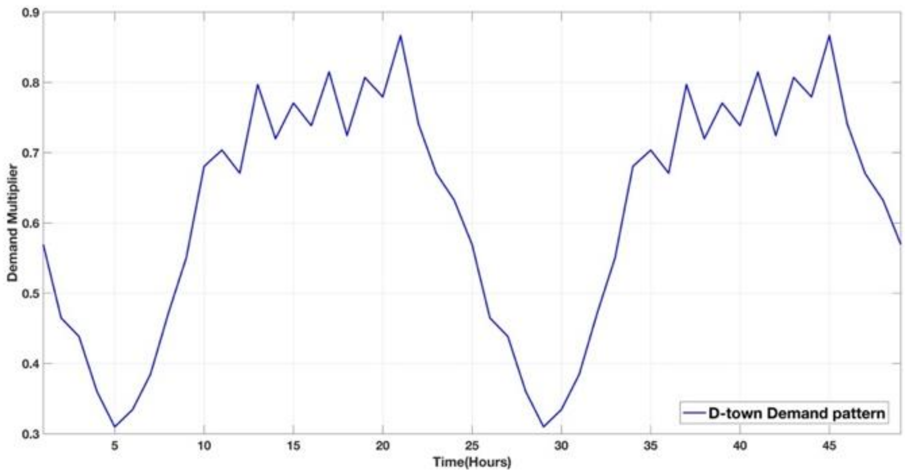


Fig 3.7. D-Town demand pattern

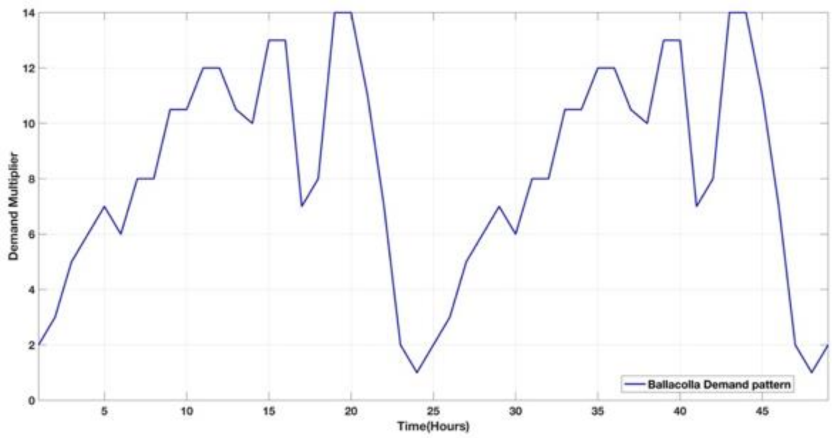


Fig 3.8. Ballacolla demand pattern

3.4 Algorithm design

The overview of the methodology is given in Fig 3.9, which illustrates the methodology step by step following the explanation afterward. Stage 1 represents the initial step in the design algorithm, at this stage, the hydraulics of the network is calculated and integrated with MATLAB via the Epanet/Matlab toolkit. At this stage, all the constraints are also formulated related to actuators (PRVs) and tank minimum and maximum levels. Once it is completed, at stage two, the theoretical curve of the suitable PAT is calculated, it is elaborated in section 3.4.3.2. Additionally, at this stage, the PAT logic is also designed based on the operating points in the network. Furthermore, this logic is integrated into the control algorithm at stage three along with the controller design. Section 3.4.3.3 elaborates in detail on how the control algorithm is formulated. Additionally, the next sub-sections 3.4.1 and 3.4.2 gives a thorough understanding of formulating the constraints and the objective function. The bigger picture of the methodology can be viewed below in Fig 3.9.

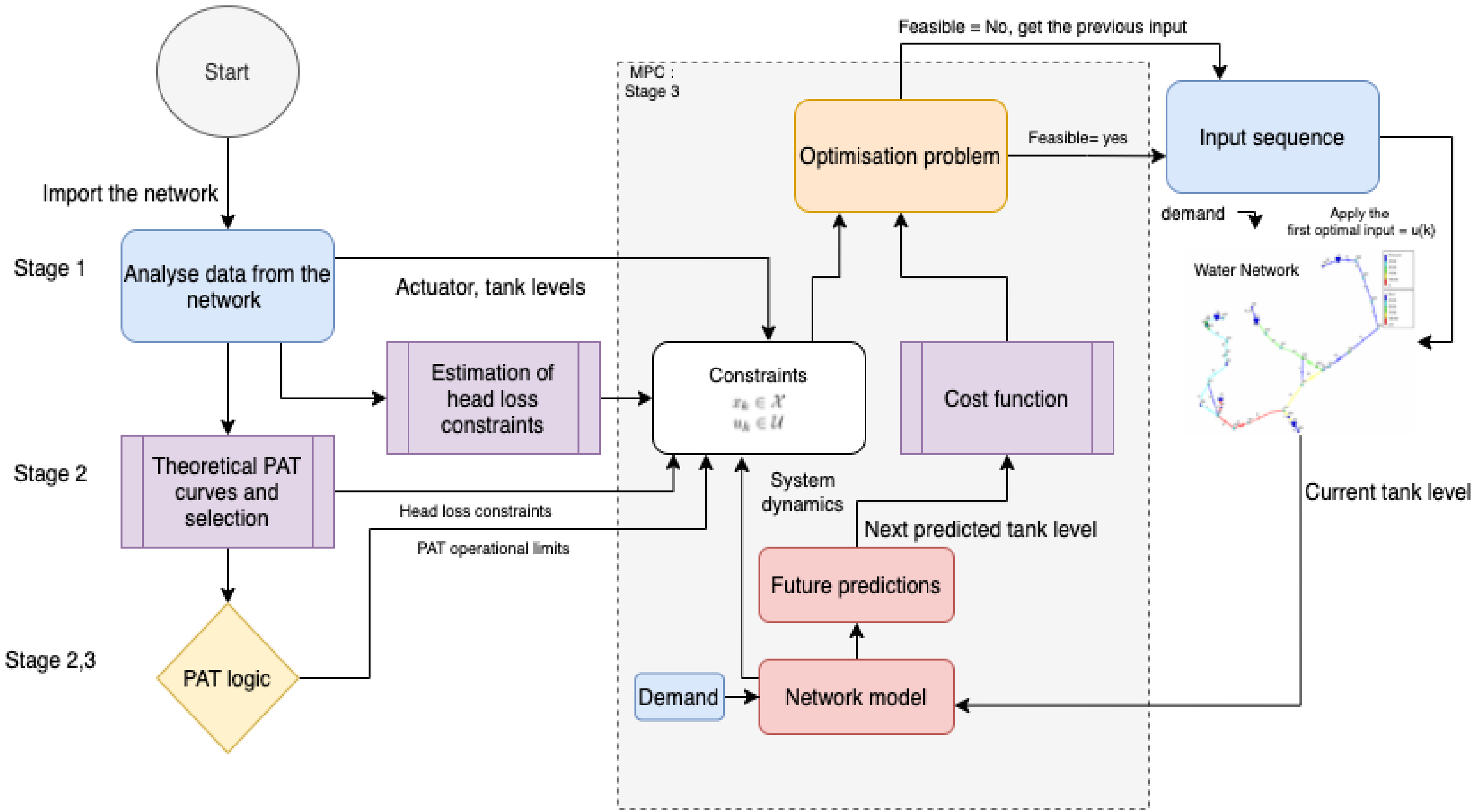


Fig 3.9. Flow diagram for the methodology

3.4.1 Constraints formulation

- The network pressure needs to be in an acceptable range throughout the time including the critical nodes (12-48m).
- Head loss constraints: As it is proposed to install PATs in a series-parallel configuration, it is important to keep the downstream head the same as it was set in the PRVs. Therefore, the head at the downstream nodes where PRVs were present is kept constant. It is validated using the Bernoulli equation by aggregating the head loss between the downstream nodes and tank nodes.
- Storage tank level constraints: the levels of the tank need to be maintained within the minimum (1m) and maximum (15m) values to meet the demand and avoid overflow. The minimum level is set as the safety level for emergency purposes. The reason to include it in the constraints instead of in the objective function is clarified later in this section.
- PAT operational constraints: PAT operation is coordinated into the prediction model in the algorithm by using logic constraints. The reason is justified further in this section.
- Flow constraints: The maximum and minimum flow allowed through the valves in the series-parallel configuration is set as:
  a) Minimum being zero (valve closed) in both series and parallel lines
  b) Maximum in the generation line (series) is the maximum allowable flow through the PAT
  c) Maximum in the bypass line (parallel) is the maximum value retrieved from the PRV which is already installed (obtained from Epanet – hydraulic simulator)

For an accurate representation of the network and applying MPC, it is worthwhile to include as many constraints as possible. Therefore, this work includes all the above constraints into the prediction model of the control design algorithm. As mentioned above, one of the most important constraints is network pressure. It is crucial to always keep the pressure at acceptable values to avoid pipe damage due to high pressure or not meeting demands due to low pressure.

Additionally, another set of important constraints is the head loss in pipes. Usually, in literature, flow models are used without considering the pressure to avoid taking head loss into account, because the equations to model the relationship between head and flow are non-linear. Nevertheless, these equations are important to give an accurate representation of the network dynamics.

There are numerous ways ranging from linearisation to approximation techniques to approximation methods and optimization algorithms, to tackle these non-linear equations. At the same time, there are also different formulas to calculate the flow pressure. Some examples include Hazen-Williams, an exponential representation between head and flow. Another example includes Darcy-Weisbach, which is a non-linear quadratic representation including a dimensionless term called friction factor. The friction factor depends on a flow regime ranging from laminar flow to fully turbulent flow. Due to the friction factor being applicable for a range of flows, Darcy-Weisbach is proven to be an accurate formula to represent the head loss in a pipe. Therefore, the latter is used to represent the head loss in pipes and an approximation method is developed using the interp1 function in yalmip.

Interp1 is a type of approximation method of constructing new data points within a range of the discrete set of known data. This is an alternative methodology to linearisation or other approximation techniques used for representing a head loss in networks. Linearisation methods use either Hazen-William and Darcy Weisbach formulas and construct a linear relationship between head and flow at a specific operating point in the network. This operating point could be the equilibrium point where the input and output derivatives are zero. Furthermore, in the current literature other approximation techniques are used, in the most common ones the head loss equations are modeled using a smooth polynomial function, and the error between the original and the modeled is reduced over a range of flow values to get the best approximation for the head loss (Pecci, et al., 2017). This method looks promising as it can be used in analyzing large-scale water networks, but the only drawback is errors still exist due to the nature of the methodology. Therefore, in this work, an improved approximation method is used as opposed to other methods available in the existing literature. Using interp1 is further explained in section 3.4.3 – Algorithm Flow

The other set of constraints is tank level maintenance. Since the network used in this work has tanks, it is important to keep their levels within the minimum and maximum levels to ensure demand is always met and tanks do not overflow in the case of flow increasing above the maximum level. For the final two sets of constraints on PAT operation and flow constraints, sections 3.4.3.4 of this thesis reveal the logic and constraints on the actuators (valves) in a comprehensive approach.

Before applying model predictive control, the prediction model needs to be designed using the constraints mentioned above and the cost function which is a multi-objective function in this work. The main challenge in applying MPC in water networks is mainly solving a large nonlinear optimization problem while considering the full dynamics of the system and a huge amount of decision variables within a sampling time. However, for WDNs the sampling time is normally selected to be one hour (Ye, et al., 2018). From referring to Fig 2.13 in section 2, MPC is in the global control layer and setpoints derived from it are in hourly time stamp but in the local control layer, sampling time needs to be less than that. The reason being local controllers such as PID need to react faster to control the opening and closing of the valves. Most of the literature focusing on the control of WDNs does not explain it or include both layers to control the plant.

3.4.2 Cost Function

The objective of this work is formulated into a multi-objective function where a trade-off is found in maximizing power and at the same time keeping the common objective of WDNs satisfied. A common way to obtain a scalar objective function is to form a linearly weighted sum of functions, f_i (Miettinen, n.d.),

$$\sum_i^r W_i f_i \quad (3.1),$$

When expanded.

$$min_{z \in Z} \, [f_1(z), f_2(z), \ldots, f_r(z)] \quad (3.2),$$

The objective function can be broken down into three parts, f_1 , f_2, and f_3

1) **Flow optimization for power maximization.**

This part of the objective function ensures that flow set-points are derived for power maximization. The range for power maximization is set as in between best efficiency flow to maximize allowable flow through the PAT. The rationale behind the range is for ensuring feasibility in the control algorithm, if the controller fails to get a setpoint close to the maximum flow it will ensure the flow set point will fall in between that range. The setpoint derived from the controller is optimal considering all the constraints and maximizing the power of all four PATs proposed at once.

$$f_1 = \|u\{k\} - u^{max}\{k\}\|^2_{w_u} = (u\{k\} - u^{max}\{k\})^T W_u (u\{k\} - u^{max}\{k\}) \qquad (3.3),$$

Where $u^{max} \in [\, Qbep\{k\}, Qmax\{k\}]$ and W_u is the weight to penalize big changes relating to $u\{k\}$. Also $u\{k\} \in [u\{k\}(1), u\{k\}(2), u\{k\}, u\{k\}(4)]$ and it corresponds to the flow setpoint in each PAT, PAT1-PAT4.

2) Stability of control inputs

Pumps and valves in networks should operate smoothly to avoid large variations in pressurized pipes that could lead to their damage. To obtain the smoothing effect, an additional term to the objective function is added which penalized the control signal variations.

$$f_2 = \|\Delta u\{k\}\|^2_{w_{\Delta u}} = \Delta u\{k\}^T W_{\Delta u} \Delta u\{k\} \qquad (3.4),$$

Where, $\Delta u\{k\}$ are the changes of the input vector and $W_{\Delta u}$ corresponds to the weight matrix of suitable dimensions. The significance of weights is explained in the constraints section under hybrid MPC (refer to section 3.4.3.3).

3) Ensuring feasibility in Tanks

An additional term is added to the cost function, which minimizes a slack variable along with the rest of the objectives and that variable is added to the inequality constraints in the tanks to ensure infeasibility is avoided when the controller derives the flow setpoints.

$$f_3 = \|s\{k\}\|^2_{w_s} = s\{k\}^T W_s s\{k\} \qquad (3.5),$$

For example: If a tank has in-equality constraints as: -

$$min_{level} \leq tank_{level} \leq max_{level} \qquad (3.6),$$

The slack variable is added as:

$$min_{level} - s\{k\} \leq tank_{level} \ \leq \ max_{level} \tag{3.7}$$

Where, min_{level} is the safety level the tank maintains and max_{level} is the maximum level for the tank before overflow. This will ensure a feasible solution is guaranteed from the controller. It is crucial to always get a feasible solution as the controller will set the control variables (flow setpoints) to zero if no viable solution is guaranteed. Therefore, this term in the cost function will allow us to alter the inequality constraint in the tank levels and further expand the range for the controller to give the optimal solution.

3.4.3 Algorithm Flow

The algorithm of the MPC used to maximize the energy production from PATs can be demonstrated in three separate stages. The first stage includes solving the hydraulics, the second is the selection of the theoretical PAT, and the third is the application of MPC which will be later called Hybrid-MPC. It is also explained in detail in stage 3 in section 3.4.3.3. The following steps are for the first stage.

3.4.3.1 Stage 1 – Hydraulic data of the network

1) The aggregated hydraulic network is imported to the Epanet Matlab toolkit (G. Eliades, et al., 2016) and the hydraulics are solved to obtain the head/flow values of the pressure-reducing valves in the network. Demand aggregation is performed by skeletonization, and a more detailed explanation is given in (Saldarriaga, et al., 2010). To solve the hydraulics, the toolkit needs to set the time duration. For this work, the time duration is set to 96 hours to simulate the network for five days. The reason is to test the controller for a longer time. The hydraulics is solved, and the surplus head and flow are passed on to stage 2 to derive the theoretical PATs.

2) The next step is to obtain data for the approximation technique which uses the interp1 function and Darcy-Weisbach equation for head loss, the friction factor part of the head loss equation attributes to non-linearity. The equation for head loss can be generally defined as:

$$h_i - h_j = k_{ij} {q_{ij}}^n \tag{3.8}$$

k_{ij} is the term containing the variable friction factor, it can be defined as:

$$k_{ij} \;=\; \frac{8*f(re)*L_{ij}}{pi^2*{D_{ij}}^5*g} \qquad (3.9),$$

Where $f(re)$ is the friction factor which depends on Reynolds number (re). In this work, this formula is used to estimate the head loss using the interp1 function from the yalmip toolbox (Lofberg, 2004). The new interp1 function developed in yalmip can overload the usual interp1 function for generating mixed integer-based approximation. i.e., if the previous interp1 function could only construct data patterns in spline, linear or quadratic trends, the new function can construct data for mixed-integer solutions. In this work, since the logic for PAT operating is included in the constraints in the form of binary constraints (this is explained in stage 3 in section 3.4.3.3), the problem to solve becomes a mixed-integer problem. Therefore, the new interp1 function is used to represent head loss constraints in the algorithm.

3.4.3.2 Stage 2 – PAT curve selection and operating points

This stage consists of three main functions to determine the optimal PATs and the theoretical curves of head/flow and power operational limits.

1) The first function is to determine the best efficiency point (flow and head) to construct the curve to get the theoretical pump as a turbine for the specific location. The results of (Mitrovic, et al., 2020) show that the best efficiency flow and the head are close to the average point at the PRV site. The optimal BEPs for power maximization correspond to 92% of the average operating flow ($Qavg$) at the site and 85% for the site's average operating head ($Havg$). Therefore, the following equations are used.

$$\frac{Qbep}{Qavg} = 0.95 \qquad (3.10),$$

$$\frac{Hbep}{Havg} = 0.85 \qquad (3.11),$$

Before the second function, three rotational speeds are used to get the suitable one for the flow/head available in this network. 1005,1510 and 3020 rpm are the three rotational speeds used because centrifugal pumps or pumps as turbines are usually coupled with asynchronous electric generators with magnetic pole pairs or either 3, 2, or 1 (Mitrovic, et al., 2020). Referring to the methodology in (Mitrovic, et al., 2020) and Fig 3.10, out of the three, 1005 rpm is chosen as the one suitable for this network. As the surplus does not exceed 30 m and the flow has a big range. Refer to Fig 3.4. for justification for the choice.

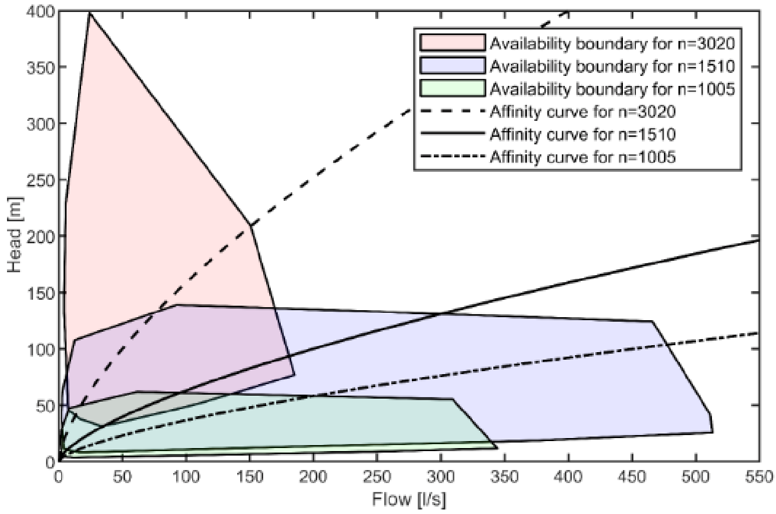


Fig 3.10. Boundaries of available PATs in the market adapted from (Mitrovic, et al., 2020)

2) Once the rotational speed is decided, the second function is used to determine the specific speed based on the best efficiency flow and the rotational speed of 1005 rpm.

$$N_s = n \frac{Q_{BEP}^{0.5}}{H_{BEP}^{0.75}} \quad (3.12),$$

3) The second function also determines the polynomial for the extrapolation of the head loss and power curves based on the design variables given by (Novara & Mc Nabola, 2018).

$$\frac{H_i^{PAT}}{H_{BEP}} = a\left(\frac{Q_i^{PAT}}{Q_{BEP}}\right)^2 + b\left(\frac{Q_i^{PAT}}{Q_{BEP}}\right) + c \quad (3.13),$$

The coefficients are as such, $a = 1.160$, $b = 0.0099N_S + 1.2573 - 2a$ and $c = 1 - a - b$, and

$$\frac{P_i^{PAT}}{P_{BEP}} = d\left(\frac{Q_i^{PAT}}{Q_{BEP}}\right)^2 + e\left(\frac{Q_i^{PAT}}{Q_{BEP}}\right) + f \quad (3.14),$$

The coefficients are such, $d = 1.248$, $e = 0.0108N_S + 2.2243 - 2d$ and $f = 1 - d - e$. The power at BEP was calculated as $P_{BEP} = \rho g Q_{BEP} H_{BEP} \eta_{max}$ where η_{max} is found using an equation defined by (Novara, et al., 2017)

$$\eta_{max} = 0.89 - \frac{0.024}{Q_{BEP}^{0.41}} - 0.076 \left(0.22 + ln \frac{N_S}{52.933}\right)^2 \qquad (3.15),$$

4) The third function is to get the optimal PAT which will produce the maximum power. Before getting the optimal PAT, the operational limits need to be derived. To get maximum and minimum flows the methodology proposed in (Mitrovic, et al., 2020) is used. And that suggests getting maximum and minimum flow by using the relative mechanical power produced by the pump as a turbine instead of relative flow. Therefore, for minimum flow, relative power limits of $P_{rel}\left(Q_{min}^{PAT}\right) = [0.25, 0.375,0.5]$ are used and $P_{rel}(Q_{max}^{PAT}) = [1,1.5,2]$ for the maximum flow in the upper limits.

   For all three lower and upper limits, the minimum and maximum flow values are derived and passed on to the PAT logic function (explained in stage 3 in section 3.4.3.3) along with other inputs. The PAT logic function returns the flow that should be passed in the generation valve and the bypass valve. Additionally, it also returns the head that can be exploited by PAT for power generation, along with the head that needs to be reduced by the PRVs in each branch. Finally, to get the suitable PAT for the control algorithm, the data from EPANET is used. This has the information on the surplus head and flows available at each PRV site. Therefore, using that and power curves the theoretical PAT which produces the maximum power is derived. At the last stage, the operational limits of PAT which produces the maximum power are passed on and MPC derives the flow setpoints based on a prediction model that is used to mimic the whole network keeping all the constraints and the objectives satisfied.

3.4.3.3 Stage 3 – MPC prerequisites

Stage three is summarised in four parts; the first part is gathering all the prerequisites for the controller and the next part is setting the feasible region for the controller to work which is also known as the constraints in the system and application of control. The third part reveals how MPC becomes Hybrid-MPC, and the final part shows how the approximation of head loss constraints is formulated in the algorithm.

1) As the first step in this stage, the matrices to define the network are derived by using the modeling techniques as explained in section 2.3.2.1 of this thesis.

2) The time step is selected as t = 3600s for the first set of results which are hourly simulations. The time step of one hour is selected as the dynamics in drinking water networks change every hour.

3) The next step is defining the control design parameters, for example, the prediction horizon is selected as 36 hours, which is the number of future control intervals the controller must calculate by prediction when optimizing the manipulated variables at any control interval *k*. The higher the prediction horizon the more the cost of computational load, whereas a lower prediction horizon may be inefficient to predict the behavior of the system and may make the controller aggressive (Ramasamy , et al., 2019).

