# OPTIMAL OPERATIONAL CONTROL OF DISTRIBUTION WATER NETWORKS BASED ON PREDICTIVE CONTROL

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**OPTIMAL OPERATIONAL CONTROL OF DISTRIBUTION WATER NETWORKS BASED ON PREDICTIVE CONTROL**

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The Academic Faculty

by

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# ABSTRACT

Energy costs for pumping account for the largest part of the total operating cost of water supply networks. In this thesis we deal with pump schedule optimization of water distribution networks based on Model Predictive Control.

Model Predictive Control (MPC) is an anticipatory control methodology, that originated in the process industry in the 70's and has been subject of research for drinking water and wastewater management over the last one or two decades.

An MPC controller for a midscale water pumping station is developed in order to optimize the operation plan of the system for minimum energy consumption. An MPC approach is used to determine the optimal operation plan of the pumps, while taking into account physical constraints of the system, such as tank water level lower and upper limits.

The MATLAB Simscape block library has been used to build a full model of a midscale pump station in a Simulink modelling and simulation environment. The system consists of four pumps, fed by a reservoir, that pump water to a tank through a pipeline. The initial model has been simulated in order to observe and examine the behavior of the system, and an updated model was designed to introduce the control methodology. The greek pump station of Vlites, in Akrotiri area of Chania (Crete island), is taken as a case study. All detailed information about the operation of this pump station is from OAK AE. The MPC control approach is tested and the results are discussed.

Finally, the case study is tested in a 24-hour time horizon and pump operation plans are proposed for different water demand scenarios. The energy costs with the MPC approach are compared to those of empirical pump operation control. The simulations show that MPC has better results regarding energy consumption for certain scenarios and worse for others. When the controller is expected to maintain the tank water level at a very high setpoint, the comparison does not favor the MPC, whereas, when the setpoint is at a lower level, MPC shows an improvement on energy consumption, over the conventional control.

# ΠΕΡΙΛΗΨΗ

Το κόστος ενέργειας για την άντληση αντιπροσωπεύει το μεγαλύτερο μέρος του συνολικού κόστους λειτουργίας των δικτύων ύδρευσης. Στην εργασία αυτή ασχολούμαστε με τη βελτιστοποίηση του προγράμματος αντλιών των δικτύων διανομής νερού βάσει Προβλεπτικού Ελέγχου.

Ο Προβλεπτικός Έλεγχος (Model Predictive Control ή MPC) είναι μια μεθοδολογία πρόβλεψης ελέγχου που ξεκίνησε στις μεταποιητικές βιομηχανίες στη δεκαετία του ‘70 και έχει αποτελέσει αντικείμενο έρευνας για τη διαχείριση του πόσιμου νερού και των λυμάτων κατά τη διάρκεια των τελευταίων ενός ή δύο δεκαετιών.

Για την βελτιστοποίηση του σχεδίου λειτουργίας του συστήματος για ελάχιστη κατανάλωση ενέργειας έχει αναπτυχθεί ένας ελεγκτής MPC για σταθμό άντλησης νερού. Μια προσέγγιση MPC χρησιμοποιείται για τον καθορισμό του βέλτιστου σχεδίου λειτουργίας των αντλιών, λαμβάνοντας υπόψη τους φυσικούς περιορισμούς του συστήματος, όπως το ανώτατο και κατώτατο όριο του επιπέδου της στάθμης του νερού της δεξαμενής.

Η βιβλιοθήκη Simscape της MATLAB χρησιμοποιήθηκε για την κατασκευή ενός πλήρους μοντέλου αντλιοστασίου μεσαίας κλίμακας σε περιβάλλον Simulink για μοντελοποίηση και προσομοίωση. Το σύστημα αποτελείται από τέσσερις αντλίες, τροφοδοτούμενες από μια δεξαμενή, που αντλούν νερό προς μία δεξαμενή μέσω αγωγού. Το αρχικό μοντέλο έχει προσομοιωθεί προκειμένου να παρατηρηθεί και να εξεταστεί η συμπεριφορά του συστήματος και ένα ενημερωμένο μοντέλο σχεδιάστηκε για να εισαγάγει τη μεθοδολογία ελέγχου. Το ελληνικό αντλιοστάσιο του Βλητέ, στο Ακρωτήρι Χανίων, χρησιμοποιείται ως case study. Όλες οι αναλυτικές πληροφορίες σχετικά με τη λειτουργία αυτού του αντλιοστασίου είναι από τον ΟΑΚ ΑΕ. Η προσέγγιση ελέγχου MPC εξετάζεται και τα αποτελέσματα συζητούνται.