   Another important step is to set the values of the weights used on the objective function. MPC is multi-objective optimization in nature, and its cost function consists of an aggregation of various performance metrics for example squared tracking error or change in manipulation. Since these metrics are related to each other, the minimization of all the metrics at the same time is infeasible. To avoid this problem weights are introduced (Aldaouab, et al., 2019). Accurate tuning of these weights can provide a reliable feasible solution. Additionally, the weights can be set according to the priority of the objectives, for example, a value of 0.05 represents a low priority on the objective, which allows a large tracking error. Whereas a value of 20 represents a high priority and a small tracking error is required (Mathworks, n.d.). For this work, the weights on the flow objective are set between 1 and 10. Where 1 represents the default value and 10 represents high priority. The weights switch among the flow objectives to find a feasible solution. Furthermore, the weights on the term with the slack variable are set to 0.01 which is a low priority

3.4.3.4 Stage 3 - MPC constraints and how MPC becomes Hybrid-MPC

1) Equality constraints –

   - The system dynamics are set as equality constraints as explained in equation (2.11) in section 2.4.2.2
   - The mass balance constraints are also another set of equality constraints as explained in the example below. Fig 3.11. shows how to write a mass balance equation at a particular location.

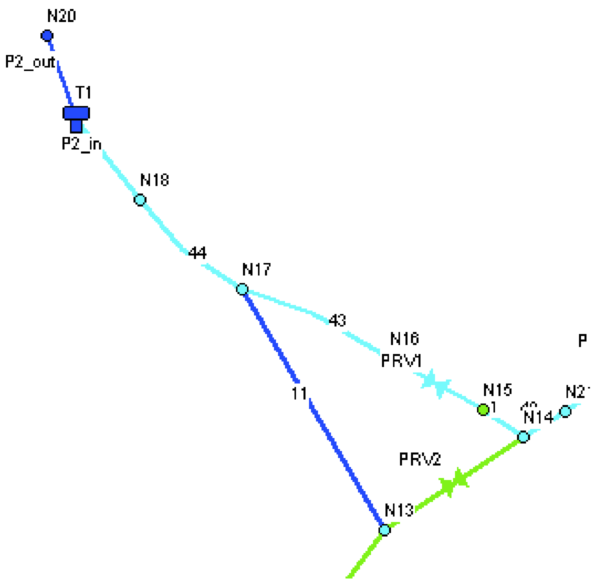


Fig 3.11. Part of the case study of the Ballacolla network

From the diagram at node N14, all the flow coming into that node is equal to the flow consumed and leaving that node, therefore, at the N14 node if the flow from N14 to N15 is denoted as q1 and the flow from N14 to N21 is denoted as q2, also if flow across the PRV2 is split between flow through generation line (q_{pat}) and bypass line (q_{bypass}) as in HR scheme and water consumed at that node is d14;

$$q_{pat} + q_{bypass} = q1 + q2 + d14 \qquad (3.16),$$

2) One set of inequality constraints is the state constraints which are the level of the tanks. The maximum and minimum levels are obtained from Epanet by simulating the network in a steady state for 7 days. Tanks 1, 2, and 3 all have a minimum level of 1m and a maximum level of 15m. Additionally, each tank has a diameter of 12 m. This value was derived after performing a trial-and-error exercise shown in the appendix of this thesis.

3) The other set of inequality constraints is on the manipulated variables (flow in the valves) in the algorithm which is the flow across the PAT and the bypass.

$$q_{min} \leq q_{pat}\{k\} \leq q_{max} \qquad (3.17),$$

$$q_{min} \leq q_{bypass}\{k\} \leq q_{max} \qquad (3.18),$$

Where, q_{min} and q_{max} are the minimum flow and maximum flow in the PRV locations. The minimum flow is zero which means the valves are closed. The maximum flow across the generation valve in which the PAT is located is the maximum allowable flow value as mentioned in section 3.4.1. The maximum flow for the bypass valve is chosen from Epanet as the maximum flow across the PRV at that location in the network.

3.4.3.5 Stage 3 - Hybrid MPC logical constraints

4) The other set of constraints is the binary/logical constraints which make up the term "Hybrid". The binary constraints are used to control the flow in each line in the HR scheme. This can be also called MLD (Mixed Logical dynamical) MPC. The binary constraints are defined below considering the scenarios of the HR scheme. Fig 3.13. shows the operational limits of Pump As Turbines and the flow/head points in the network for one theoretical PAT proposed to be installed in the HR scheme as shown in Fig 3.12. The PAT curve was chosen after analysis in section 3.4.3.2.

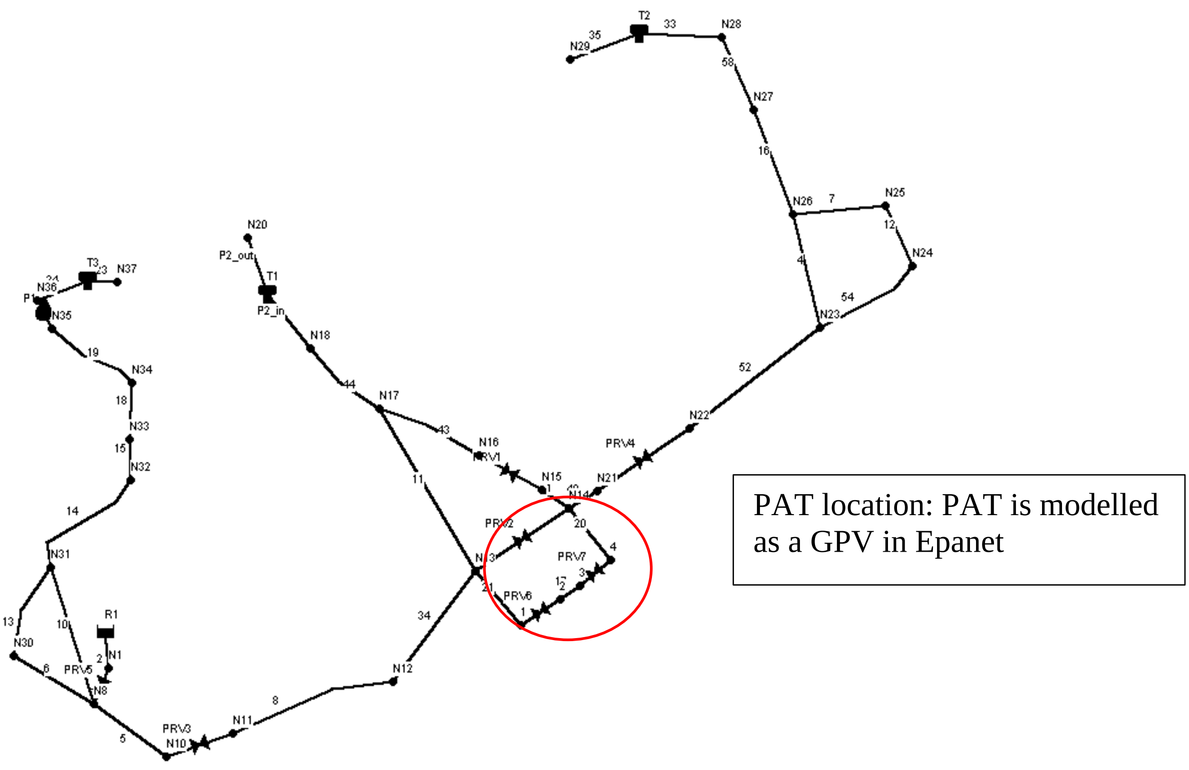


Fig 3.12. Ballacolla modified network with PAT installation

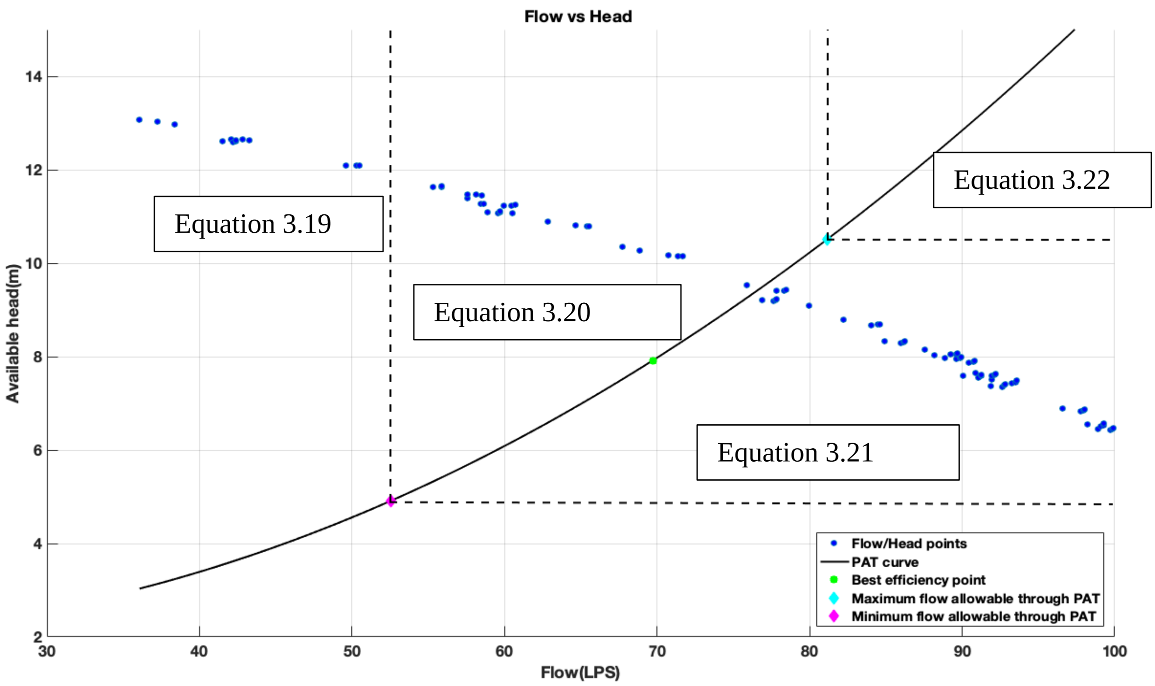


Fig 3.13. Head/Flow points with PAT curve and limits

The control variables in the algorithm are the flow setpoints derived using Hybrid MPC. Hybrid MPC (HMPC) is derived after the dynamical model defined in equation (2.13) in section 2.3.2.2 employs binary control variables or logic states. The water network model becomes known as the hybrid dynamical model. As the objective is a linear objective, the hybrid dynamical model is piecewise linear, and the problem can solve using a mixed-integer linear solver. The framework used in the modeling of HMPC is called Mixed logical dynamical systems (MLD), in this framework, both linear dynamical systems (water network model) and logical variables (logic constraints) are included. For example, if the controller gives zero flow for the bypass as the total flow is favorable for power generation, then the dynamical model in equation (2.13) in section 2.3.3.2 accommodates the change for the binary variable.

The flow across each line can be seen in the configuration as previously shown in Fig 2.22, an HR scheme. The configuration is composed of the PAT and a control valve in series and the bypass line which has a control valve in parallel. The scenarios for the PAT operation are defined below and these are incorporated into the dynamical model of the water network.

Scenario 1: In the case where the total flow is less than the minimum flow for power generation or the head is less than the minimum head for power generation, then the generation line is closed and the bypass is opened. This prevents the potential operation of the generator as a motor. The control valve in the bypass line reduces the excess head.

$$Q_t < Q_{\min}^{PAT} \; or \; < H_{min}^{PAT} \qquad (3.19),$$

Scenario 2: In the case where the total flow is between the minimum and maximum flow for power generation, and the total head is greater than the head of the PAT curve, the bypass is closed, and the total flow goes through the generation line for maximum power production.

$$Q_{min}^{PAT} \leq Q_t < Q_{max}^{PAT} \; and \; H_i \geq H^{PAT}(Q_t) \qquad (3.20),$$

Scenario 3: The case where the total head is between the minimum and maximum head for power generation, and the total flow is greater than the PAT flow corresponding to the curve. Then part of the flow is bypassed, and the exact flow should be passed through the PAT to further maximize the energy recovery which corresponds to the flow from the PAT curve.

$$H_{min}^{PAT} \leq H_t < H_{max}^{PAT} \; and \; Q_i > Q^{PAT}(H_t) \qquad (3.21),$$

Scenario 4: The case where the total flow is greater than the maximum permissible flow for power generation and the total head is greater than the maximum head for power generation. The bypass is active allowing all the flow greater than the maximum flow and the rest is passed through the generation line for maximum power generation. Both control valves are active to regulate the excess head. The PAT curve shown in Fig 3.13 does not have points in this region, but it is defined for the rest of the PATs.

$$Q_t \geq Q_{max}^{PAT} \; and \; H_t \geq H_{max}^{PAT} \qquad (3.22),$$

3.4.3.6 Stage 3 - Hybrid MPC head loss constraints

5) The constraints explained below are the approximation of non-linear head loss equations, this also includes the available head approximation of pressure-reducing valves. An adjacency matrix of a weighted directed graph is used to model the relationship between nodes and links (in this work the direction of flow is considered). Fig 3.14 shows the transformation from a network to a matrix representation.

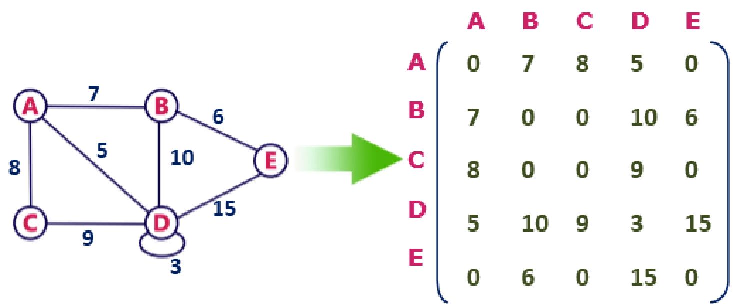


Fig 3.14. Adjacency matrix with weights in links adapted from (Jaiswal, 2011)

The weights of the links are represented by the head loss equation by

$$h_i - h_j = k_{ij}{q_{ij}}^n \qquad (3.23),$$

Where n = 2 as the Darcy-Weisbach equation is used. Additionally, to obtain the value of the head loss, the flow chart below is incorporated into the algorithm. See Fig 3.15 for reference

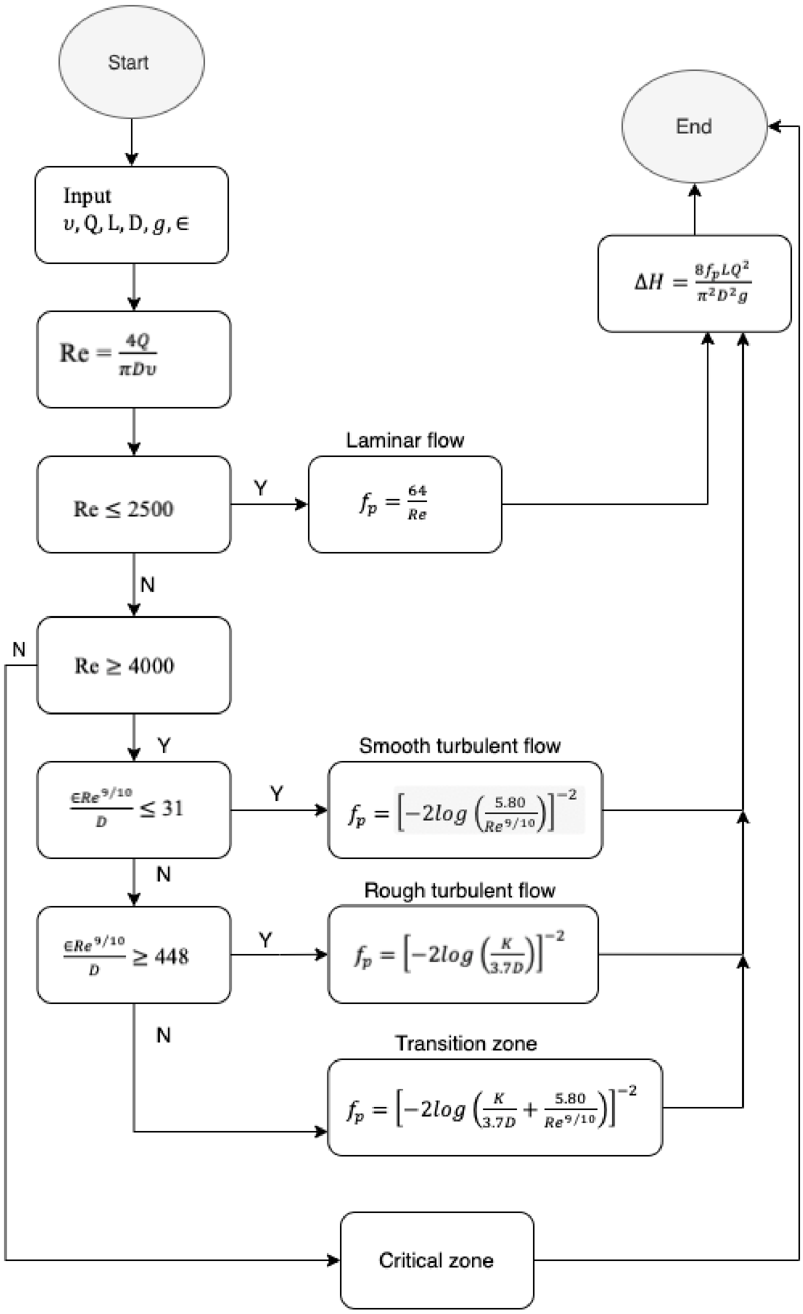


Fig 3.15. Head loss calculation adopted from (Diniz & Souza, 2009)

Where the inputs are as follows, υ is the viscosity of water, Q and L are the flow and pipe length. D and $\in$ are the pipe diameter and roughness. Depending on the flow and Reynolds number the friction factor is determined, and head loss is calculated at the last step. Moreover, to illustrate the head loss approximation, an example of a small water network is shown below (see Fig 3.16.).

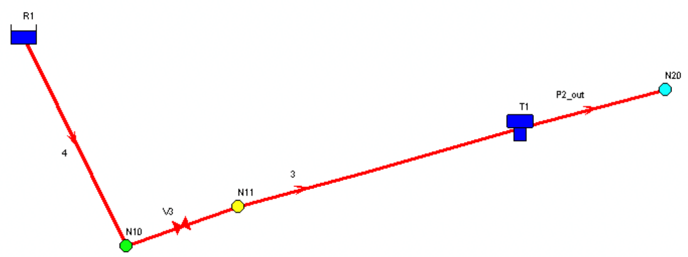


Fig 3.16. A small water network for illustration purposes

The directed adjacency matrix for this network is as follows:

$$\begin{array}{c} \\ R1 \\ N10 \\ N11 \\ T1 \\ N20 \end{array} \begin{array}{c} \begin{array}{ccccc} R1 & N10 & N11 & T1 & N20 \end{array} \\ \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array} = \begin{array}{c} k_4 * {Q_4}^2 \\ k_{v3} * {Q_{v3}}^2 \\ k_3 * {Q_3}^2 \\ k_1 * {Q_{p2\_out}}^2 \\ 0 \end{array} \qquad (3.24),$$

Since N20 is not connected to another node, that row can be ignored in the calculation. The next step is to write all the non-manipulated flows in terms of manipulated flows and demands. For this demonstration, only the first row in the matrix is considered for the sake of brevity.

$$k_4 * {Q_4}^2 \text{ --- row 1} \qquad (3.25),$$

Q_4 can be written using mass balance equations as:

$Q_4 = Q_{v3} + D_{10}$, where D_{10} is the demand of N10 therefore equation (3.25) becomes:

$$k_4 * (Q_{v3} + D_{10})^{\,2} \tag{3.26}$$

$Q_{v3} + D_{10}$ are the manipulated variables that are used in the hybrid MPC problem and demand which is considered a disturbance. The next step is for approximation since the equation (3.26) is non-linear, a piecewise affine function representation as its also non-differentiable. *Interp1* function in yalmip is used with the flag as “mixed-integer-linear-programming”. Therefore, the constraint becomes:

$$\min(H_u - H_d) \leq interp1\left(Q_4, k_4 * {Q_4}^2, (Q_{v3} + D_{10})\right), 'milp') \leq \max(H_u - H_d)$$
(3.27),

This is written for each row in the adjacency matrix and included in the constraints space in the control algorithm.

4 Validation

Validation for the head loss constraints between the approximation method with interp1 function in yalmip and the actual head loss function using the Darcy-Weisbach formula. The section below shows the validation areas in the network. The network is given below for reference, see Fig 4.1.

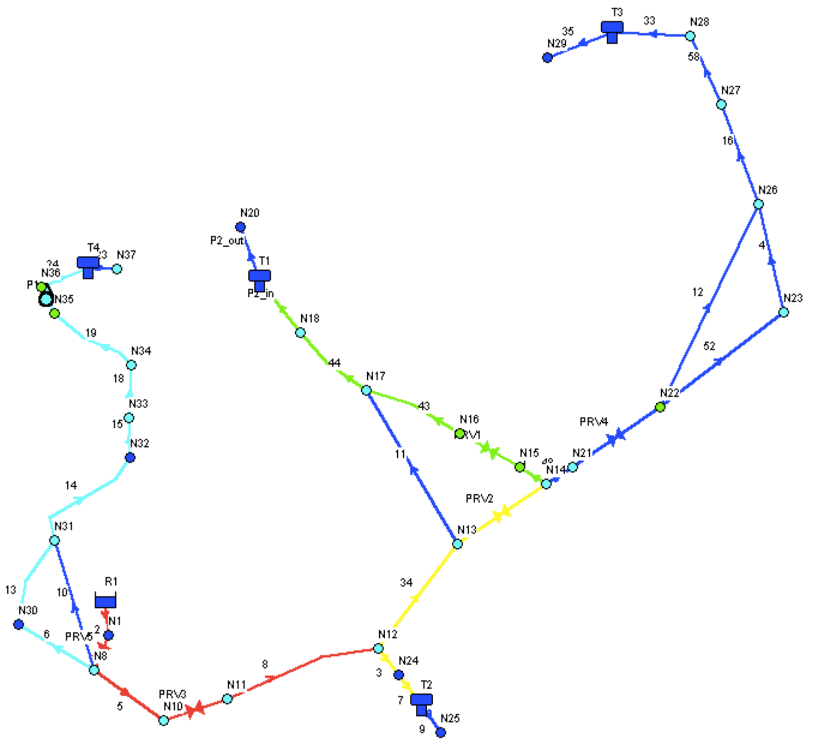


Fig 4.1. Ballacolla network

Validation has been performed for three branches:

1) **Validation 1**: From the downstream node, N16 to N17 in pipe 43 (this is the branch where the PAT1 will be installed closer to T1 (Tank 1)
2) **Validation 2**: From the downstream node, N11 to N12 in pipe 8 (this is the pipeline that branches out to pipe 3 and pipe 34 at Node N12
3) **Validation 3**: From downstream node, N26 to N27 in the pipe 16

These validations are selected at random from the network. It also works for all other pipes other than the ones validated.

Validation 1: Head loss predicted by the approximation technique should be equal to the head loss between N16-N17 using the original Darcy-Weisbach formula. Therefore, the following steps are performed to compare the two. For the first step, the head loss is estimated using the interp1 function individually between N16-N17. The flow between the pipes is derived from mass balance equations and the head loss is finally estimated from the interp1 function. After the flow is derived, the Darcy-Weisbach formula is used to predict the actual head loss. Both trends are then plotted to see if there is any visible error. Fig 4.2 shows the head loss approximated and the actual head loss followed by Fig 4.3 showing the actual error between the two trends and the mean error, also suggests how to make it more accurate.

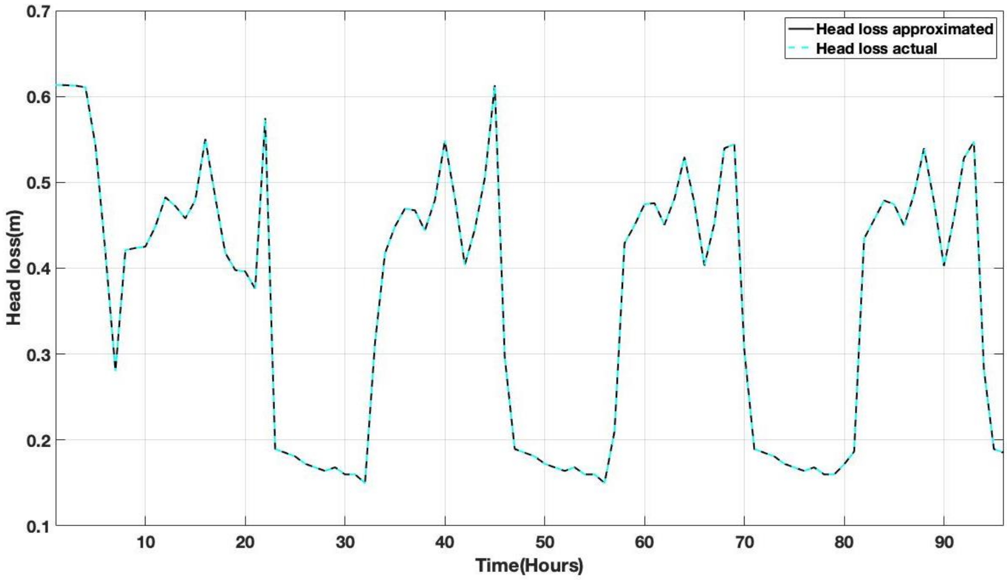


Fig 4.2. Head loss comparison in pipe 43

To demonstrate the accuracy, the flag in equation 3.27 is changed. Spline is the flag that is set initially, and Fig 4.3 shows the results. Spline is a function that is defined in a piecewise nature by polynomials. For accuracy is it often advised to use spline as it generates similar results as compared with the original function (Pelinovsky, n.d.). For comparison purposes, the flag is now set as “linear” (head loss is approximated as a linear function) and Fig 4.4 shows the results.

Mean error is calculated as: 2.25e-15 m ~ 0 m

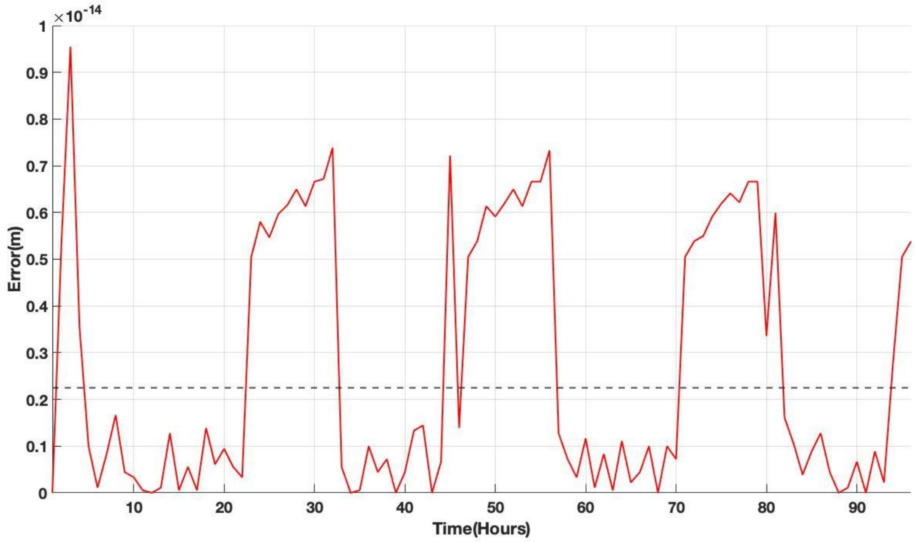


Fig 4.3. The error between the two trends using the flag spline

Mean error is calculated as: 2.60e-07 fluctuating around the mean

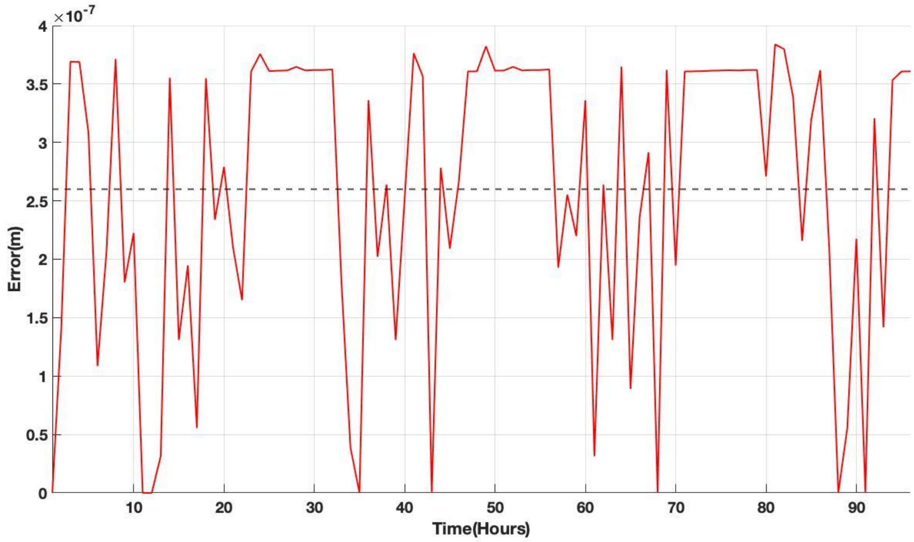


Fig 4.4. The error between the two trends using the flag linear

The mean error calculated in Fig 4.3 is approximately zero whereas, the mean error calculated using the “linear” flag is 2.6e-07 and the error in head loss is seen fluctuating around the mean error. Therefore, using spline has proven to yield a more accurate representation of the original formula. It is also proven in the next validations.

Validation 2: Like the first validation, the second one is performed. The head loss in pipe 8 between node N11 and N12 (from Fig 4.1) is validated by comparing the head loss approximated using the interp1 function and the actual head loss calculated using the Darcy-Weisbach formula. The results are given in Fig 4.5

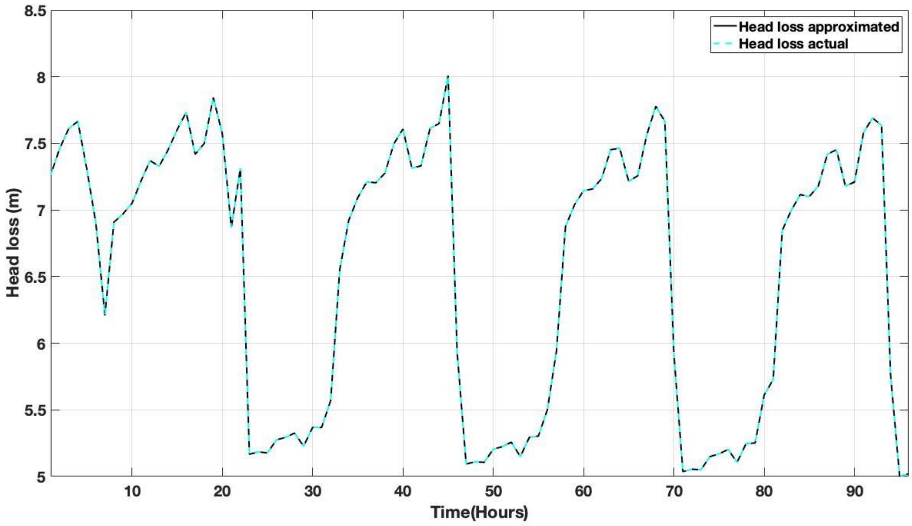


Fig 4.5. Head loss comparison in pipe 8

The mean error is calculated as: 1.11e-16 ~ 0 m

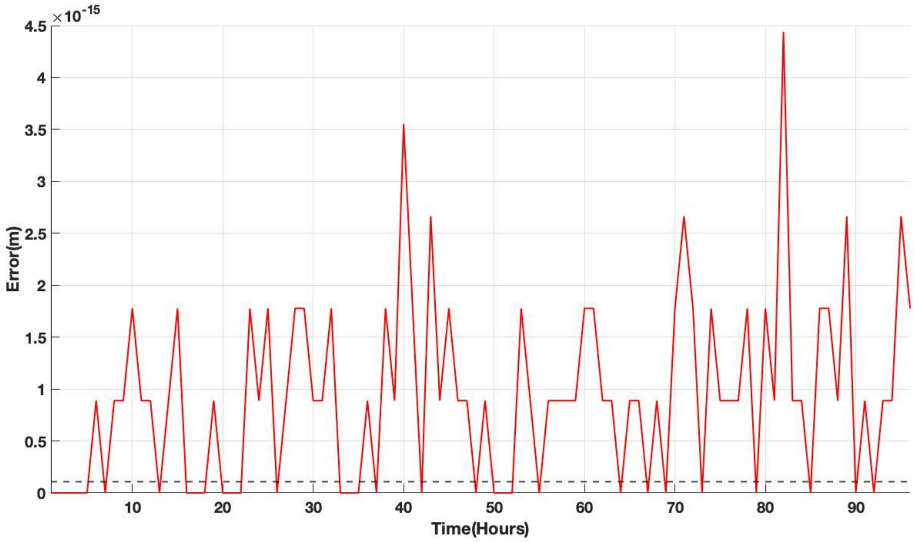


Fig 4.6. The error between the two trends using the flag spline

The mean error is calculated as 3.42e-7

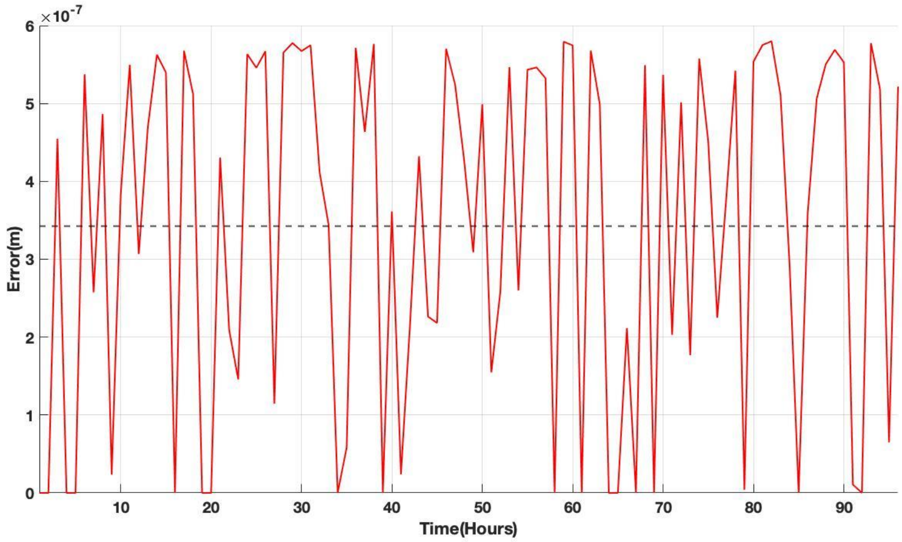


Fig 4.7. The error between the two trends using the flag linear

The mean error calculated in Fig 4.6 is approximately zero whereas, the mean error calculated using the “linear” flag is 3.42e-7 and the error in head loss is seen fluctuating around the mean error

Validation 3: Like the first and second validation, the third one is performed. The head loss in pipe 16 between node N26 and N27 (from Fig 4.1) is validated by comparing the head loss approximated using the interp1 function and the actual head loss calculated using the Darcy-Weisbach formula. The results are given in Fig 4.8

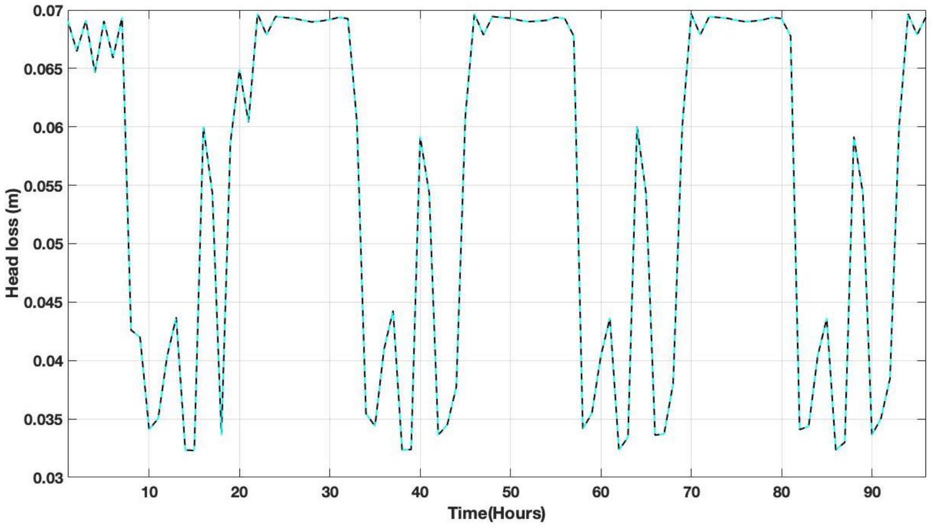


Fig 4.8. Head loss comparison in pipe 16

The mean error is calculated as: 7.43e-15 ~ 0 m

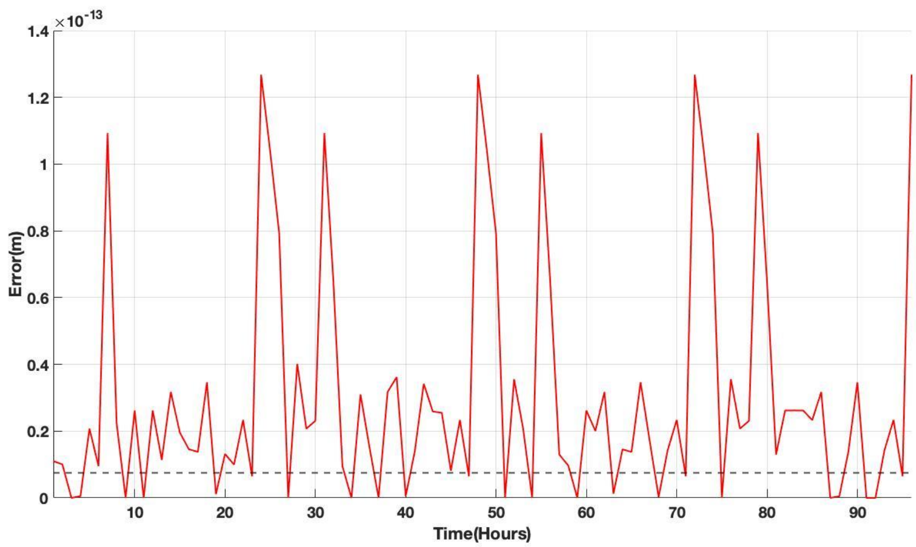


Fig 4.9. The error between the two trends using the flag spline

The mean error is calculated as 1.83e-7

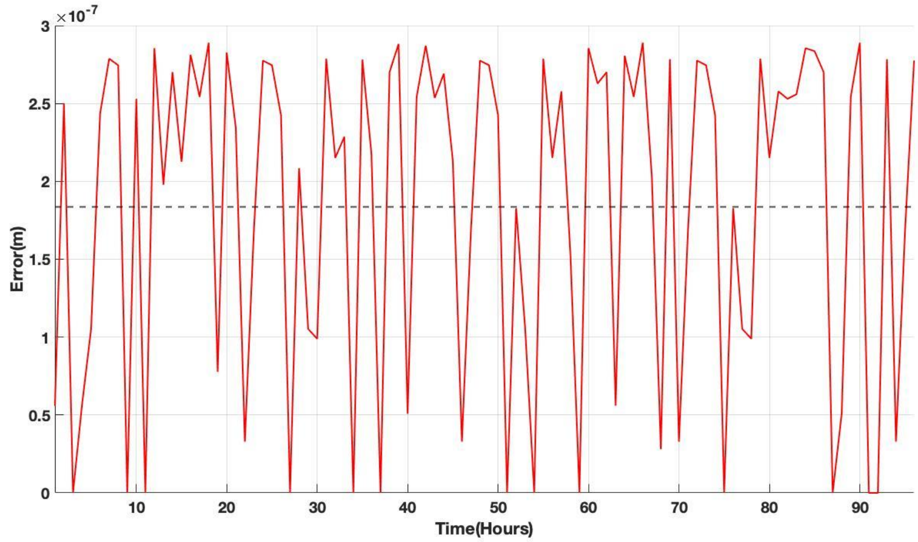


Fig 4.10. The error between the two trends using the flag linear

The mean error calculated in Fig 4.9 is approximately zero whereas, the mean error calculated using the "linear" flag is 1.83e-7 and the error in head loss is seen fluctuating around the mean error.

A similar pattern is seen for comparisons in the trends using two different flags in the equation (3.27) with validation 1,2,3. Therefore using a spline flag has proven to be more accurate than the linear flag. It was also tested for linear type flag as yalmip does not support quadratic or cubic representation. The validation of the interp1 function is proven to be accurate using the spline flag and it can be used as an alternative for linearisation. Linearisation usually is time-consuming as an operating point needs to be derived and it can be only accurate around that operating point. The difference between this method and linearisation is, that the full non-linear function is considered making it a more accurate representation of the head loss constraints.

5 Results

A case study of 29 nodes and 29 links is used to apply power maximization through flow optimization using Hybrid-MPC. This is a gravity-fed network with a reservoir at 160 m a.s.l. Initially, this network is tested in Epanet (Hydraulic simulator) to ensure the network adheres to basic principles in hydraulics. Next, the network is exported to MATLAB and the methodology is applied. Four theoretical PATs are installed at the location of the existing PRVs. The methodology proposed in this work is applied to the network and the results are plotted for five days. The reason for five days is a random selection, the controller works for any period between 1-10 days. To test if the controller can take on unmeasured disturbance, such as changing demand randomly and adjusting its ability to derive the optimal flow setpoints, the demand is changed in the simulation loop (a random number is generated and added to the demand – The demand patterned used for this work is the ballacolla demand pattern in Fig 3.7 and the d-town demand pattern in Fig 3.8) which means the controller does not know what the demand will be at each time step.

As mentioned in the methodology a hybrid-mpc is used to maximize the power generation through the PATs by deriving the optimal setpoints for the lower-level control layer (this layer performs the physical opening of valves, and it has PIDs giving instructions obtained from the upper layer which has the mpc). This methodology is compared with linear mpc without logic constraints. PAT operation is done after deriving the setpoints in linear mpc. This comparison is done to answer two sub-questions from chapter 1 derived from the research question:

1) Is there an improvement in maximizing the power of all PATs simultaneously between the controllers called hybrid MPC and linear MPC

2) Which controller performs better for it to be suitable for near real-time operation

For the first question, the results of the four PATs are shown below and an explanation is given comparing both controllers.

5.1 Flow results for PAT1

To observe if there is any change in theoretical power generated when comparing the two controllers, linear mpc and hybrid mpc, two figures are shown which plot the flows in the generation line, and bypass line respectively for PAT1. From Figs 5.1 and 5.2 a comparison in the flows is shown along with tank level changes that occur due to the inflow coming from the valve line and outflow flow which has a downstream demand node. The main difference observed between the two is that flow through the hybrid mpc remains between the minimum flow allowable and the maximum flow allowable.

PAT 1 in the location of PRV1

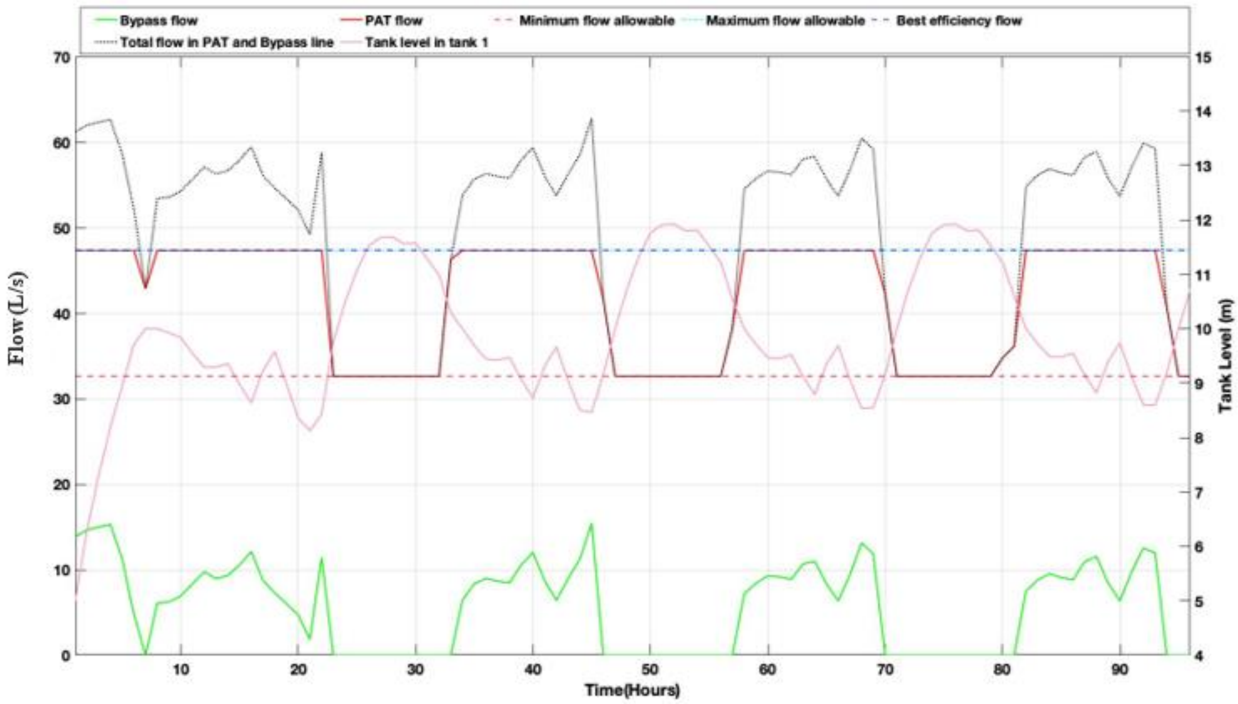


Fig 5.1. Flow in PAT1 and Bypass for Hybrid MPC

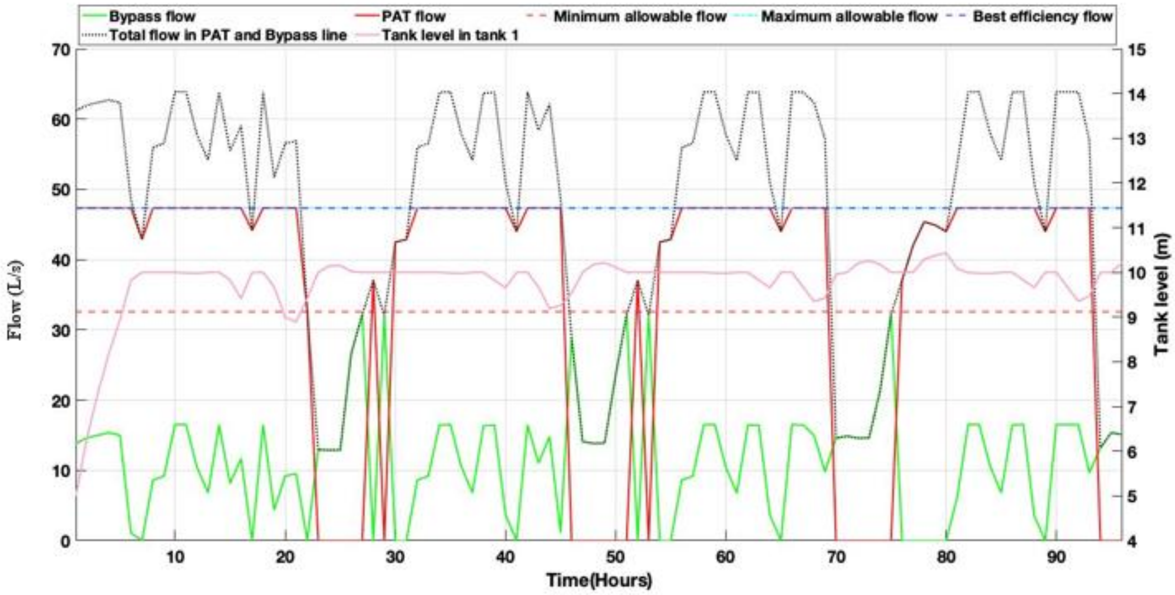


Fig 5.2. Flow in PAT1 and Bypass for Linear MPC

For linear mpc the variation is not limited to that range but from 0 to the maximum flow allowable. This means the bypass is active for most of the time and in linear mpc, the controller cannot derive the optimal setpoints as the PAT operational constraints are outside of the algorithm, therefore the power generated by hybrid mpc overpowers the power generated using linear mpc. Another important observation is that the flow in hybrid MPC is mostly constant for the five days simulation, the bypass flow has large variations to compensate for the constant flow in the PAT (even though it looks constant, there are small variations that are not very visible in Fig 5.1). (Voltz & Grischek, 2019) states for maximizing power generation, it is most suitable if the flow through the PAT is a constant flow and not fluctuating. Therefore, the controller is trying to keep the flow through the PAT constant.