Τέλος, το υπό μελέτη σύστημα δοκιμάζεται σε χρονικό ορίζοντα 24 ωρών και σχέδια λειτουργίας των αντλιών προτείνονται για διάφορα σενάρια ζήτησης. Το κόστος ενέργειας με την προσέγγιση MPC συγκρίνεται με εκείνο του εμπειρικού ελέγχου λειτουργίας αντλιών. Οι προσομοιώσεις δείχνουν ότι ο MPC έχει καλύτερα αποτελέσματα όσον αφορά την κατανάλωση ενέργειας για ορισμένα σενάρια ζήτησης νερού και χειρότερα για άλλα. Όταν ο ελεγκτής αναμένεται να διατηρήσει τη στάθμη του νερού της δεξαμενής σε ένα πολύ υψηλό σημείο, η σύγκριση δεν ευνοεί τον MPC, ενώ όταν το σημείο αναφοράς βρίσκεται σε χαμηλότερο επίπεδο, ο MPC εμφανίζει μια βελτίωση στην κατανάλωση ενέργειας σε σχέση με τον συμβατικό έλεγχο.

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# LIST OF SYMBOLS AND ABBREVIATIONS

| | |
|---|---|
| DCS | Distributed Control System |
| DMC | Dynamic Matrix Control |
| DMPC | Decentralized Model Predictive Control |
| GA | Genetic Algorithm |
| MPC | Model Predictive Control |
| MV | Manipulated Variable |
| OAK AE | Organization for the Development of Crete A.E. |
| OV | Output Variable |
| PLC | Programmable Logic Controller |
| RTO | Real-Time Optimization |
| SCADA | Supervisory Control and Data Acquisition |

# CHAPTER 1. INTRODUCTION

## 1.1 Motivation and Goals

Water, vital for all known forms of life, is an increasingly significant global problem because it is becoming scarcer as a natural resource and its availability is a major social and economic concern. There is an obvious correlation between access to safe drinking water and gross domestic product per capita [1]. A large proportion of the world's population is currently experiencing water stress and rising water demands greatly outweigh greenhouse warming in defining the state of global water systems to 2025 [2]. According to the World Health Organization, by 2025, half of the world's population will be living in water-stressed areas.

The problems mentioned above, as well as the complexity introduced by water distribution networks make water management a challenging control problem. Optimization and optimal control techniques provide an important contribution to strategy computing in drinking water management. Similarly, the problems related to modelling and control of water supply and distribution have been the object of important research efforts in the last few years [3]. For such complicated optimal control problems, more intelligent control plans are used in the advanced control level.

Thus, the focus of this thesis is to study and implement an approach on Model-based Predictive Control (MPC) in water networks. The author deals with pump schedule optimization and aims to model a water supply network and design an MPC controller for a midscale pumping station.

## 1.2 Model-based Predictive Control

### *1.2.1 MPC for Water Distribution Networks*

Water network systems consist of pumps, valves, pipes, reservoirs and other hydraulic elements, which carry water to demand nodes from the supply areas, with specific pressure levels to provide a proper service to consumers [4]. The interconnectivity of such elements increases the complexity of the dynamics of the system and the control management. The control strategies are supposed to achieve an optimal operation plan ahead of time to provide a good network performance, while achieving certain goals, including maximizing the water quality, minimizing pumping or other costs, ensuring safety levels, etc. Water networks are often large-scale and may consist of hundreds of actuators, sensors and local controllers, as well as storage and other hydraulic elements which operate under specific operational and physical constraints. Conventional controllers cannot properly deliver for such multi-variable systems with time-varying elements and high non-linearities.

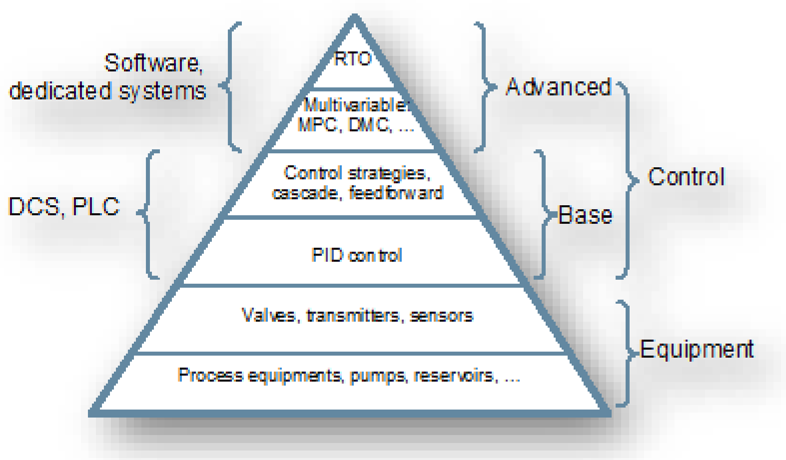
More advanced intelligent control systems can solve the optimization problem periodically taking into account all changes in the system including predicting response of the system in a defined future period using the mathematical model of the system [5]. Such a control strategy is Model-based Predictive Control.

### *1.2.2 MPC Control*

"MPC is a set of control methodologies that use a mathematical model of a considered system to deliver control signals over a time horizon that minimize a cost function related to selected indexes associated to a desired system performance." [6]

This set of methodologies are suitable to be used in the advanced control of networks related to water supply and irrigation within a hierarchical control structure. Figure 1-1 illustrates the hierarchy, where the upper levels include the advanced control methodologies, such as Real–Time Optimization and multivariable control (MPC, DMC) and moving down the pyramid, there is the local control and the instrumentation of the network (equipment, actuators, sensors).

**Figure 1-1: Control Pyramid. Taken from [7]**




As presented in [8], the ideas appearing in the predictive control family are:

- explicit use of a model to predict the process output at future time instants (horizon)
- calculation of a control sequence minimizing a cost (objective) function and
- receding strategy, so that at each instant the horizon is displaced towards the future, which involves the application of the first control signal of the sequence calculated at each step.

A model of the plan is used to predict the evolution of the process and the set of future control signals is calculated by solving the optimization problem, taking into account the current state of the system, the estimated values of the disturbances and the predictive response of the system. Figure 1-2 is a simple diagram of the MPC scheme.

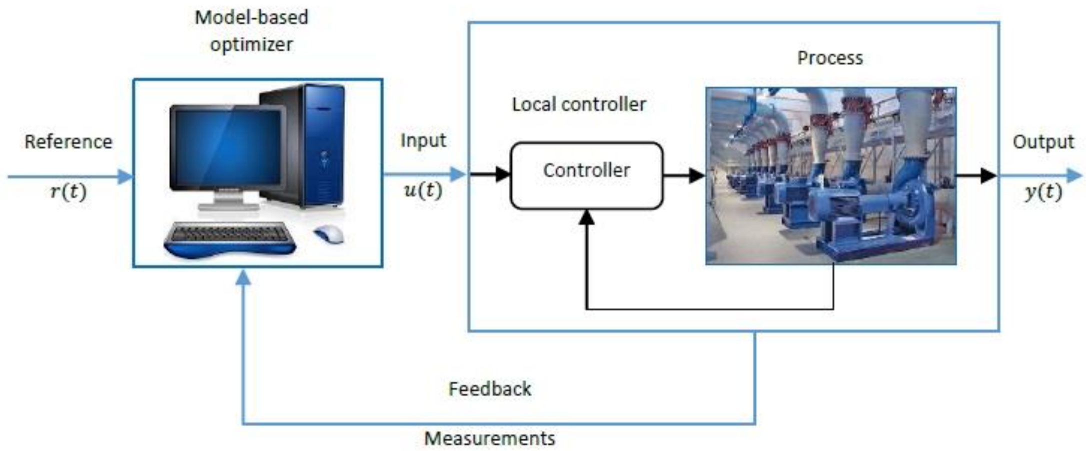



**Figure 1-2: MPC block diagram. Taken from [5]**

The control signal (Figure 1-2, u(t)) is sent to the process, but only the control action for the first time slot will be performed, whilst the next control signals calculated will be rejected. The optimizer will repeat the optimization for the next time slot considering the measured variations in the system. Thus, although the control signal is calculated over a future time horizon, the optimization takes place every one time slot, using the receding horizon concept.

MPC has gained popularity in the process control industry, because it presents significant advantages over other control methods. A few of the advantages, as described in [8], are outlined below:

- It is easy to use for people with limited knowledge of control, because its concepts are very intuitive and it is has relatively easy tunability.
- It can be used to control a great variety of processes, from those with simple dynamics to more complex ones.
- It intrinsically has compensation for big delays and dead times.
- It allows multivariable control and the use of constraints.