The tank levels are shown in the pink line in Fig 5.1 and 5.2 shows the level changes in tank 1 which is situated downstream of PAT 1. From Fig 5.1, in hybrid mpc, the tank level increases in the first 10 hours because the sum of the flow in bypass and generation line (total flow in the black dotted line) is increasing before it starts to decrease. This makes the tank level peak up to about 10m and soon after the total flow starts to decrease to a downward peak, this makes the tank level start to decrease soon afterward before it starts to fluctuate around 9m. This is partly due to the outflow from the tank as the demand node is also attributed to the changes in the tank level. The same pattern is seen repeating in the next hours up to 96 hours. However, the important thing to note here is that total flow through PAT and bypass is only varying because of the flow in the bypass, it has the same trend. The flow through PAT is more or else constant which is favorable for power generation (Voltz & Grischek, 2019). On the other hand, for linear mpc, the controller predicts the total flow instead of going through the PAT logic to give PAT flow and bypass separately (hybrid MPC). After the controller predicts the total flow, the logic is applied which determines the best operation for the PAT to generate power. The tank level starts to increase as the total flow is high for nearly 5 hours. Soon afterward the tank level starts to become constant as the PAT flow is constant. This is also due to the outflow from the tank serving the demand node downstream of the tank like the inflow (influenced by the total flow in bypass and PAT). Moreover, Fig 5.3 for hybrid MPC below shows the total flow/ available head points (red dots) derived by the controller and the flow/head (black dots) through PAT 1. The logic is seen to be operating correctly inside the predictive model and there are no flow/head points below the minimum flow value (not favorable for power generation). Another interesting discovery is that the maximum flow allowable is also the best efficiency flow through the PAT. This limit was derived after analyzing the average operating points for PRV 1 from EPANET and using the second section in the methodology to obtain the PAT with maximum power generation

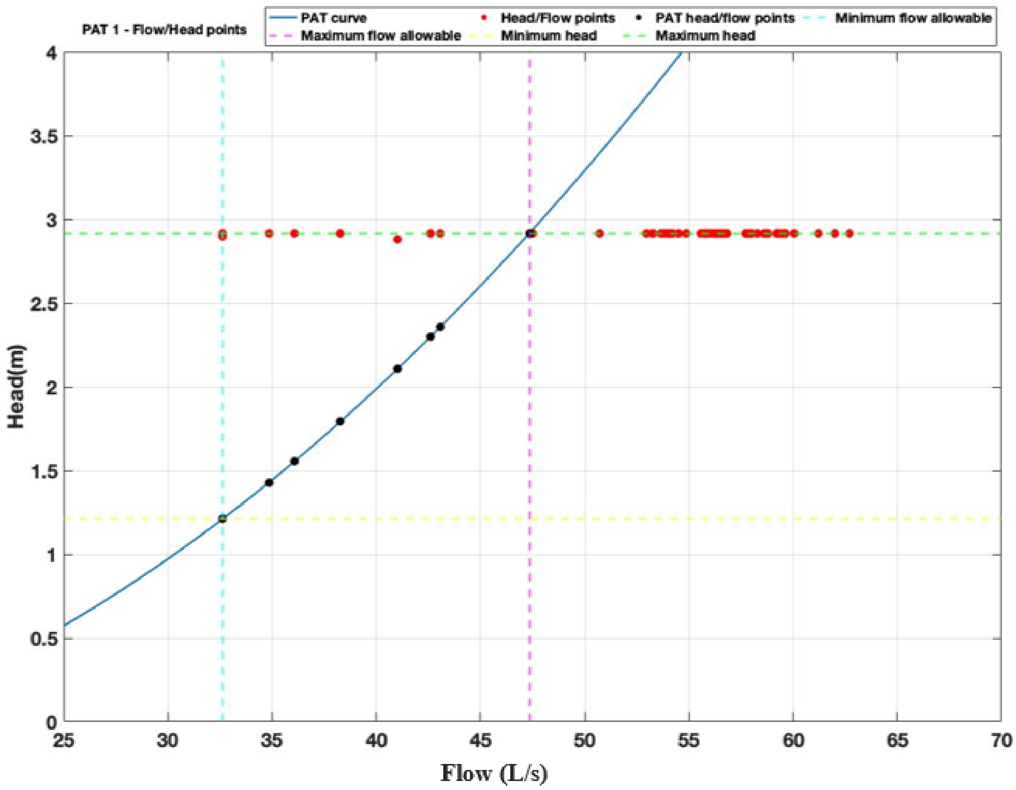


Fig 5.3. Flow-Head points in Hybrid MPC for PAT 1

5.2 Flow results for PAT 2

PAT 2 is located between node N13 and node N14 in Fig 4.1. PAT 2 is not influencing any tank level except the flow through PAT 1 and PAT 4. The objective for generating the optimal setpoints for this has the second priority in the cost function for power maximization term. The priority for power maximization term has different values. The order of priority can be ranked as follows:

High – Low priority: PAT 3 – PAT 2 – PAT 1 – PAT 4

This is due to the way the PRVs are present in the branches. The branch closer to the reservoir has the highest priority and the farthest one has the lowest. If the other way is done, then PAT 3,2,1 will have no improvement in power generation. This theory was tested numerous times and the weights are tuned accordingly.

Fig 5.4 and 5.5 shows the flow through PAT and bypass. Since it does not directly influence the inflow to any tank, no tank levels are shown. The total flow in the hybrid mpc setup becomes equal to the flow through the PAT when the bypass flow becomes zero. Another observation is that the flow through the PAT in hybrid MPC does not fall to zero, this is because since the logic is integrated into the algorithm the controller can decide in advance to prioritize for power maximization. Hence the flow setpoint derived from the controller is the total flow that is passed through the PAT with the bypass being closed. This does not allow for the PAT flow to become zero like in linear mpc. In the linear mpc, the opposite happens, as the controller is unable to prioritize the power maximization as it does not know in advance the logic, which makes the total flow unfavorable for power generation. This theory further confirms the findings of (Voltz & Grischek, 2019) where author says for maximizing power generation, is most suitable if the flow through the PAT is a constant flow and not fluctuating. Additionally, from Fig 5.6, it can be observed that there are some points less than the maximum flow, which explains the fluctuations in the flow in Fig 5.4, also the points where the bypass is closed (left side), total flow is passed through PAT 2 and the PRV in the generation line reduces the head.

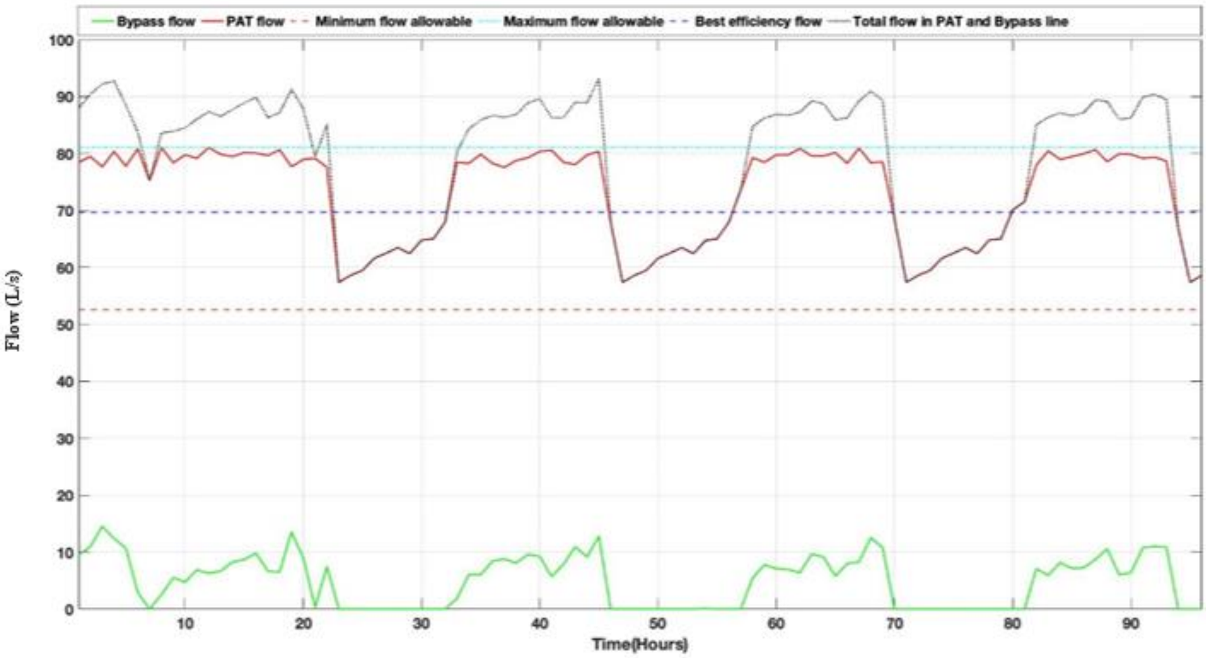


Fig 5.4. Flow in PAT2 and Bypass for Hybrid MPC

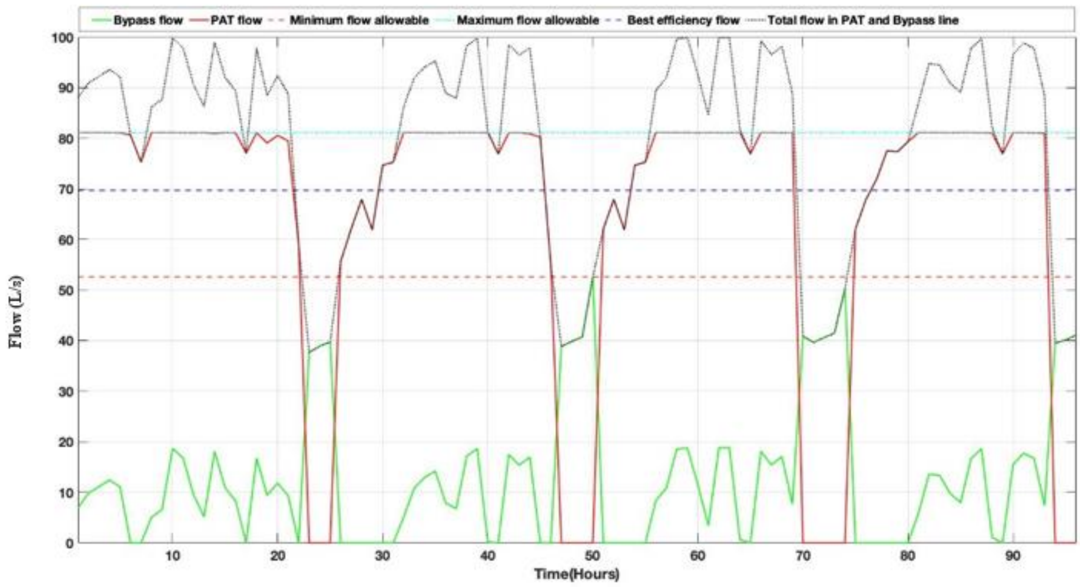


Fig 5.5. Flow in PAT2 and Bypass for Linear MPC

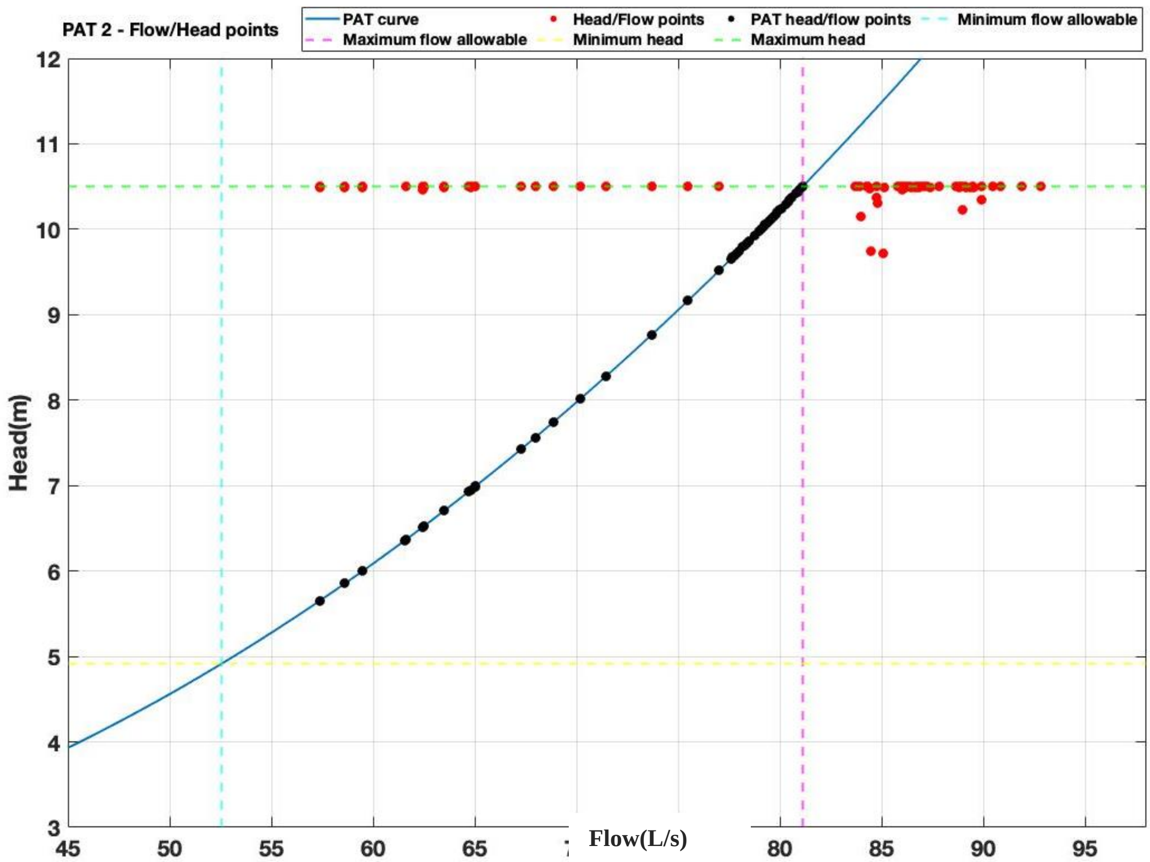


Fig 5.6. Flow-Head points in Hybrid MPC for PAT 2

5.3 Flow results for PAT 3

PAT 3 is located between nodes N10 and N11 (refer to Fig 4.1). PAT 3 is influencing the inflow to tank 2 as it is to be installed in the main branch dividing the pipeline, with one towards the tank and the other towards PAT 2. Therefore, it has the main priority as the flow setpoint derived from the controller will affect the other PATs in the other branches.

From Figs 5.7 and 5.8, the total flow in linear mpc and hybrid mpc has a similar trend with different fluctuations. This part is the reason the tank level stays almost the same. Although it is not very visible there is a slight increase in tank level in hybrid mpc. Nevertheless, it is because the total flow is also slightly higher, which means the inflow to the tank is also higher. It is not very clear but if zoomed in the change is visible. Moreover, the head/flow points in the PAT 3 operation are given in Fig 5.9. From Fig 5.8 it is visible that for one flow head point the logic does not work correctly as planned, it bypasses the flow instead of allowing total flow to pass through the PAT 3. The reason is due to the mixed integer nature of the logic operation. As the quadratic PAT curve (discrete trend) is also approximated using the interp1 function, the controller is unable to derive the flow point right below the curve, so it opts to find the next suitable flow point hence some flow is bypassed in the process.

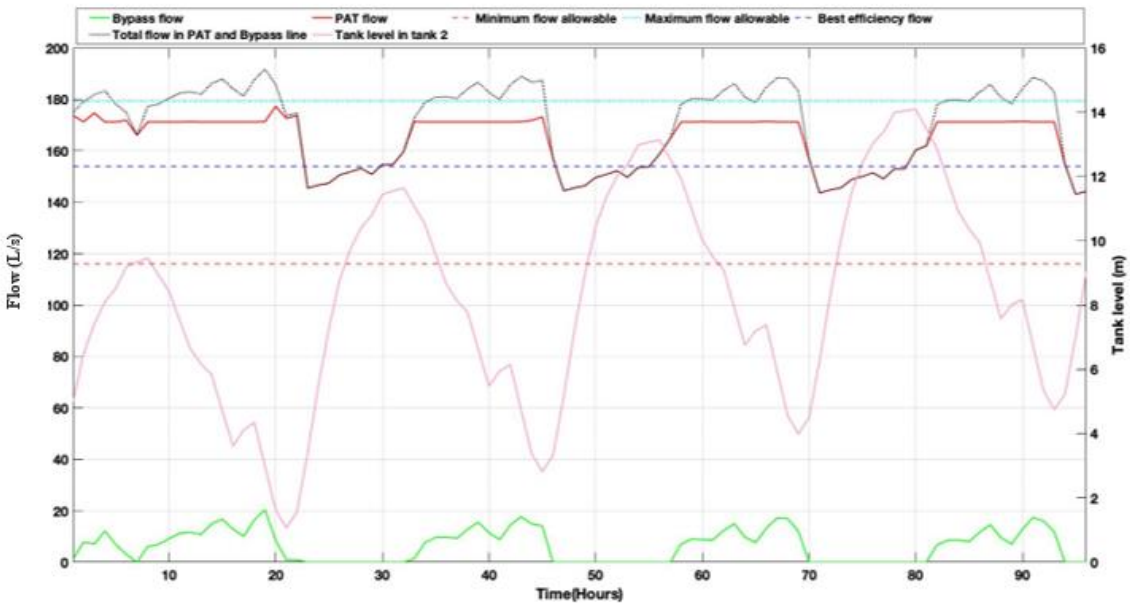


Fig 5.7. Flow in PAT3 and Bypass for Hybrid MPC

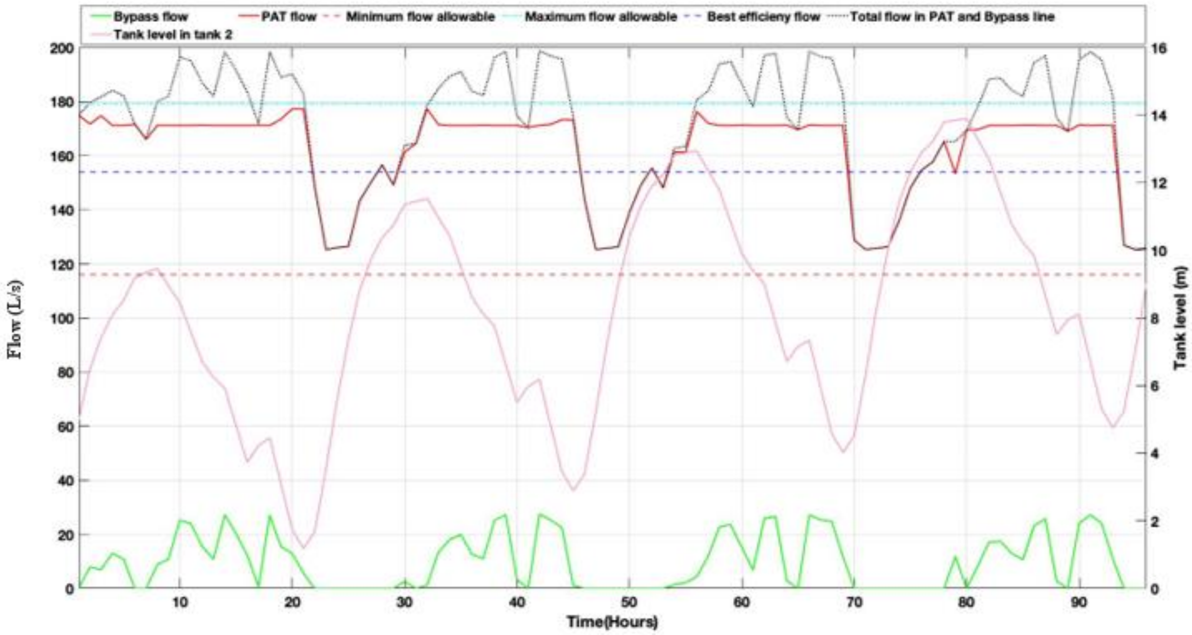


Fig 5.8. Flow in PAT3 and Bypass for Linear MPC

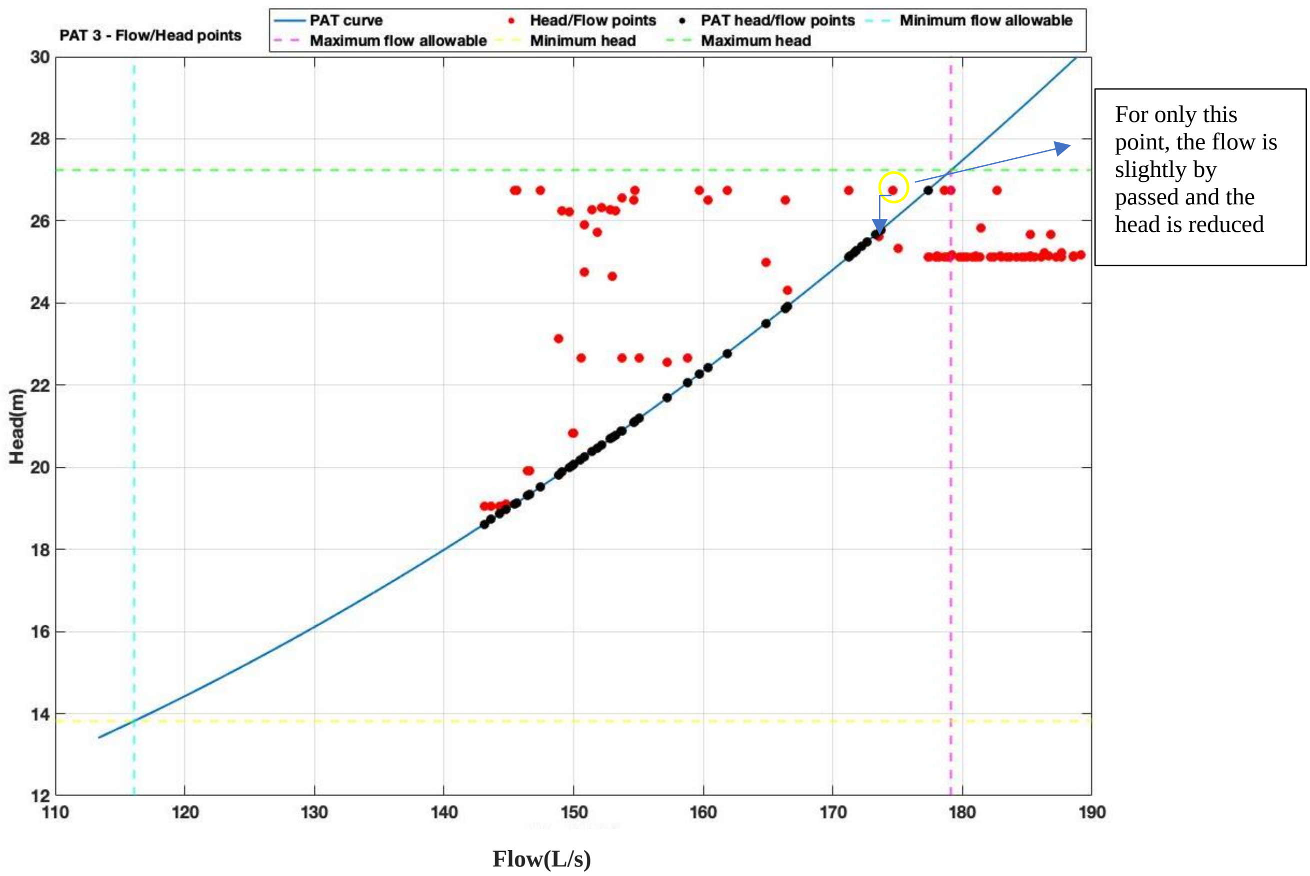


Fig 5.9. Flow-Head points in Hybrid MPC for PAT 3

Additionally, Fig 5.10 below shows a close-up of Fig 5.9 where where the flow is greater than 170 L/s