Naturally, MPC also has some drawbacks, such as the high amount of computation of the control law, which is not essential with the computing power available today. The main disadvantage is that there needs to be an appropriate model of the process available. It is obvious that the more close the used model is to the actual process, the better the performance of the MPC will be.

## 1.3 Case Study: Vlites Pumping Station

The pump station in Vlites, Akrotiri has been chosen as a case study for this thesis, because it is a mid-scale pump station, part of the water supply network in the area of Akrotiri, Chania. Moreover, detailed data for the Vlites pump station has been provided by

The Organization for the Development of Crete A.E. (O.A.K. A.E.) and a network model has been designed and simulated in the EPANET hydraulic modelling software [9]. A revised and simplified version of this model with an implementation of an MPC controller is designed in a Simulink environment and presented in this thesis.

## 1.4 Literature Review

A lot of research has been done on implementing MPC on drinking water network systems, irrigation systems, wastewater treatment, as well as optimal pump scheduling and water distribution system optimization techniques.

A great deal of published papers studied MPC applied on water supply networks. An optimal control tool, developed in the context of a European research project is described and the application to the city of Sintra (Portugal) is presented by (G. Cembrano, G. Wells, J. Quevedo, et al.)[10]. (J. Pascual, J. Romera, V. Puig, et al.) describe the application of MPC techniques to the supervisory flow management in large-scale drinking water networks, using a model of a real case study, the drinking water transport network of Barcelona (Spain)[11]. (P.J. van Overloop, R.R. Negenborn, B. De Schutter et al.) introduced MPC for national water flow optimization in The Netherlands, discussing control of rivers, lakes and canals [12].

A methodology for the optimal management of a combined irrigation and water supply system based MPC is proposed by (V. Puig, C. Ocampo-Martinez, J. Romera, et al.) with application to the Guadiana river (Portugal, Spain)[13].

Other published researches studied Decentralized Model Predictive Control (DMPC) of water networks. MPC strategies have been designed and tested for the global centralized and decentralized control of drinking water networks, using the Barcelona case study, by (V. Fambrini, C. Ocampo-Martinez)[4]. (S. Leirens, C. Zamora, R.R. Negenborn, et al.) propose the application of a distributed control scheme for control of urban water supply networks, studying a simulation based on a part of the urban supply network of Bogota (Colombia)[14].

Genetic algorithms for optimal pump scheduling were studied by (L. Ormsbree, S. Lingireddy, D. Chase)[15]. (J. E. van Zyl, D. Savic and G. Walters) introduced a hybrid method which combines the GA method with a hillclimber search strategy [16].

## 1.5 Outline of the Thesis

There are five chapters in this thesis. Chapter 1 is an introduction. Chapter 2 concerns modelling a pump station, part of a water distribution network, using Matlab Simscape language in the Simulink modelling environment. Chapter 3 presents the mathematical model and equations of the system under consideration. In Chapter 4, the case study is described and the simulation and results are presented. The final chapter will conclude the thesis and suggest future work.

# CHAPTER 2. WATER NETWORK AND PUMPING STATION MODEL

## 2.1 Background

This section describes the general concepts and definitions of water supply networks and introduces the typical elements of a drinking water network.

### *2.1.1 Water Supply Networks: Description and Main Concepts*

A *water supply network* or *water supply system* is a system of hydraulic components which provide water supply. A water supply system typically includes:

i. A raw water collection point.
   Raw water may come from groundwater sources, or surface waters such as lakes, rivers, canals and reservoirs.
ii. A water treatment facility.
   Raw water is usually transported to a water treatment plant, where it is processed to produce treated water, also known as potable water or drinking water.
iii. A water distribution network.
   Water distribution systems consist of an interconnected series of components, including pipes, storage facilities and components that convey drinking water [17].

In Figure 2-1, an example of a water supply system is shown.