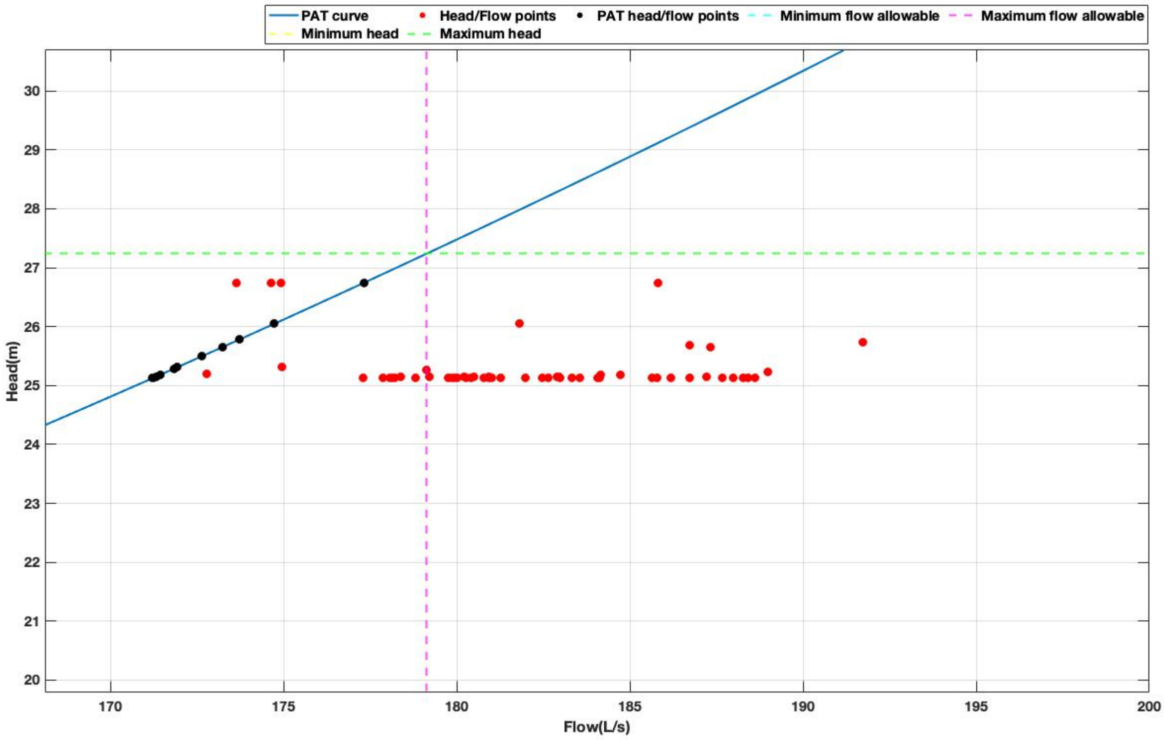


Fig 5.10. Close up of the Flow-Head points in Hybrid MPC for PAT 3

5.4 Flow results for PAT 4

PAT 4 is located between the nodes in N21 and N22 (refer to Fig 4.1). The flow through the Bypass and this PAT is directly influenced by the flow through PAT 2 and PAT 3. Moreover, the inflow to the tank (tank 3) downstream of this tank will also get affected because of this PAT.

From Fig 5.11 and 5.10, it can be observed that the trend in the hybrid mpc flow is similar to the PAT flow in PAT 2 (refer to Fig 5.4). This is because both PATs are to be installed in the same line, therefore this PAT which is called PAT 4 is influenced by the optimal flow through PAT 2 and PAT 3. Therefore, the controller has the least priority for this PAT. If the controller weights are set to be equal for all flow setpoints in PATs, results from it will generate more power, but other constraints will not be satisfied e.g.: tank levels will go beyond the maximum level to cause overflow.

Additionally, from Fig 5.11 and 5.12 for linear mpc, the bypass flow is more than in the hybrid mpc, this is because the total flow, which is the flow in bypass and the flow in PAT is higher for linear mpc. This is the reason for the rise in the tank level trend in the linear mpc. Furthermore, as the trend in PAT flow for hybrid mpc and linear mpc is similar, no improvement in power generation is seen. This will be clearer when observing the power curves for this PAT. Also, from Fig 5.13 most of the flow setpoints are on the right side of the diagram, which means the bypass is switched on. The only times both bypass is closed is for the points toward the left side of the diagram.

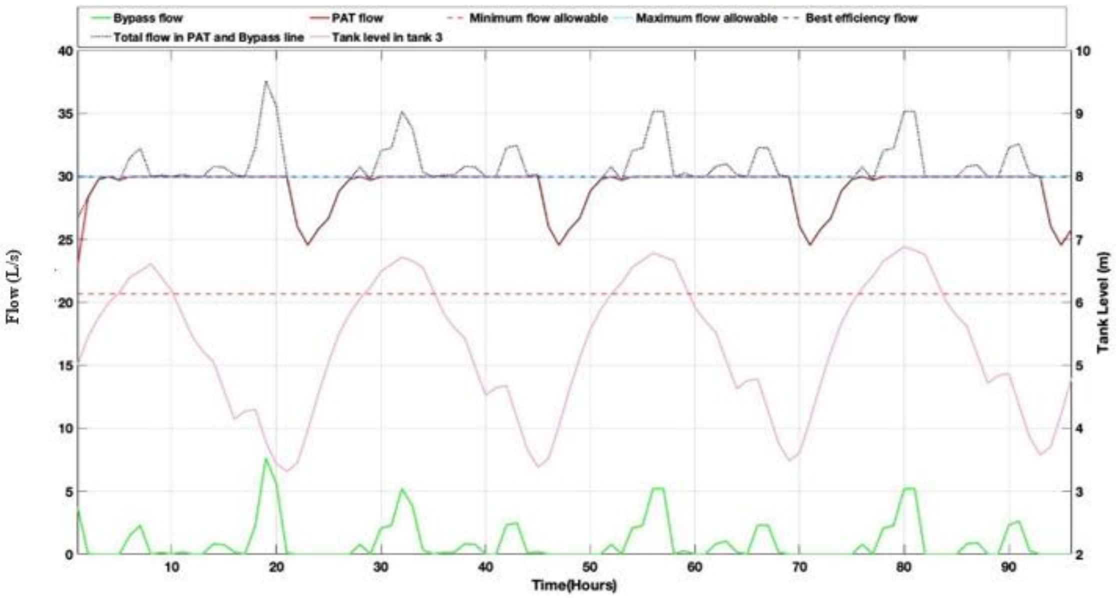


Fig 5.11. Flow in PAT4 and Bypass for Hybrid MPC

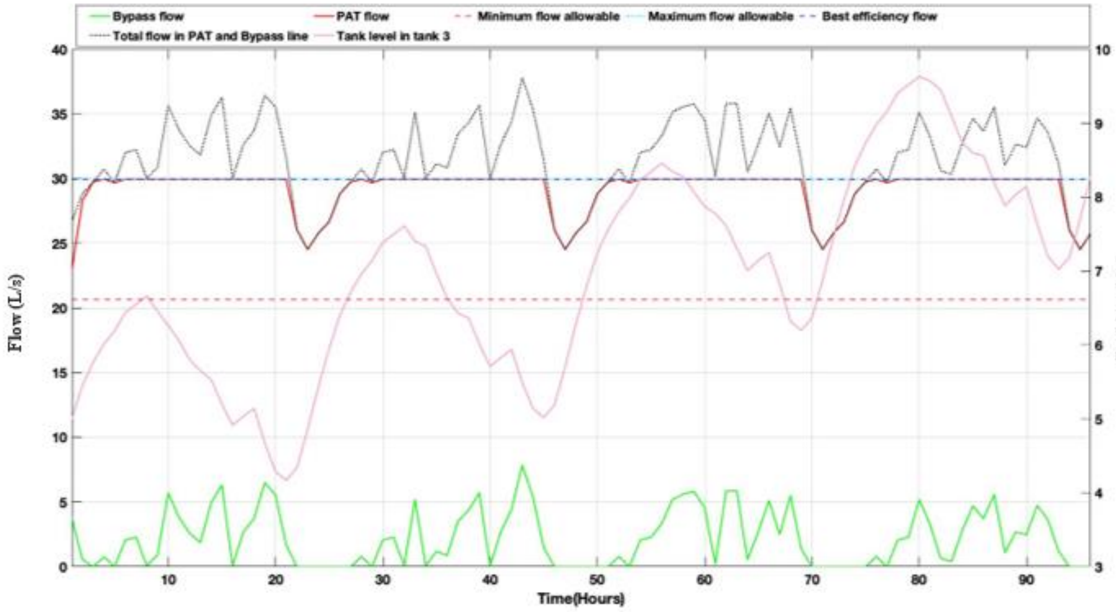


Fig 5.12. Flow in PAT4 and Bypass for Linear MPC

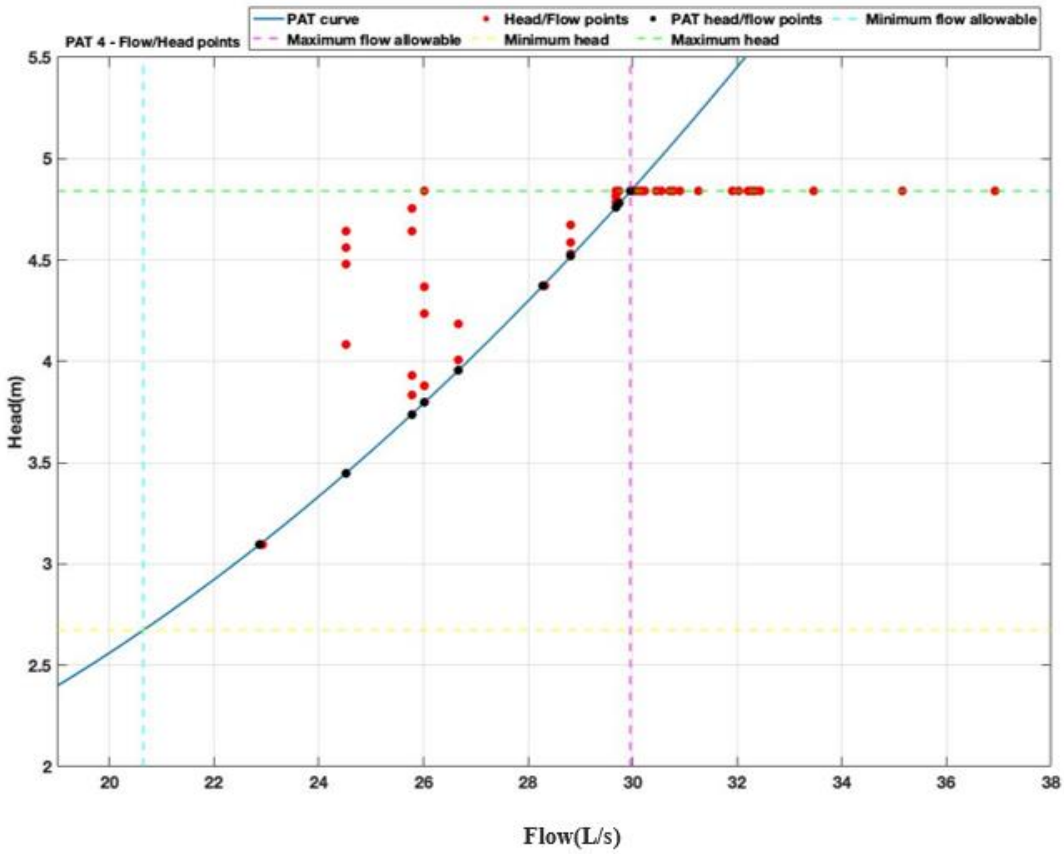


Fig 5.13. Flow-Head points in Hybrid MPC for PAT 4

Moreover, the next sections demonstrate the stability aspect of the controller. As mentioned before the cost function is a multi-objective function and has three terms, (i) maximize power (ii) stability (iii) ensure tank levels are maintained. Therefore, the next section will show how stability changes when that term is omitted in the objective function.

5.4 Stability

For smooth operation of valves, the range of ΔQ (change in flow between one-time steps) is kept between 0 - 50 L/s, this is chosen for a valve with a ranged ability of equal percentage. This is the most chosen range for control valves used in practice. Even though the top layer of control is deriving the setpoints from MPC, the bottom layer (PIDs) is controlling the opening/closing of valves. PID controllers are linear devices and for optimal performance, the process should behave linearly too, but that is not the case in practice. The pressure difference is not always constant, and it is a function of the flow, and it changes with the valve position. Due to this, the inherent flow characteristics are often distorted by the process, and the resulting curve is known as the installed valve characteristic. Therefore, to refine the linearity requirement to reflect the installed valve characteristic, it is advised to use a control valve with an equal percentage of inherent characteristics to obtain a linear installed characteristic (Smuts, 2013).

The below Figs 5.14 - 5.17 are plotted with and without the stability term in the objective function. The changes in the PAT flow are not shown as it is not very visible as the bypass flows. Because of previous sections, it can be concluded that PAT flow does not change frequently, only the bypass flows show a variation in flow. Nevertheless, it is seen that without the stability term, the valves' opening degrees fluctuate higher with time, whereas, with the stability term added, the valves do not change their opening degrees frequently. Therefore, it is safe to conclude that adding the stability term has improved the valve performance thus keeping sudden variations from occurring which in turn will cause an unsteady state in the network. The next section shows if there is any improvement in the power generation between the two controllers, answering a sub-question from the main research question.

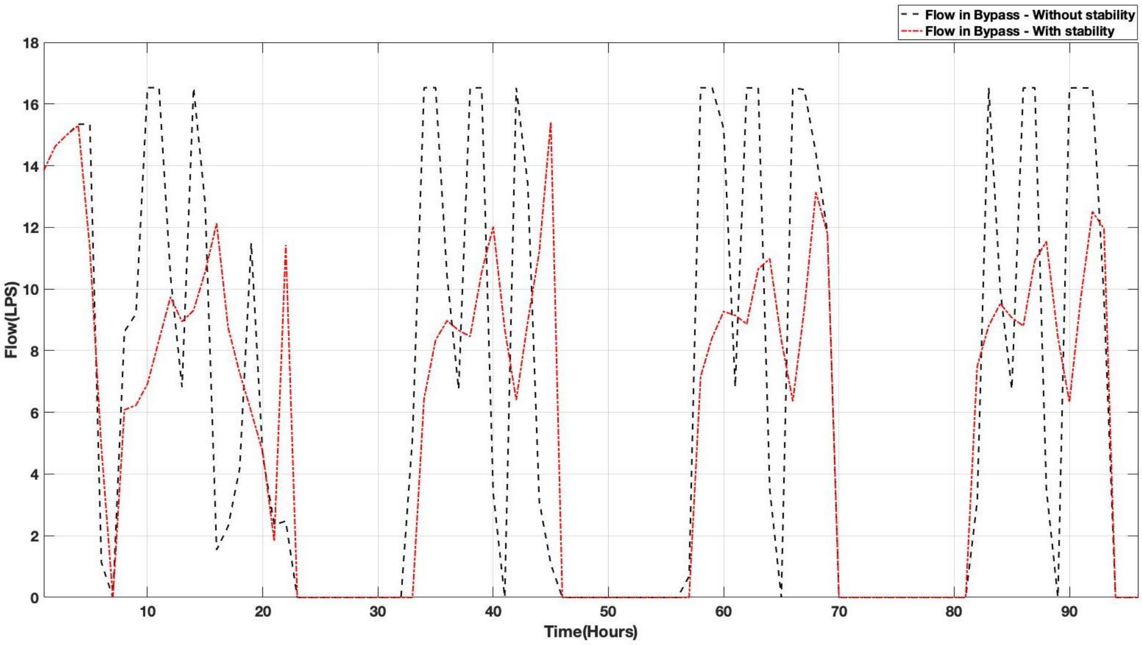


Fig 5.14. With and without stability in the bypass of PAT 1

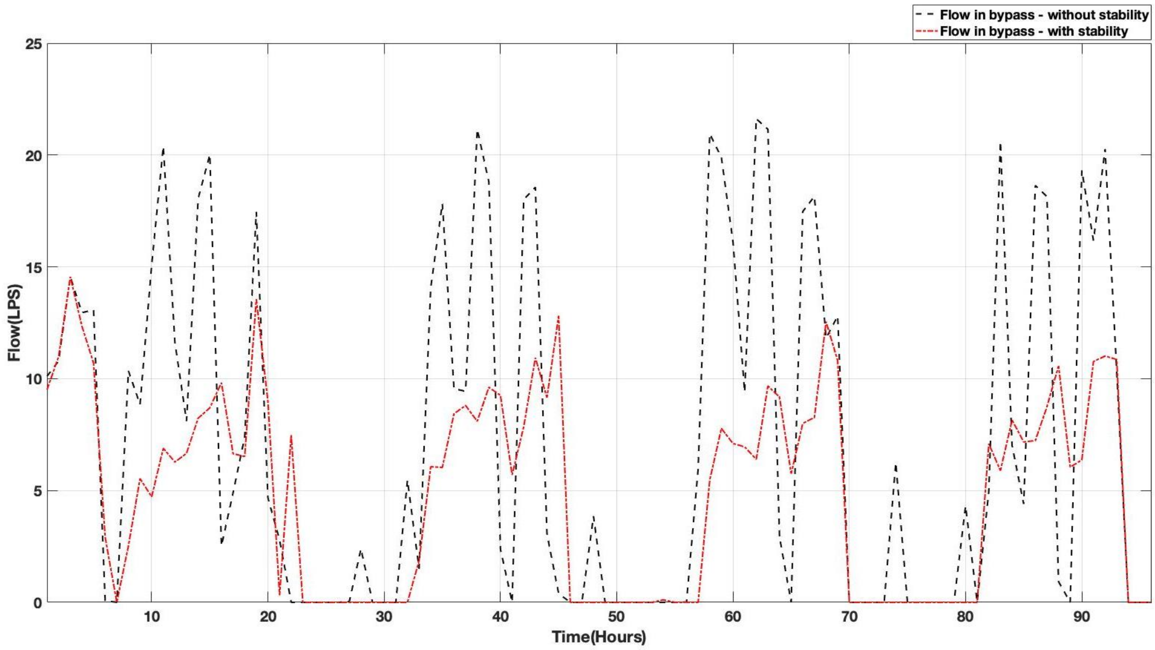


Fig 5.15. With and without stability in the bypass of PAT 2

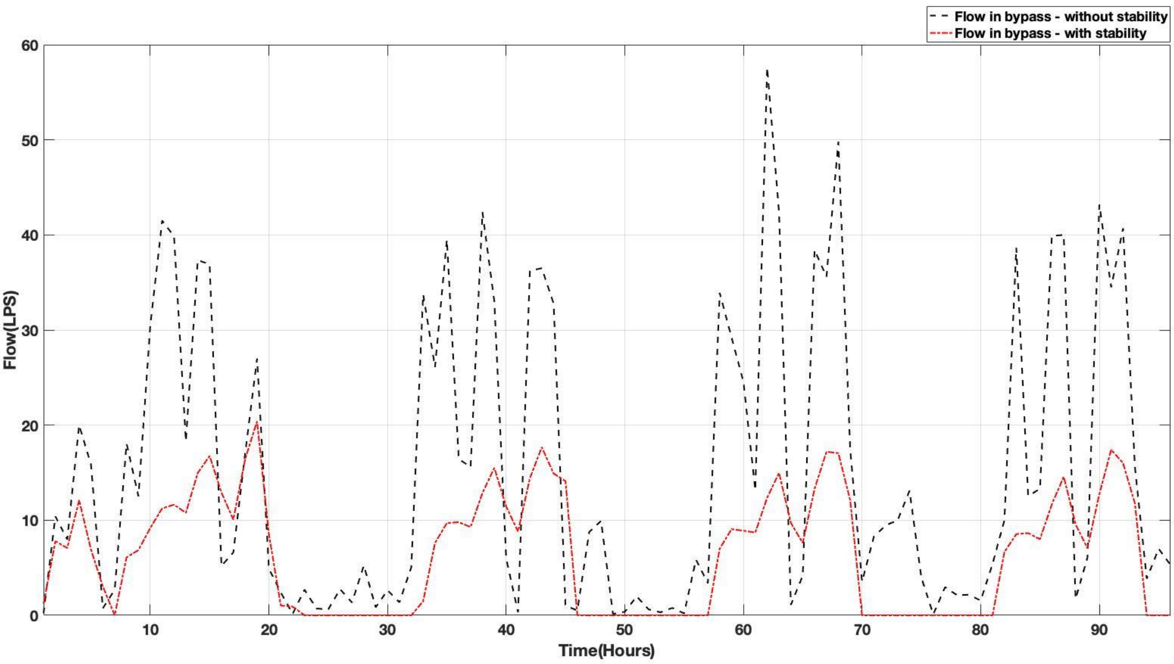


Fig 5.16. With and without stability in the bypass of PAT 3

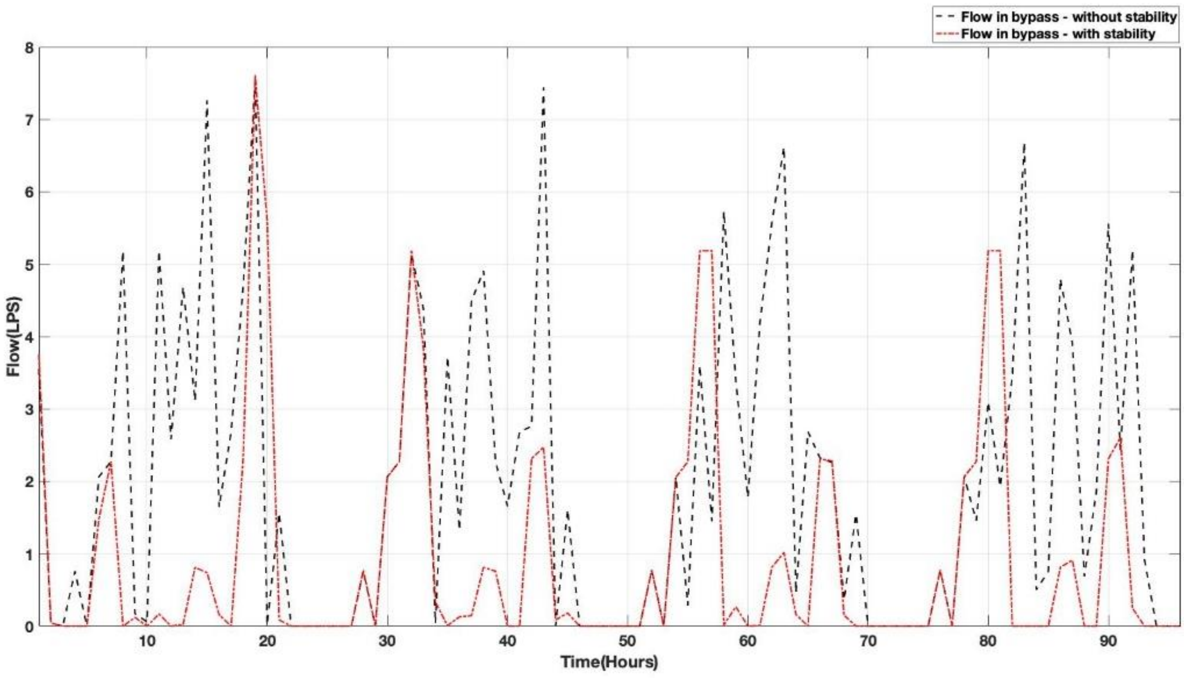


Fig 5.17. With and without stability in the bypass of PAT 4

5.5 Power improvement between Hybrid MPC and Linear MPC

The section will demonstrate if there is any improvement in using hybrid mpc over linear mpc and how much extra power will hybrid mpc generate. Table 5.1 is also provided to show the total power generated with each controller respectively and show if there is any improvement.