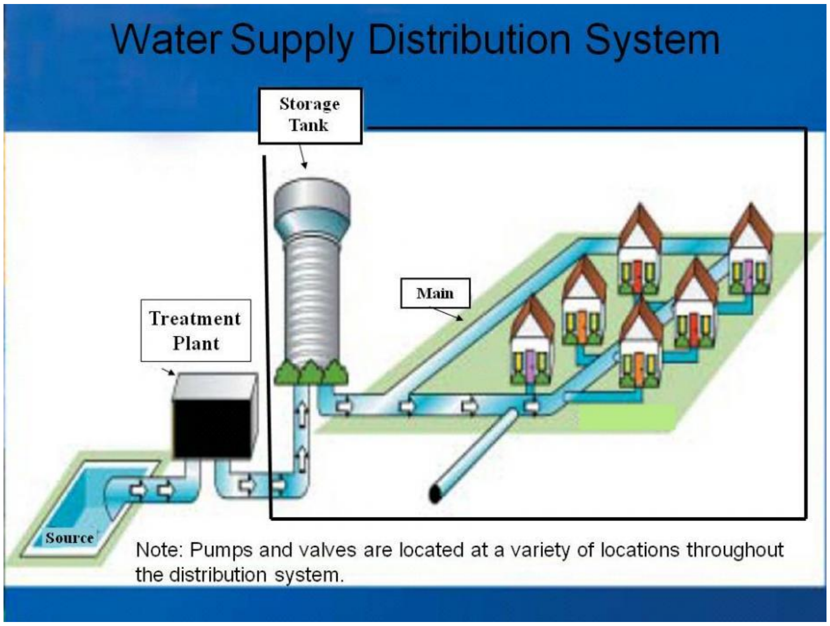



**Figure 2-1: Water Supply Distribution System. Taken from [17]**

Raw water is collected from a water source and transferred to a water treatment facility, usually through underwater pipes. The degree to which the untreated water is processed to achieve potability depends on the characteristics of the water, relevant drinking water standards posed by global or national organizations, such as the World Health Organization (WHO), or the United Nations (UN), the type of treatment processes used and the distribution system characteristics. Public water systems depend on distribution systems to provide an uninterrupted supply of pressurized safe drinking water and irrigation to all consumers. Homeowners, hospitals, businesses, industries and hundreds of other types of consumers are the points of consumption that a water distribution system delivers to. Transferring water from the source to the demand nodes requires a network of pumps, pipes, valves and other hydraulic elements. Storing water to meet the needs for fire protection or to accommodate for rise in demand due to varying rates of usage requires storage facilities, such as tanks and reservoirs. Piping, storage, along with the supporting infrastructure are referred to as the *water distribution network*.

The hydraulic elements in a network may be classified into two categories: *active* and *passive*. The active elements are those which can be operated to control the flow and/or the pressure of water in specific parts of the network, such as pumps, valves and turbines. The pipes, tanks and reservoirs are passive elements, in the sense that they receive the effects of the operation of the active elements, in terms of pressure and flow, but they cannot be directly acted upon [10].

### *2.1.2 Water Distribution Network Elements*

A set of the typical elements in a network are described below. The figures presented are taken from Vlites Pump Station, which is described in Section 2.4 as the case study of this thesis.

**Pumping Stations** *Pumping Stations* are facilities that include pumps and equipment needed for pumping fluids from one place to another. In water networks they are needed to take the water that cannot flow by gravity, either to draw from natural or underground sources, or to carry the water where there is an elevation difference between two parts of the network.

**Figure 2-2: Pomona pumps in Vlites pumping station**

**Valves** A *valve* is a device that regulates or controls the flow of water, by opening/closing or partially obstructing various passageways [18]. They may operate manually or be automatic, driven by pressure, flow or temperature changes. Modern control valves may operate on sophisticated automation systems, based on external input, in which case an actuator will stroke the valve depending on its input and set-up, allowing control over a variety of requirements.

**Pipes** A *pipe* is a tubular section used to convey fluids from one location to another. In drinking water system, it is used as the connection between network pieces.

**Tanks** A water tank is a water storage container, which accumulates water for drinking water, irrigation, agriculture, fire suppression and many other uses. A tank has physical limits, related to the minimum and maximum capacity of water storage.

## 2.2 Modelling Environment

MATLAB is a high-level language and a desktop environment for scientific and engineering computing. It is used for a range of applications, including signal processing, machine learning, control design, robotics and much more [19].

Integrated with MATLAB comes Simulink, a block diagram environment for multidomain simulation and Model-Based Design. It provides a graphical editor, libraries of pre-defined blocks for modelling continuous-time and discrete-time systems and solvers for modelling and simulating dynamic models [20].