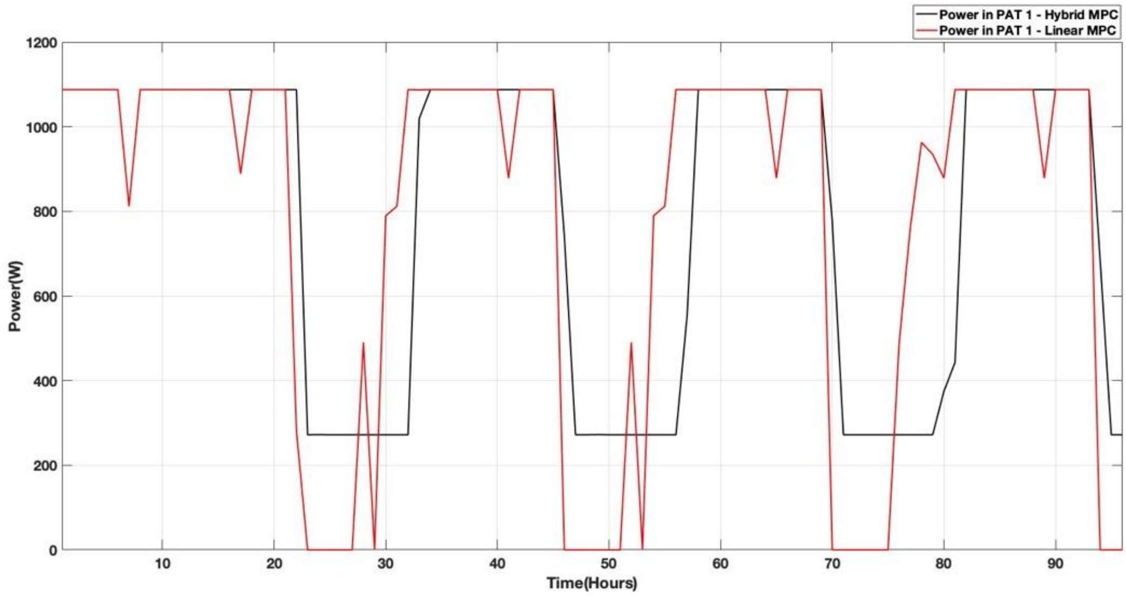


Fig 5.18. Power generated in Hybrid MPC and Linear MPC for PAT 1

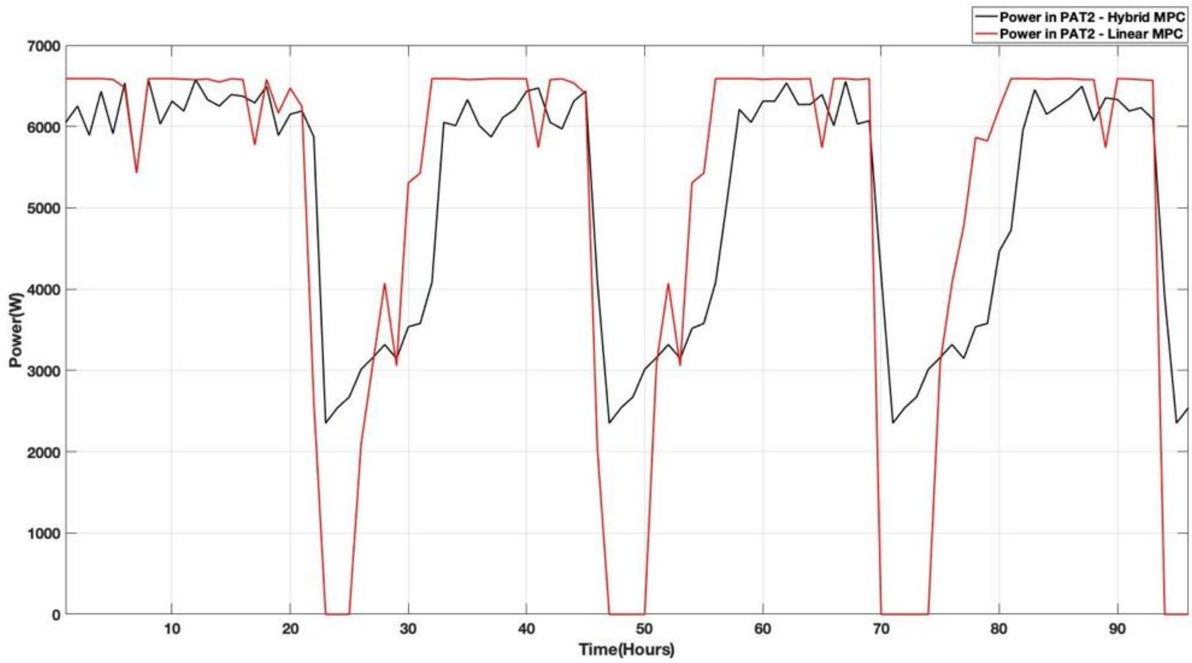


Fig 5.19. Power generated in Hybrid MPC and Linear MPC for PAT 2

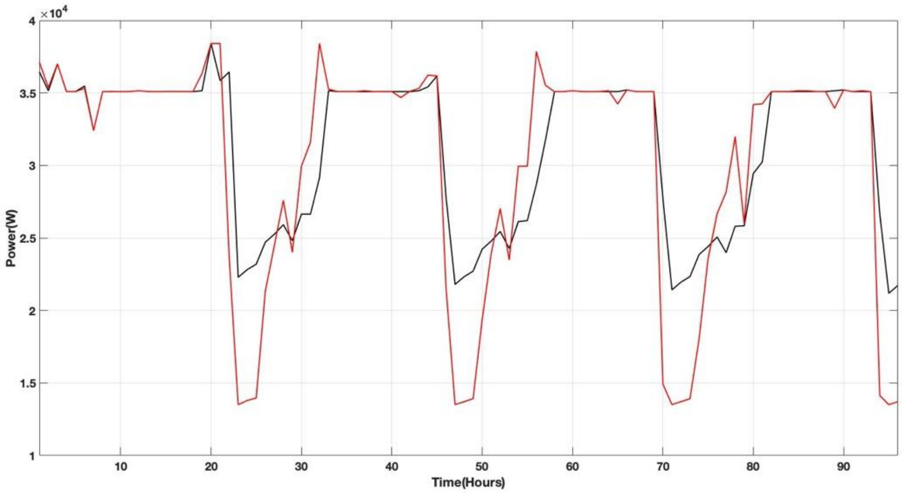


Fig 5.20. Power generated in Hybrid MPC and Linear MPC in PAT 3

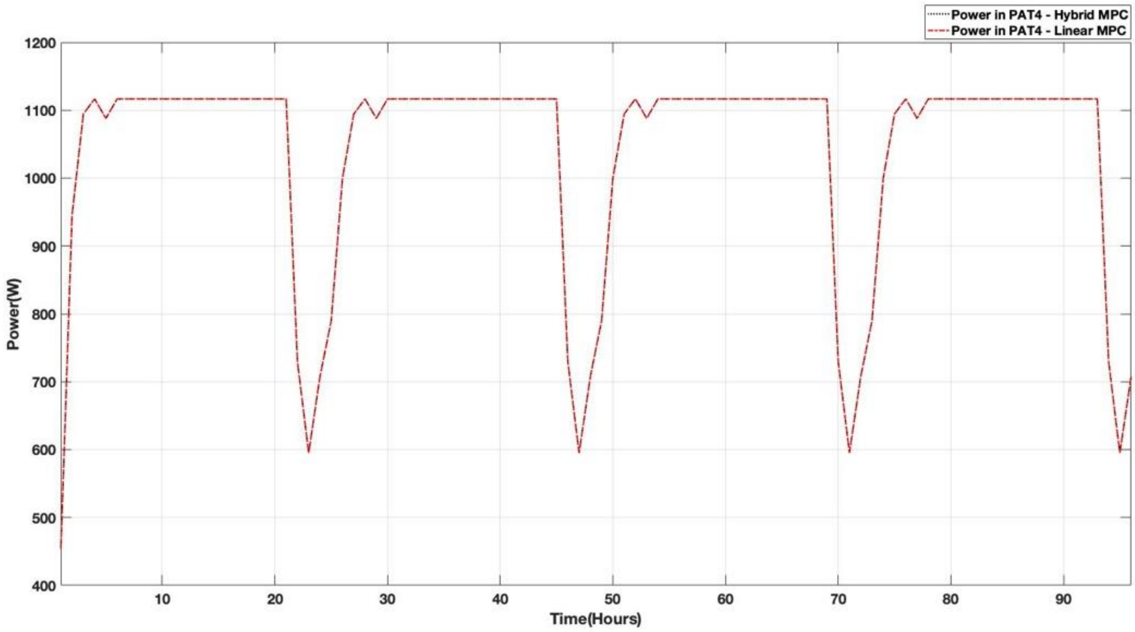


Fig 5.21. Power generated in Hybrid MPC and Linear MPC in PAT 4

	Total power in Hybrid MPC (kWh)	Total power in Linear MPC (kWh)	% Improvement
PAT 1	488.16	481.041	1.48
PAT 2	75.83	74.82	1.35
PAT 3	3008.330	2918.428	3.08
PAT 4	99.56	99.56	0

Table 5.1. Power generated in PAT1-PAT4

The table shows the total power in (kWh) generated by hybrid mpc and linear mpc for the five days of simulation. The first PAT has only a 1.48% improvement, PAT 2 has 1.35% and PAT 3 has a 3.08% improvement and PAT 4 has no improvement. This is due to the prioritization of the power maximization term in the objective function. The order of priority is as follows: *High – Low priority: PAT 3 – PAT 2 – PAT 1 – PAT 4*. However, as PAT 3 has the highest priority, the power generated is almost double that of PAT 1 and PAT 2. Also, since PAT 4 is getting the effects of PAT 3 and PAT 2, has no improvement been shown. Additionally, part of the reason for the improvement in PATs 1 2, and 3 is due to using tanks to store water and use them at a later stage to maintain the PAT flow. Moreover, from this conclusion, it is evident that hybrid mpc has the upper hand in power generation. The next section shows how the algorithm honors other constraints such as keeping pressure in the critical node above the required pressure.

5.6 Pressure at critical node

The network has a critical node at N20, which is downstream of tank 1. As per the constraints in the algorithm, it is designed to always maintain the pressure between 12 m – 40 m. Therefore, from Fig 5.22 it can be seen that both for linear mpc and hybrid mpc, the pressure is kept within the required range.

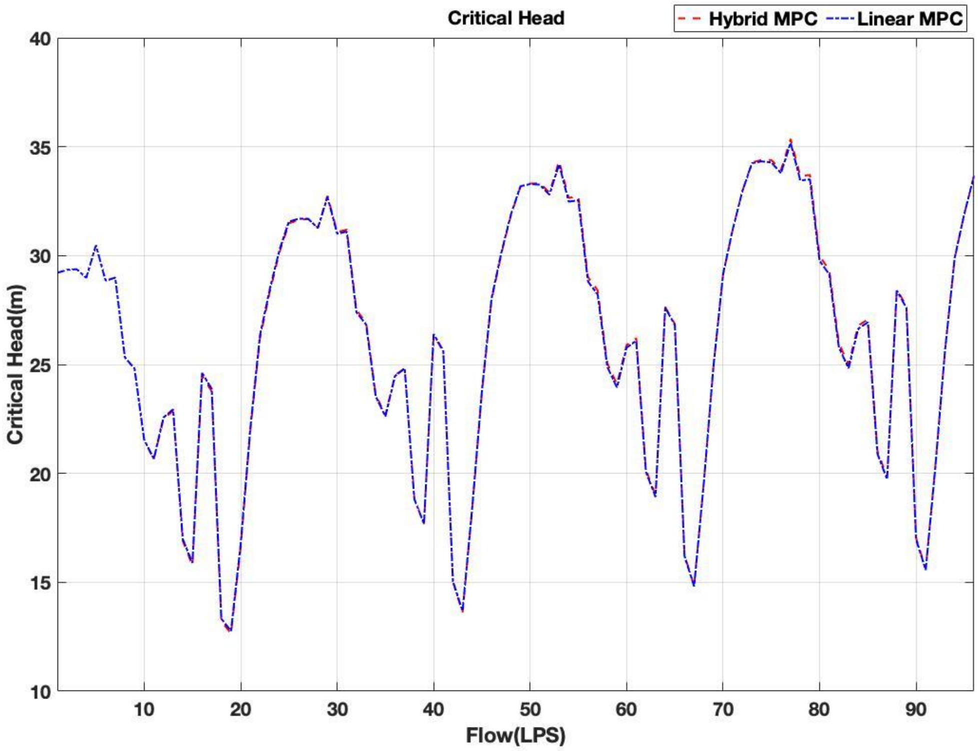


Fig 5.22. Critical head comparison

5.7 Unmeasured disturbance – changing demand

To further test the performance and the quality of the hybrid controller, an unmeasured disturbance was added to the model. This is in the form of demand; the interesting point is that the controllers do not know what the demand is before predicting as the demand is added only in the simulation loop and the controller needs to act immediately in real-time. This study was done purely for stretching the controller's ability to predict unforeseeable future events. For this work, the demand is changed every hour to both the Ballacolla demand pattern and the D-town demand pattern. The flow through PATs 1 - 4 and bypass is shown below in Fig 5.23 - 5.26. To see a difference in the flows in the generation lines and by-pass lines, the lines are plotted in different colors. The tank level is also plotted to show the reason for the variation of the total flow in the PAT and Bypass lines. PAT 2 has no direct influence on any tank, so Fig 5.24 only shows the flow comparison.

For the unmeasured disturbance, a random demand is generated using the rand function in MATLAB. The demand patterns for the Ballacolla demand pattern and D-town demand pattern from Epanet are multiplied by a random number and simulated at each time step. From Fig 5.23 – 5.26 it can be observed that the algorithm can consider the unmeasured disturbance and react accordingly. Moreover, the tank level is kept within the minimum and maximum level keeping an extra volume in case of an emergency. Furthermore, it is not tracking the changes to the flow in the PAT and bypasses demand as it is generated randomly.

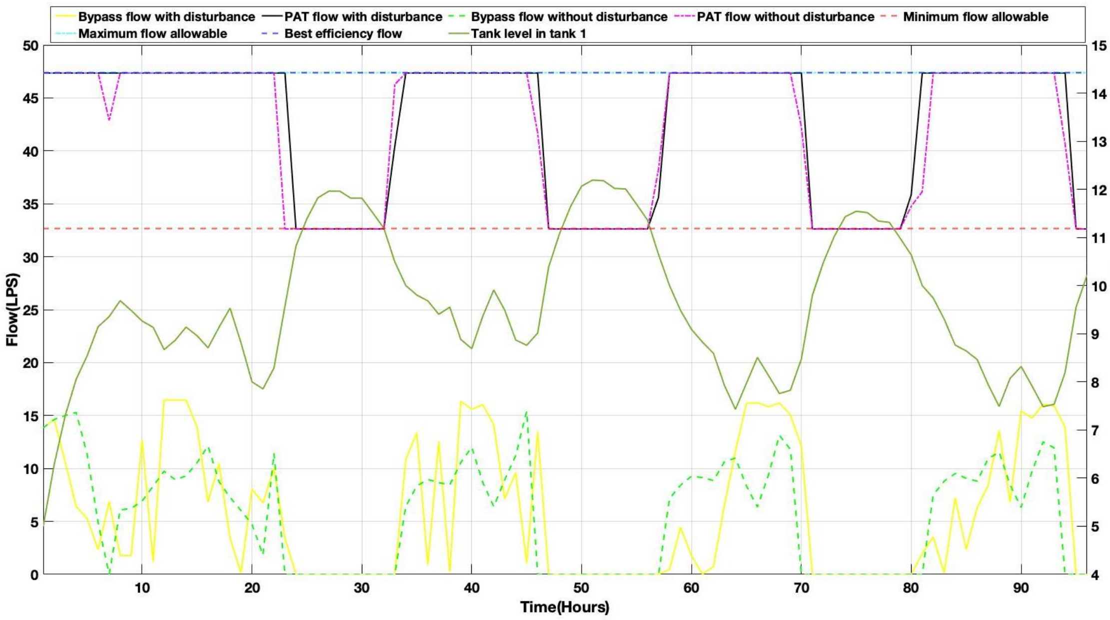


Fig 5.23. Flow comparison between demand derived from demand patterns and unmeasured demand in nodes for PAT 1 in hybrid MPC

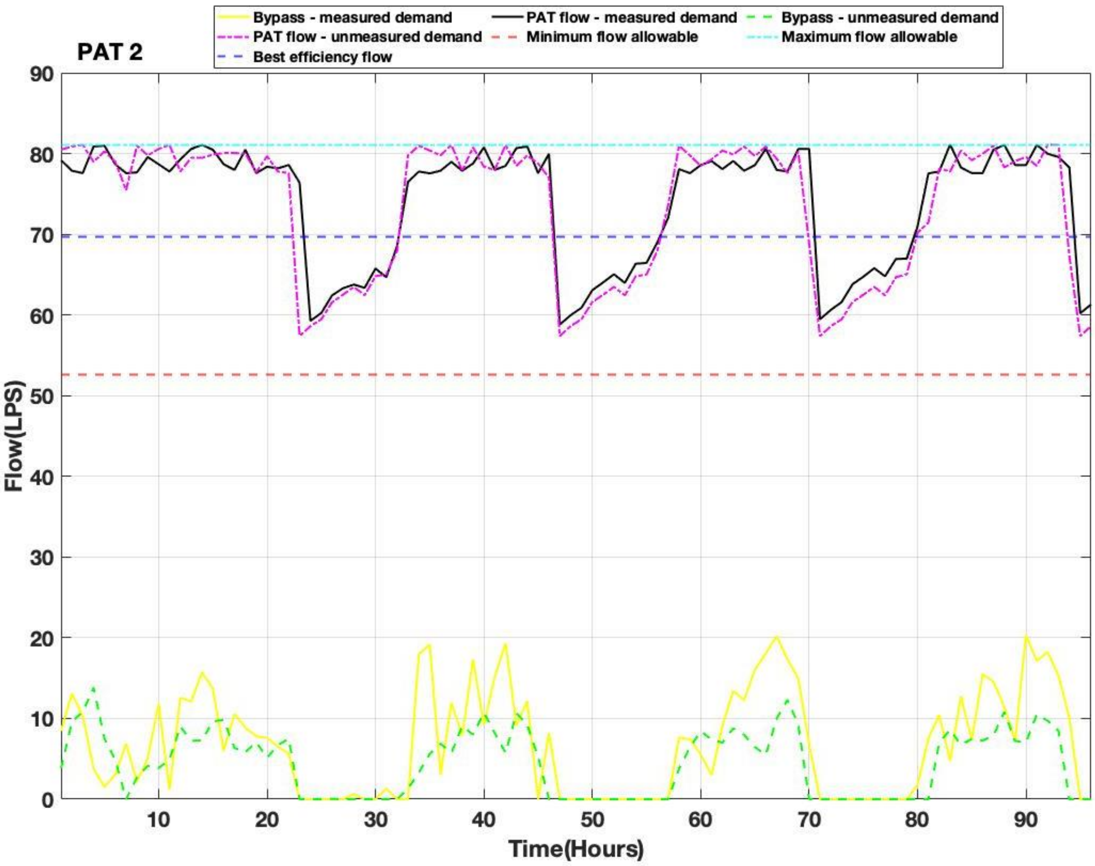


Fig 5.24. Flow comparison between demand derived from demand patterns and unmeasured demand in nodes for PAT 2 in hybrid MPC