Simulink can employ two different approaches to modelling and simulating systems:

1. The Simulink modelling approach, where algorithms and physical systems are modelled using block diagrams. Blocks are connected by way of signal lines to establish mathematical relationships between system components.

2. The Simscape physical network approach, where blocks correspond to physical elements, such as pumps, motors and op-amps. The lines connecting these blocks correspond to the physical connections that transmit power. This approach describes the physical structure of a system, rather than the underlying mathematics.

While the traditional approach is an excellent tool for simulating control systems, Simscape is more suitable for modelling and simulating systems that consist of real physical components, in our case a pumping station, because the designed model will be a closer match to the structure of the system we are studying in this thesis. Simscape libraries contain a comprehensive set of elements and blocks for modelling multidomain physical systems (electrical, mechanical, hydraulic, thermal liquid, etc.). These libraries provide fundamental blocks (electrical resistance, hydraulic reference…etc), as well as high-level blocks (variable-displacement pump, servomotor…etc). A Simscape Hydaulics library is shown in Figure 2-3.

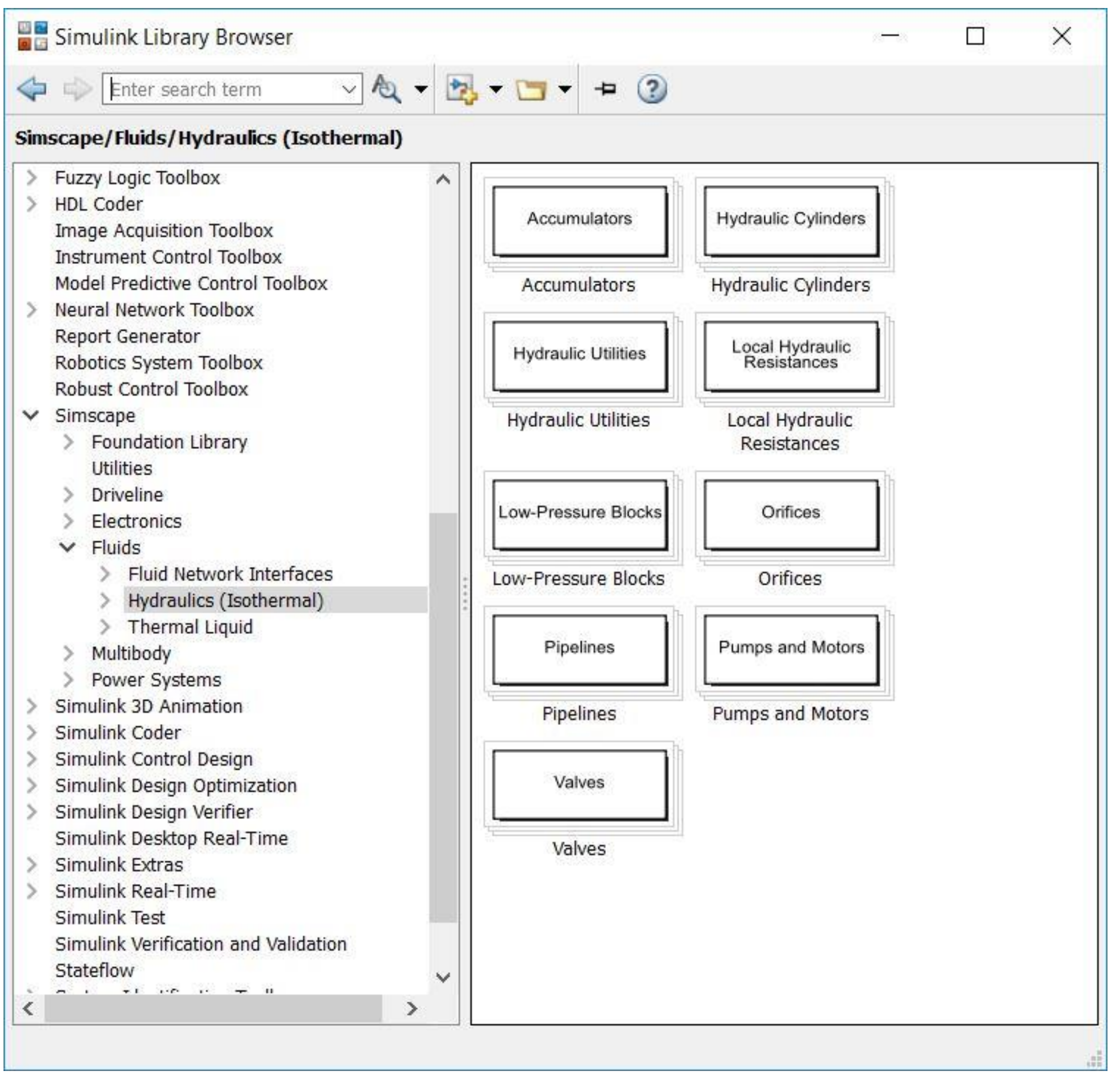



**Figure 2-3: Simscape Fluids Hydraulics block library**

## 2.3 System Components

### *2.3.1 Centrifugal pump*

A centrifugal pump is a machine that imparts momentum to a fluid by rotating impellers that are immersed in the fluid. The momentum produces an increase in pressure or flow at the pump outlet [21]. The centrifugal pump consists mainly by an impeller rotating freely inside a casing (volute) which is driven by a motor (Figure 2-4).

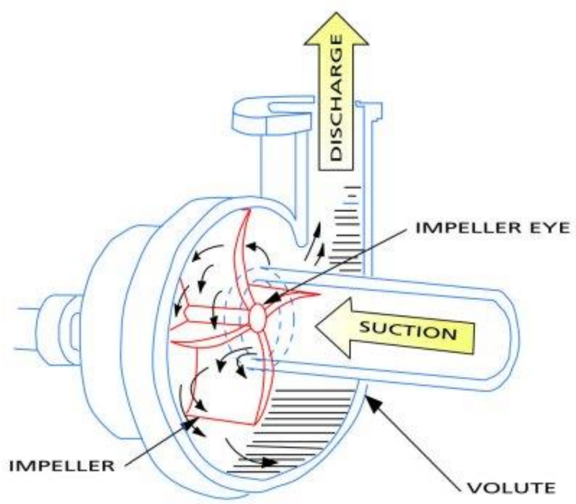



**Figure 2-4: Centrifugal Pump main parts**

A centrifugal pump is identified by its characteristic curves, which show the relationship between the total output pressure (or head) and the liquid flow at different shaft

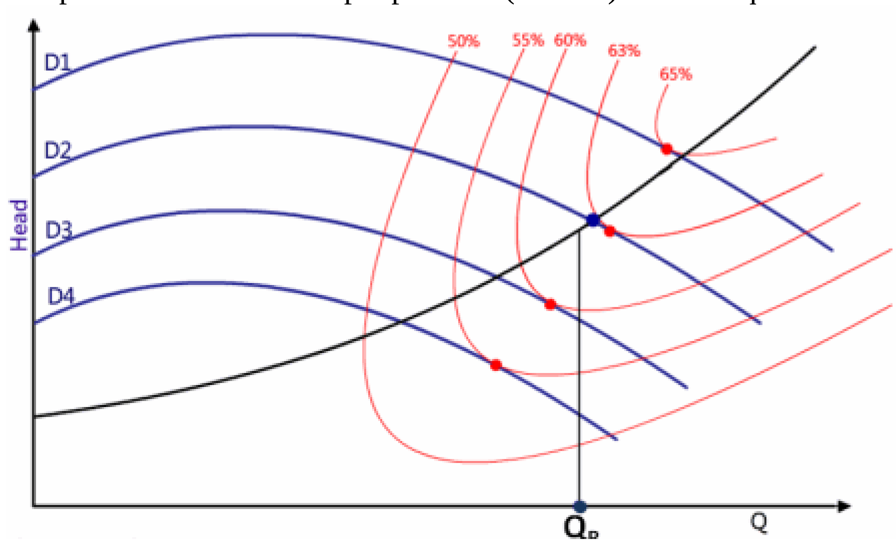



**Figure 2-5: Iso-efficieny curves from which we can determine efficiency of pump at operating condition**

speeds or impeller diameters. A typical pump characteristic curve is shown in Figure 2-5.