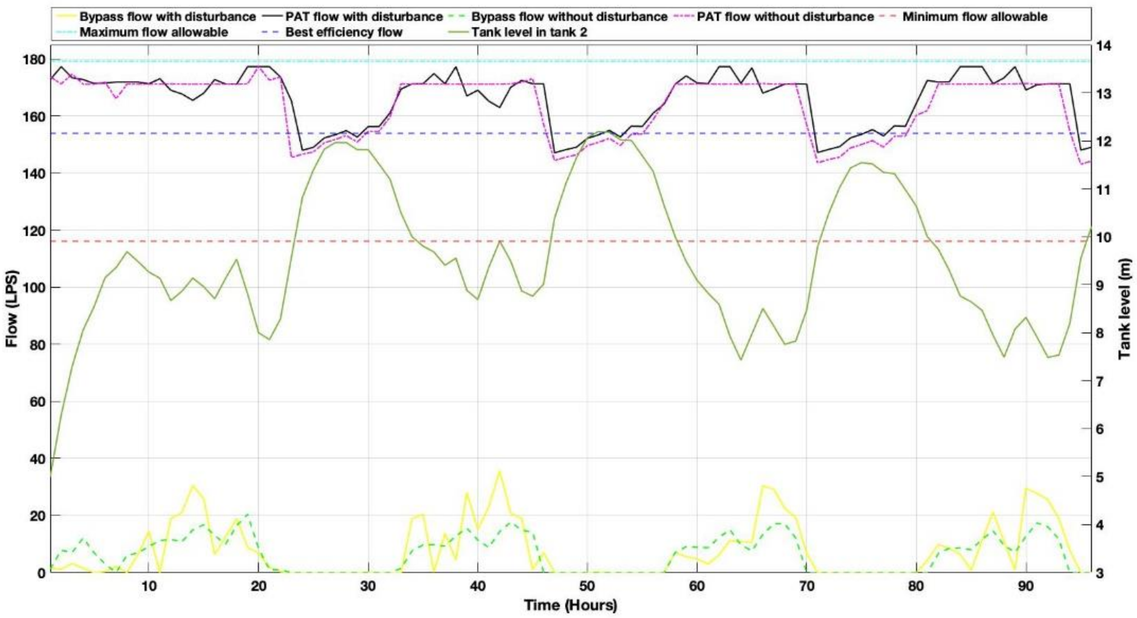


Fig 5.25. Flow comparison between demand derived from demand patterns and unmeasured demand in nodes for PAT 3 in hybrid MPC

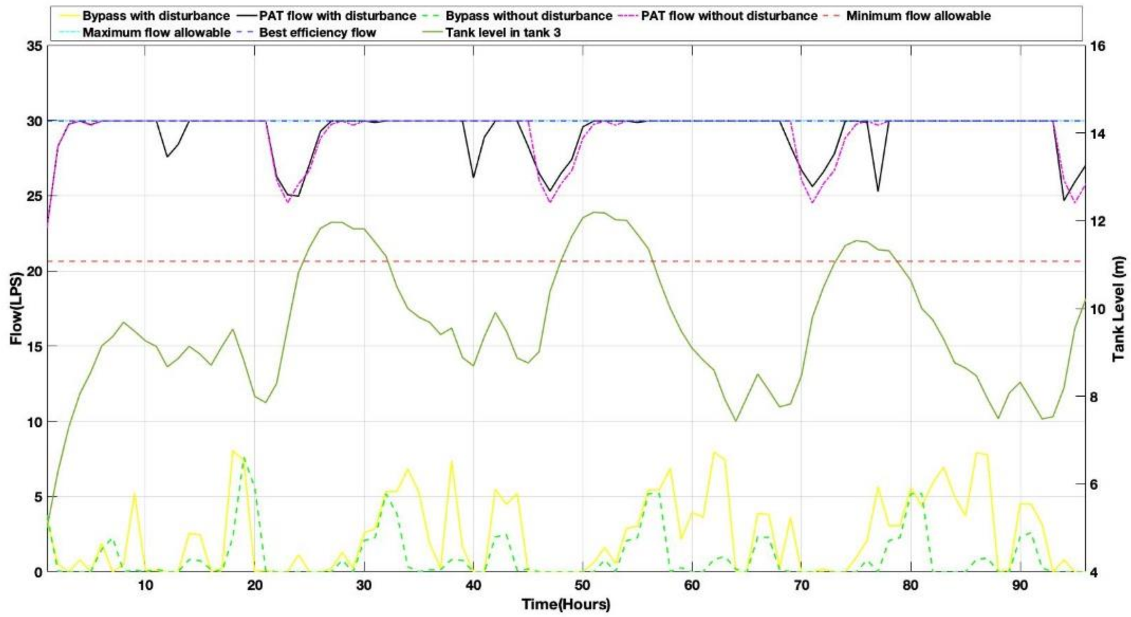


Fig 5.26. Flow comparison between demand derived from demand patterns and unmeasured demand in nodes for PAT 4 in hybrid MPC

5.7 Performance of Linear and Hybrid MPC

To test which controller can be used in a near real-time operation, the time taken for simulations done for five days was recorded. First, the time taken for each time step using hybrid mpc was recorded and from the simulation, it took an average of 3.7 s. Fig 5.27 shows a snapshot of the simulation time of hybrid mpc in which the average time was calculated for 96 hours. Fig 5.27 and Fig 5.28 merely show a small section of the long simulation. Similarly, Fig 5.28 shows a snapshot of the simulation using linear mpc. From the results, it was evident that the simulation for the linear mpc is faster than the hybrid mpc by almost 2.5s. Moreover, the reason for faster performance is merely due to the logic being implemented inside the control algorithm in the hybrid mpc.

```
Elapsed time is 7.607213 seconds.
Elapsed time is 5.739413 seconds.
Elapsed time is 3.386611 seconds.
Elapsed time is 4.775737 seconds.
Elapsed time is 2.978151 seconds.
Elapsed time is 3.194131 seconds.
Elapsed time is 4.099251 seconds.
Elapsed time is 2.914248 seconds.
Elapsed time is 4.464191 seconds.
Elapsed time is 3.101582 seconds.
```

Fig 5.27. Snapshot of simulation time using hybrid mpc

```
Elapsed time is 1.361300 seconds.
Elapsed time is 1.309257 seconds.
Elapsed time is 1.260754 seconds.
Elapsed time is 1.234677 seconds.
Elapsed time is 1.703539 seconds.
Elapsed time is 3.940587 seconds.
Elapsed time is 2.460529 seconds.
Elapsed time is 2.651444 seconds.
Elapsed time is 2.323221 seconds.
Elapsed time is 1.580445 seconds.
```

Fig 5.28. Snapshot of simulation time using linear mpc

Furthermore, the simulation was performed for 96 hours (five days) and the prediction model was only for 36 hours (1.5 days). The prediction time was chosen in a trial-and-error method and it will change the performance of the controller if reduced or increased. For example: if the prediction model is less than 1 day, the controller becomes more aggressive and gives infeasible solutions, and if it is more than 2 days the controller takes time (> 1 min) to give solutions. The reason for keeping it at 1.5 days is to allow for real-time operation of the controller in the future work

6 Discussion and Conclusion

6.1 Discussion

The main aim of this thesis is to find a way to maximize the power generated from PAT technology in Water Distribution Networks during their operation. To do that, the second chapter focused on a thorough background study in understanding the hydraulic principles of WDNs. Soon afterward a study on energy consumption of WDNs was performed in understanding the consumption at each process involved from sourcing raw water – to treating – distributing – usage. This concluded that not only is it energy intensive, but harmful GHG emissions are also associated with each process. Therefore, it is important to make WDNs energy efficient. One of the ways to make it energy efficient is by introducing pressure management (PM) to networks. One of the ways to introduce PM is by installing Pressure Reducing Valves at locations where higher pressure is noticed. However, it was noticed that PRVs have disadvantages themselves. They lack the reliability to regulate pressure at various times of the day. For this reason, the next study was conducted to analyze the existing control techniques for PRVs.

Model Predictive control was finalized as the best way to control PRVs and a process because it can capture all the dynamics of a certain process and predict its output based on the current inputs to the controller. Now looking back at PRVs, the next study was done to find a method to recover the lost excess energy that is dissipated when associated with the pressure reduction. Therefore, PATs were seen as an attractive option to couple with PRVs to recover that potential. The next study then focused on the PAT technology and the best way to install it in a water network like the case study. This sparked a gap in the literature, using model predictive control to maximize the power in PAT installed within WDNs is not focused anywhere. Although it was noticed there is limited literature on how to control large hydro-turbines using MPC as well.

This led to the development of a controller which is based on MPC to generate flow setpoints which will be passed on to the actuators (PRVs) to open/close depending on the inputs. The first part was to model the network using modeling techniques and the dynamics from

EPANET. The next step focused on obtaining the best theoretical PAT that will be available in the market. Even if a PAT is available most manufacturers do not give those curves therefore researchers need to find solutions on how to derive them. (Novara & McNabola, 2018) proposes a method to extrapolate the curves using polynomial equations. Those equations need the best efficiency flow/head point of a PAT. To obtain the BEP point, practical and theoretical experiments need to be performed. (Mitrovic, et al., 2020), suggests a methodology get the optimal BEP from analyzing a PRV database and choosing the correct limits for PATs that are currently available in the market. The author states that the best efficiency flow is always close to its average point of the PRV site. Moreover, as the author suggests, the optimal BEPs for power maximization correspond to 92% of the average operating flow ($Qavg$) at the site and 85% for the site's average operating head ($Havg$). Therefore, for this work has its limitations as it uses the method proposed by (Mitrovic, et al., 2020) in obtaining the optimal BEPs.

After finding the theoretical PATs, the model of the network is derived using the system dynamics and their corresponding matrices are entered into the algorithm. The constraints are also added as shown in the methodology. One such constraint is the head loss constraint. This work uses an approximation technique to approximate the quadratic terms of the head loss using the interp1 function in yalmip. Again, limitations exist as any other quadratic approximation technique in the literature, as it does not fully capture the quadratic nature. Therefore, in this work, the value of mean error calculated by comparing the approximated head loss and the actual head loss is 10^{-15} and it is derived from using the Darcy-Weisbach formula. Nevertheless, the error is almost ~ 0m but future work could be focused on reducing this error and enhancing controller performance.

Moreover, for the maximization of power, two types of controllers are compared. One is called linear mpc, which used the same objective, but the logic operation is outside the algorithm and the latter is called hybrid mpc which has a logic operation in the algorithm itself. The objective is to derive the optimal set points by minimizing the error between the desired and the actual flow value. From the results, it can be observed that for three PATs hybrid MPC outperforms the linear MPC. The generated power in all PATs differs according to their priority set in the weights of this algorithm. PAT 3 which is located closer to the reservoir has high priority and it generates twice the amount generated from PAT 1 and PAT 2. However, in PAT 4 there is no improvement observed. For future work, it could be better to see if there is any other way to tune the weight so that these are dynamic instead of static. Moreover, the algorithm also has a stability term added to avoid unnecessary variations in the valves causing an unsteady state in the network. Therefore, some results are shown comparing the performance with the stability and without the stability, term added. From the results, it could be seen that there is a difference when the stability term is omitted in the objective function. Moreover, the pressure at the critical node is also kept well within the range and an extra challenge to the algorithm is also shown. The demand of the network is changed at random. This means the controller does not know the demand in advance to react to the changes. It must decide in real-time to give the optimal solution. This change is referred to as an unmeasured disturbance to the controller. From the results, it could be seen that the controller behaves in the way it takes in this unpredicted change and gives the best optimal solution for the flow setpoints in each PAT.

Looking back at the research question, "How to maximize the energy generation of PATs in WDNs using model predictive control?"

- What technology can be used to maximize the potential of PATs in WDNs – From this work, MPC was seen as the best option to control WDNs while maximizing the power generation in the PATs

- While maximizing the potential can model predictive control to fulfill the common objectives in water networks such as pressure management – MPC was able to maximize the power while keeping the head loss constraints satisfied as well as the pressure at the critical node. It was also able to avoid water hammer situations by adding a stability term to the objective function. Moreover, it was able to keep the tank levels well within the range with saving an extra volume in case of an emergency

- Is there an improvement in maximizing the power of all PATs simultaneously between the controllers called hybrid mpc and linear mpc – Hybrid MPC showed the best performance, PAT 1 and PAT 2 an average of 1.5 % increase was observed while PAT 3 had a 3 % increase. Nevertheless, there was no improvement in PAT 4.

- Which controller performs better for it to be suitable for near real-time operation for the performance aspect of the two controllers, from simulations, it was observed that each run took an average of about 3.7s for hybrid mpc whereas for linear mpc it only took 1.5s. The simulation was performed for 96 hours (five days) and the prediction model was only for 36 hours (1.5 days). This means the controller predicts its behavior well in advance for the 36 hours and therefore it has an idea of the future events that can occur.

Additionally, for MPC to act in real-time, the sampling time of the model and simulation time can be set as seconds rather than hours/minutes. Although it would then increase the computational load, proper design of the model can reduce it immensely. Some best practices include choosing linear objective functions and avoiding quadratic objective functions where possible. Caching solvers in the optimizer also reduces the time for the controller to find an appropriate solver repeatedly for every simulation. Minimizing a slack variable in the objective function will also help to ensure feasibility by relaxing some hard constraints which means using fewer equality constraints. All the modeling, predictions, and simulations were performed in Yalmip 2019/MATLAB R2021a environment. Additionally, a method is given in the appendix which will help derive the tank diameter which will discrete equations for numerical modeling of WDNs.

6.2 Conclusion

This work presents a methodology by combining MPC with logic giving it the name Hybrid-MPC to cater to PAT operation. The goal of this work is to maximize power while keeping the objectives in the water network satisfied. From the results it can be summarised as Hybrid-MPC controller performed better at maximizing the power of multiple PATs while keeping tank levels satisfied, demand nodes satisfied, and head loss constraints satisfied. It can also keep the actuators working smoothly as it is one of the objectives. Throughout one can argue the purpose of bypass valve for Hybrid-MPC, it is essential to keep the bypass in case the controller is unable to cater for keeping the flow in between the BEP and maximum power value the flow will be essentially bypassed to avoid the PAT operating as a motor or to avoid overheating scenarios. To compare the work, linear MPC is formulated having the same objective function but the difference is that the logic is inserted outside of the predictive model. Therefore, linear MPC only derives the total flow/head setpoints predicted and simulated for 5 days.

From the results, it can be seen that PAT1 and PAT2, each have a percentage increase of ~1.5%, PAT 3 had a 3 % increase and PAT 4 had 0% of extra power that is generated when using hybrid MPC compared with linear MPC. This is because the priority of the weights included the objective function for all the PATs. If the tuning of the weights changes and their priority changes, the percentage will also change. As for this work, the aim is to maximize power, the tuning is performed in a way the highest priority is given to the PAT closer to the reservoir.

Each run took an average of about 1.5s for hybrid mpc whereas it took only 3.7s for linear mpc. This concludes for the performance scenario in operating in near real-time, hybrid mpc is much faster than linear mpc. The simulation was performed for 96 hours (five days), and the prediction model was only for 36 hours (1.5 days). This means the controller predicts its behavior well in advance for the 36 hours and therefore it has an idea of the future events that can occur. An additional set of results are given with a varying demand in the simulation loop. This exercise was performed to stretch the ability of the controller to take corrective actions in the case of an accounted circumstance. The results clearly show that both controllers were able to take proper steps to ensure the objectives were met and the constraints were satisfied. For future work, it would help to study how model predictive control would act in real-time and take valve dynamics into account when predicting the flow set points.

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8 Appendix

Method to derive the diameter for tanks in numerical modeling

To use MPC in a water network, the network dynamics need to be modeled using continuous or discrete equations, if the dynamics of the next stage of the network is depending on the previous state, discrete equations can be used, if not continuous algebraic equations are used. Since this work used discrete equations to model the dynamics of the network relating to the volume of the tanks, it is essential to verify if the equations give an accurate representation of the dynamics. The volume of a tank in a water network can be related by the following discrete equation with the sampling time (Δt) of one hour.

$$v_n(k+1) = v_n(k) + \Delta t \left(\sum_i q_{in,i}(k) - \sum_j q_{out,j}(k) \right) \quad (9.1),$$

The volume of the tank is related to the previous volume with the change in the flow of inflow and outflow in the tank. Therefore, the pressure equation at the tank node also known as the tank level can be derived by dividing (9.1) by the area of the tank (S_n). It was assumed cylindrical tanks are used.

$$h_n(k+1) = h_n(k) + \Delta t \left(\frac{\sum_i q_{in,i}(k) - \sum_j q_{out,j}(k)}{S_n} \right) \quad (9.2),$$

The equation (9.2) was validated with the pressure equation which is the Bernoulli principle used in Epanet. Fig 9.1 demonstrates a simple example of how Epanet calculates the pressure head at the tank node using the principle. For illustration purposes, if a pipe with a constant diameter is used between points 1 and 2 in Fig 9.1, point one is a node in the network and point two is the tank node, then the Bernoulli equation relating the energy can be written as equation (9.4). Where E_1 and E_2 are elevations of points 1 and 2 and H_l = The head loss between the two points is due to friction and minor losses and since the diameter is constant the velocity remains constant for a time step, therefore, $V_1 = V_2$, If the kinetic energy relating to the velocity is ignored equation 30 can be rearranged to equation 31, where the pressure head/tank level is $\frac{P_2}{\rho g}$.

Fig 9.1. Example diagram to illustrate Bernoulli equation

$$E_1 + \frac{P_1}{\rho g} + \frac{{V_1}^2}{2g} = E_2 + \frac{P_2}{\rho g} + \frac{{V_2}^2}{2g} + H_l \qquad (9.3),$$

$$\frac{P_2}{\rho g} = \Delta E + H_l + \frac{P_1}{\rho g} \qquad (9.4),$$

If both the tank levels (T1 and T2) in the network are simulated using equation (9.2) (discrete equation) and simultaneously if the tank levels are simulated in Epanet using equation (9.4), through trial and error, for certain diameters of the tanks the equations tend to become near close to equal with a minute error. Two different sets of results are generated for two different diameters to check if the error decreases or increases. This error can be improved by more trial and error or by using an optimization algorithm to get a global optimum for when both equations become equal.

For tank 1, two diameters are set at one instance, D = 12.2m and at the other D = 12.5m, in Fig 9.2 the results for a comparison between the equations (9.2) and (9.4) are shown for D = 12.2 m and Fig 9.3 shows the results for the absolute error and the average error. Similarly, Fig 9.4 shows the results for D = 12.5m and Fig 9.5 shows the results for the absolute error and mean error between the equations (9.2) and (9.4).

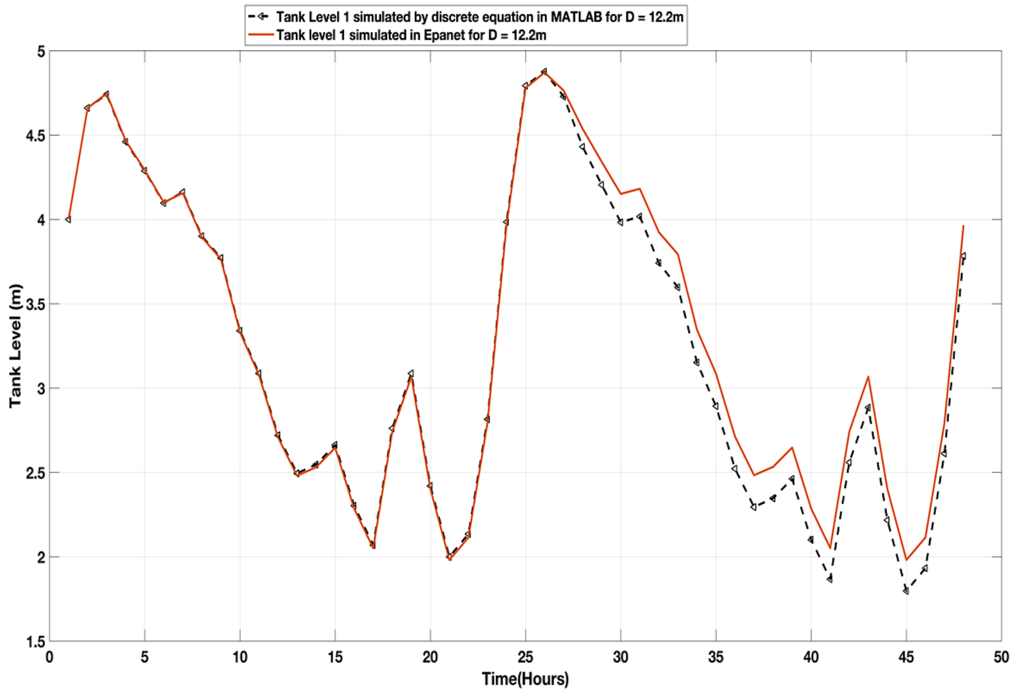

Fig 9.2. Comparisons between equation (9.2) and (9.4) for D = 12.2 m in Tank 1

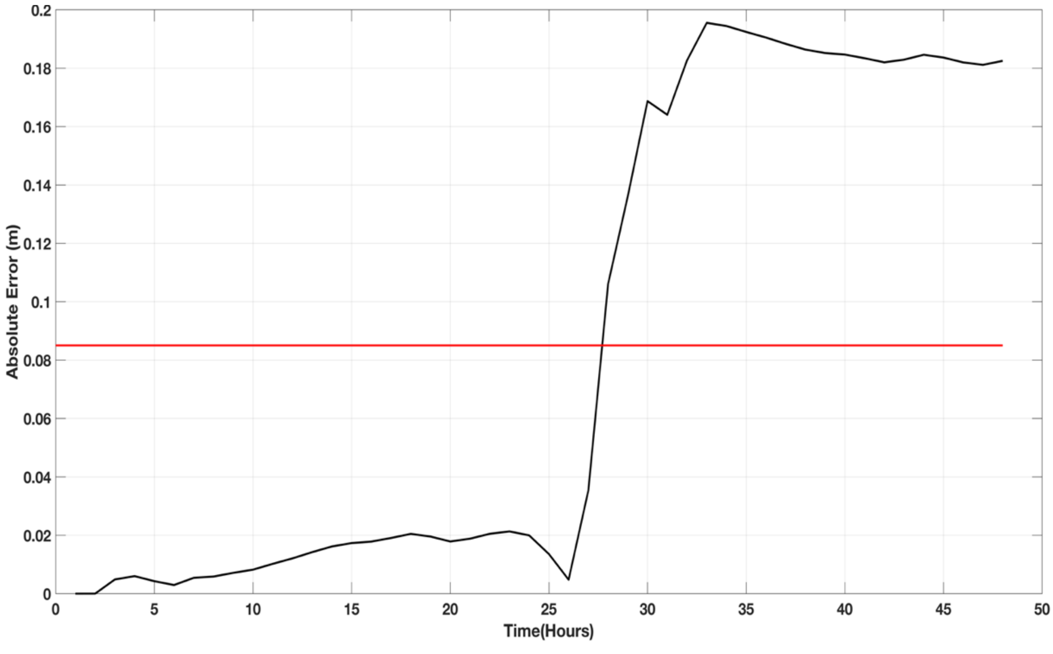

Fig 9.3. Absolute error(black) and Mean error(red) in Tank 1 for D = 12.2m

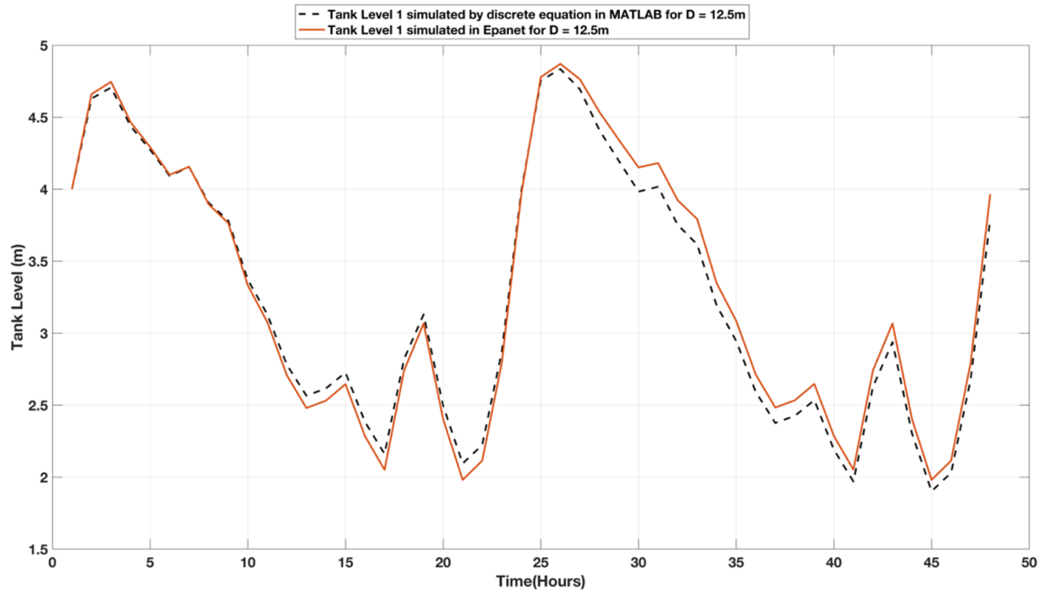

Fig 9.4. Comparisons between equation (9.2) and (9.4) for D = 12.5 m in Tank 1

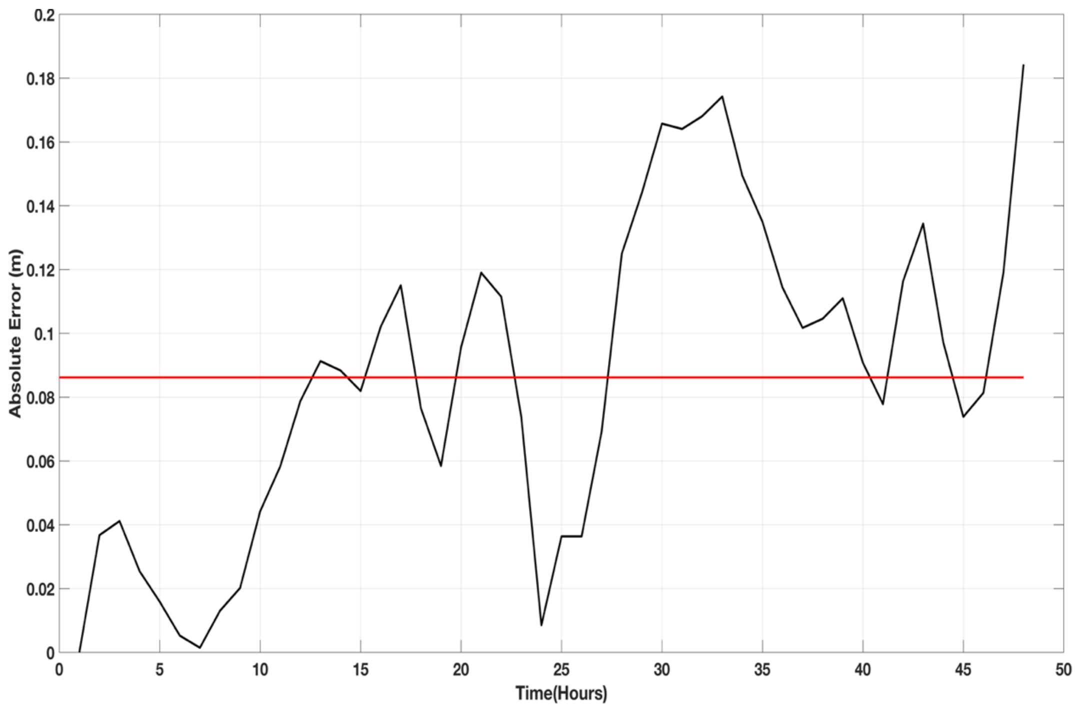

Fig 9.5. Absolute error(black) and Mean error(red) in Tank 1 for D = 12.5m

In Fig 9.4 in tank 1 for D = 12.2m, it can be observed that for the initial 27 hours of simulation when comparing equations (9.2) and (9.4), the error remains less than 0.02m but for the next 21 hours the error increases and stay between 0.16m and 0.18m. The mean error for this scenario is 0.085m but it can be noted that the absolute error does not stay stable, it is stable for the first day but there is a sharp increase on the next day. Whereas in Fig 9.4 for tank 1 for D = 12.5m, the absolute error is seen to fluctuate around the mean value of 0.086m from 12 hours onwards. The mean error is still slightly higher for D =12.2m but there is no sharp increase or decrease in the absolute error, only a small change is noticed. Therefore, it can be concluded that 12.5m is a better design value for the diameter of tank 1 than D = 12.2m for the above reasons. The ideal situation would be for the absolute error to fluctuate and remain closer to zero, but this can be done by performing more trial and error or using an optimization algorithm by having a diameter as the design parameter.

Often in the literature using discrete state space equations for modeling water networks, they do not mention the validation aspect. Choosing the correct diameter for the tank in the network is crucial as it can depend on if the discrete equations can be used to model the network or not. For tank 1, if a diameter less than 12.2m is chosen, modeling using the discrete equations can become invalid the results generated from using model predictive control can be inaccurate and a different method should be chosen to accurately represent the network dynamics.

Similarly, for tank 2, instead of two sets, three sets of results comparing the two equations (9.2) and (9.4) are generated for three different diameters. For the first scenario, the diameter is chosen as 12m the results are shown in Fig 9.6 and Fig 9.7. For the second scenario, the diameter is changed to 12.2m and the results are shown in Fig 9.8 and 9.9 below. Finally, the diameter is changed to 12.5m and the results are shown in Fig 9.10 and 9.11, the reason behind choosing three different diameters is to support the conclusion reached for tank 1 results. The discussion is given below the results.

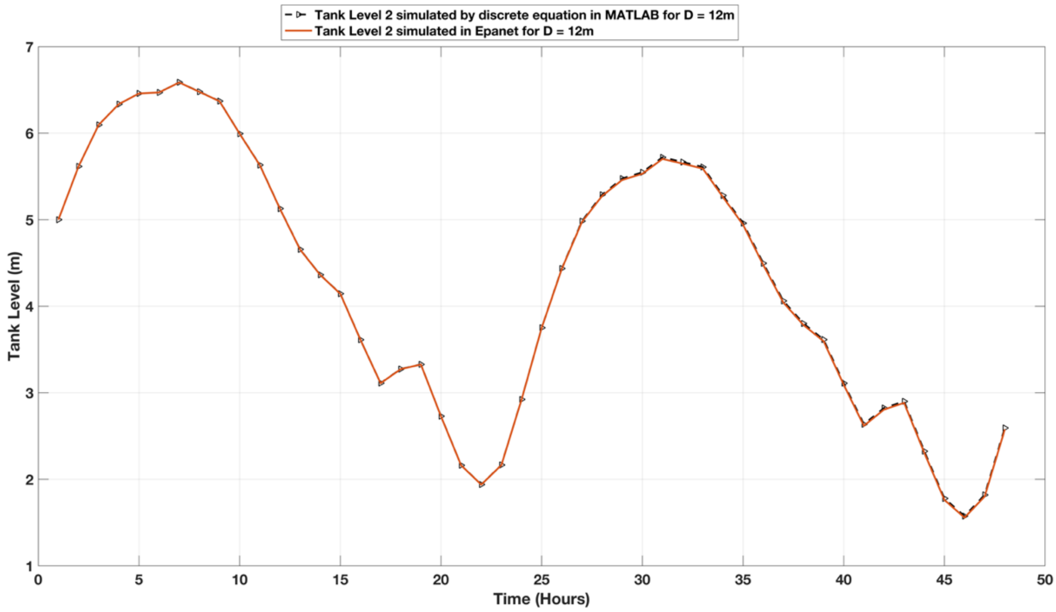

Fig 9.6. Comparisons between equation (9.2) and (9.4) for D = 12m in Tank 2

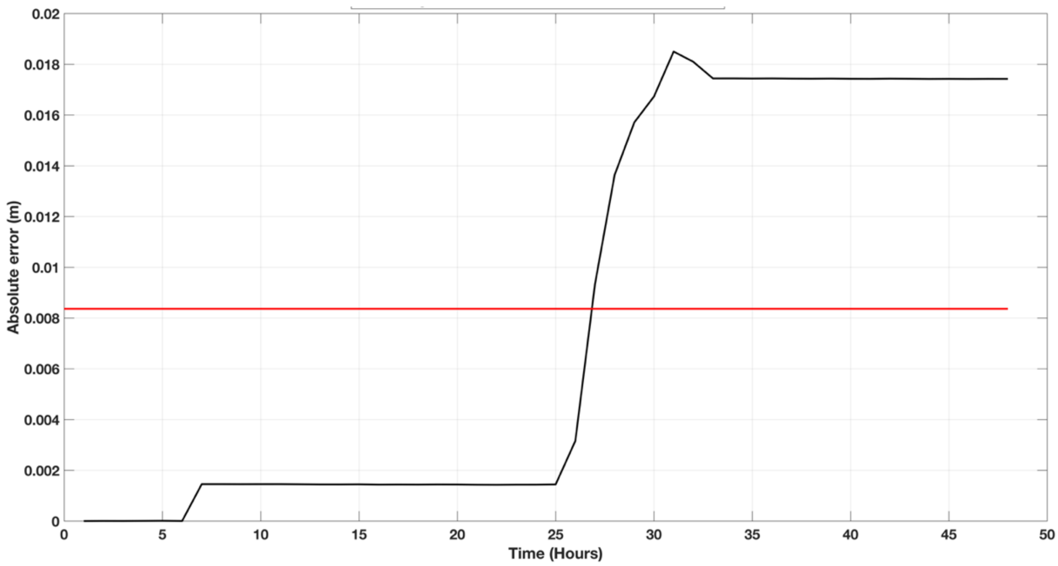

Fig 9.7. Absolute error(black) and Mean error(red) in Tank 2 for D = 12m

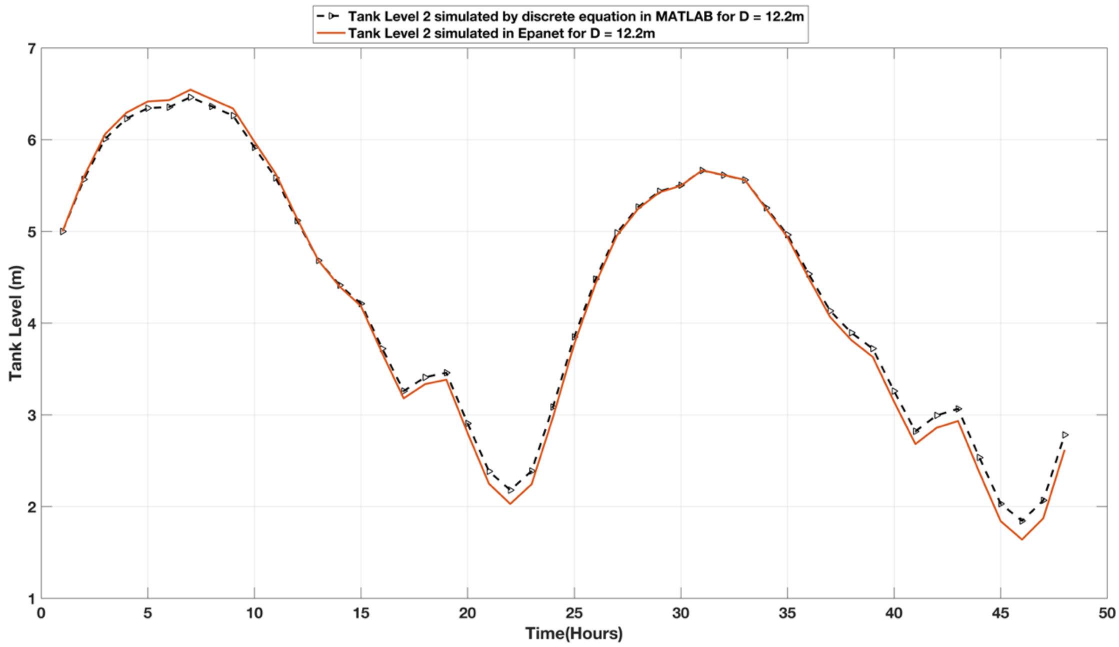

Fig 9.8. Comparisons between equation (9.2) and (9.4) for D = 12.2m in Tank 2

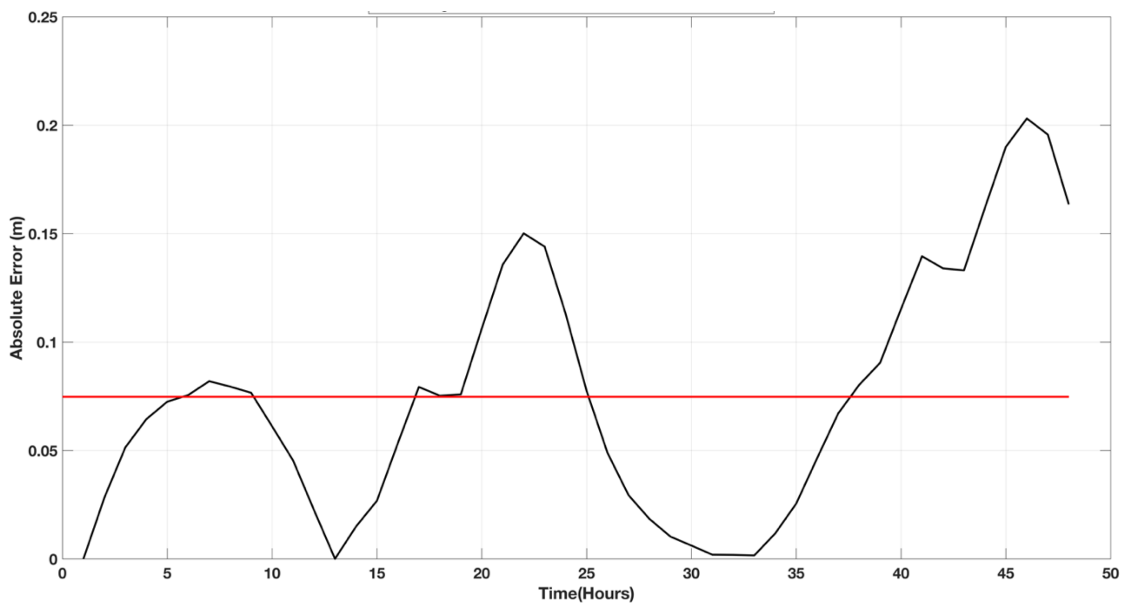

Fig 9.9. Absolute error(black) and Mean error(red) in Tank 2 for D = 12.2m

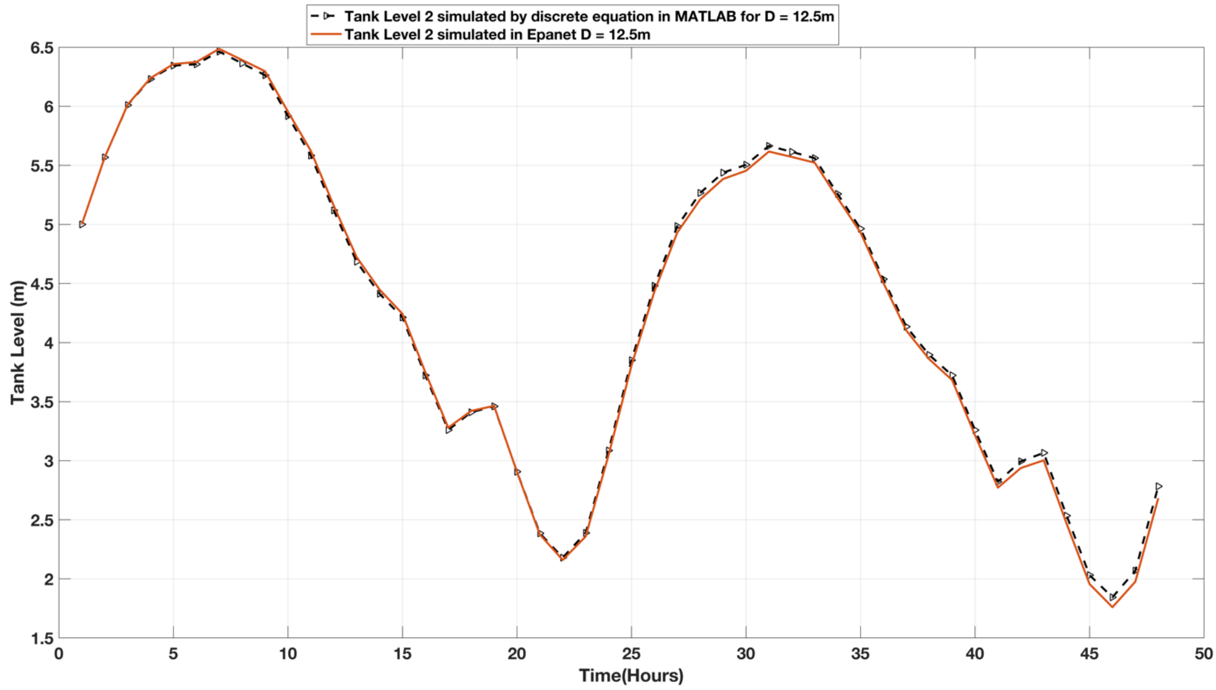

Fig 9.10. Comparisons between equations 30 and 33 for D = 12.5m in Tank 2

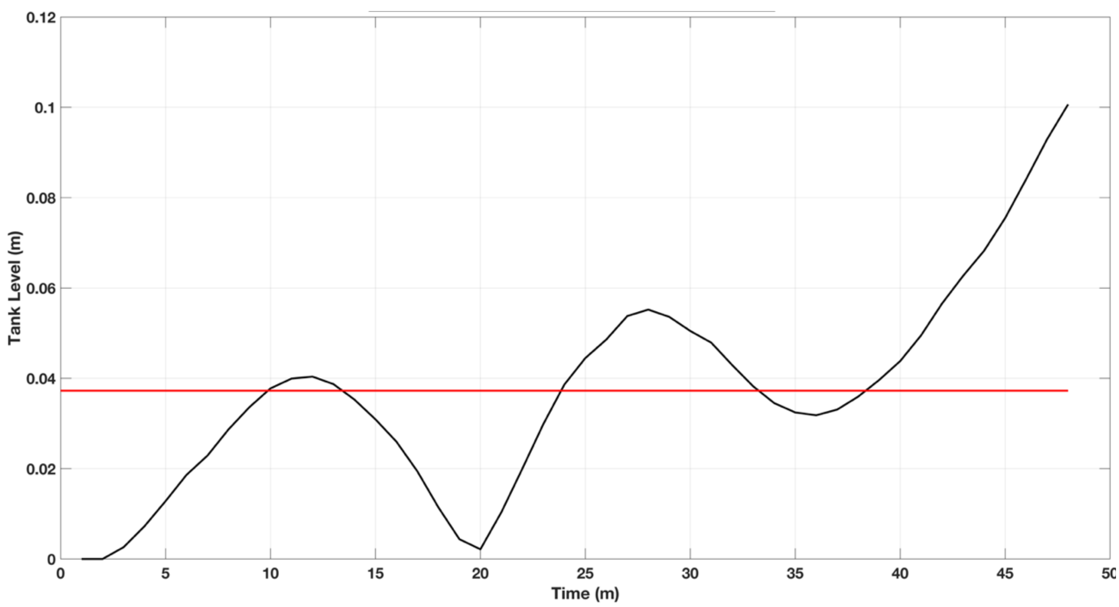

Fig 9.11. Absolute error(black) and Mean error(red) in Tank 2 for D = 12.5m

The diameter is set as 12m for the first scenario and Fig 9.6 is the comparison of the results of two equations (9.2) and (9.4) for tank 2. It can be seen from Fig 9.7, that there is not much difference between the two equations. Although this diameter setting looks promising, from Fig 9.7, it can be observed that there is a sharp increase in the absolute error after 25 hours. Nevertheless, the mean error which is 0.00837m is very low compared with other diameter settings. For scenario 2, for diameter = 12.2m, it can be seen from Fig 9.8 and 9.9, that the absolute error is fluctuating around the mean error. The mean error is 0.0748m it can be noted that it is higher than for diameter = 12m, but there is a pattern in the absolute error. It remains around the mean error for the first 35 hours and gradually increases and comes down after 46 hours. However, for diameter = 12.5 it can be seen from figures 9.10 and 9.11, that the absolute error also has a pattern and is around the mean error of 0.0373m but it increases without any signs of decreasing after 38 hours.

The interesting fact is that for three different diameter settings the absolute error in the comparing equations (9.2) and (9.4) show different patterns. The diameter of 12m looks promising as the absolute error remains stable for the first 24 hours at less than 0.002m and then there is a sharp increase at the 25th hour up to 0.0175m. for the simulation of the next 24 hours, the error remains around 0.0175m. Nevertheless, it can be seen that 12.2m offers more stability in the absolute error as it fluctuates around the mean value for the simulation of 2 days but for the diameter setting, 12.5m shows otherwise. It does fluctuate around the mean error for less than 38 hours but keeps on increasing after that. Due to no definite pattern with diameter settings 12m and 12.5m, 12.2m is chosen as the optimal setting in this case for tank 2. This also proves the point stated in tank 1 results as if the diameter is less than or greater than the near-optimal value the equations (9.2) and (9.4) tend to become more independent with no pattern in the absolute error.

- **PAT curves**

Theoretical PAT curves for three rotational speeds:

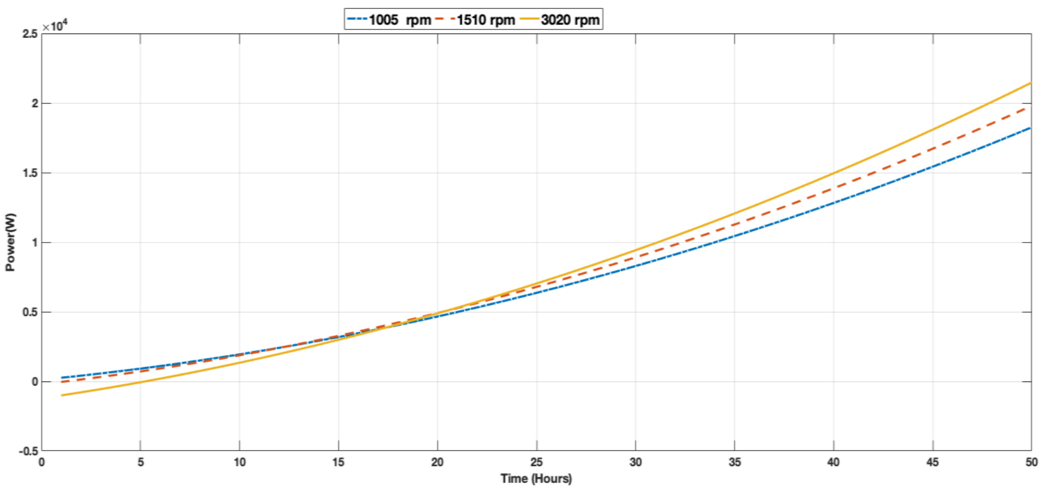

Fig 9.12. PAT curves for different rotational speeds