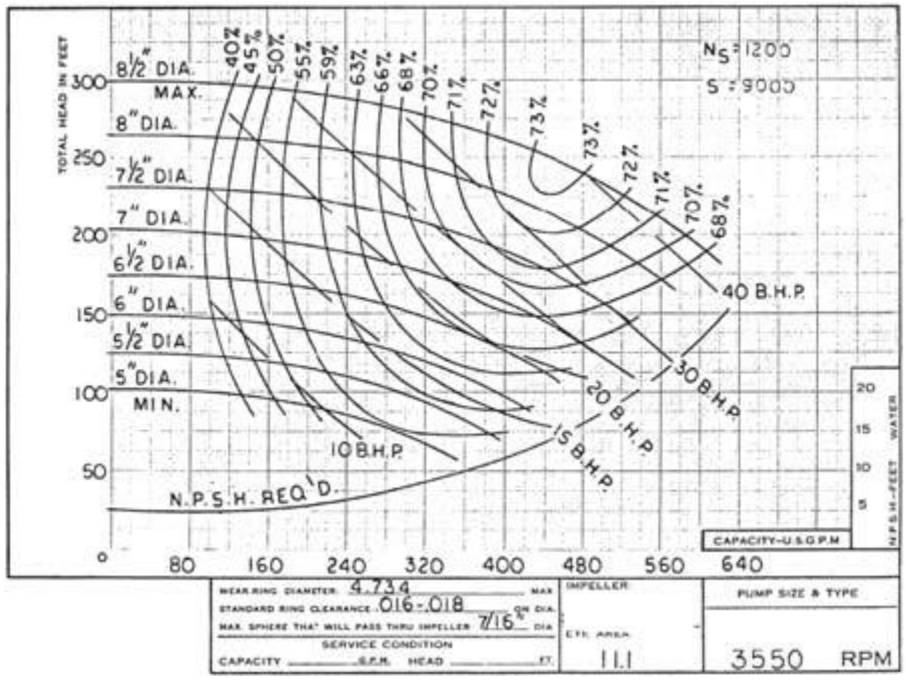



**Figure 2-7: Typical published Pump Performance Curve**

In Simscape, the *Centrifugal Pump* block represents a centrifugal pump as a data-sheet-based model, that can be parameterized depending on the data sheet for a specific pump.

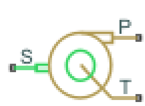



**Figure 2-6: Centrifugal Pump block**

Connections P and T are hydraulic conserving ports associated with the pump outlet and inlet, respectively. Connection S is a mechanical rotational conserving port associated with the pump driving shaft. The block positive direction is from port T to port P. This means that the pump transfers fluid from T to P as its driving shaft S rotates in the globally assigned positive direction [20].

### *2.3.2 Pipe*

The pipe can be modelled by the pressure difference between the inlet and the outlet of the pipe and the flow of the liquid in the pipe. The pressure loss (or head loss) due to friction along a given length of pipe can be computed with the Darcy-Weisbach equation, in which losses are proportional to the flow regime-dependable friction factor and the square of the flow rate. The friction factor is determined with the Haaland approximation [22].

The *Resistive Pipe LP* block found in Simscape libraries models a hydraulic pipeline which accounts for friction losses and port elevations, using the Darcy equation and the Haaland approximation.


**Figure 2-8: Resistive Pipe LP block**

Connections A and B are hydraulic conserving ports. The block positive direction is from port A to port B. This means that the flow rate is positive if fluid flows from A to B, and the pressure loss is determined as p = p_A - p_B.

### *2.3.3 Tank*

*Variable Head Tank* represents a pressurized tank in which fluid is stored under a specified pressure. The pressurization remains constant regardless of volume change. The block accounts for the fluid level change caused by the volume variation and pressure loss in the connecting pipe that can be caused by a filter, fittings, or some other local resistance.

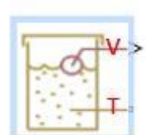



**Figure 2-9: Variable Head Tank**

Connection T is a hydraulic conserving port associated with the tank inlet. Connection V is a physical signal port. The flow rate is considered positive if fluid flows into the tank.

### *2.3.4 Other parts*

A variety of other Simscape blocks are needed to model a water network, these parts are shown in Figure 2-10.

The *Reservoir* block represents a pressurized hydraulic reservoir, in which fluid is stored under a specified pressure, which remains constant regardless of volume change.

The H*ydraulic Fluid* block is used to specify the hydraulic fluid type, providing properties such as density, viscosity, bulk modulus, temperature, etc, for all components assigned in a particular loop.

The *Hydraulic Reference* block represents a connection to atmosphere. It is the equivalent of the ground in electrical circuits.

The *Check Valve* block is used to permit flow in one direction and block it in the opposite direction. This will prevent the liquid from flowing back through Off pumps.

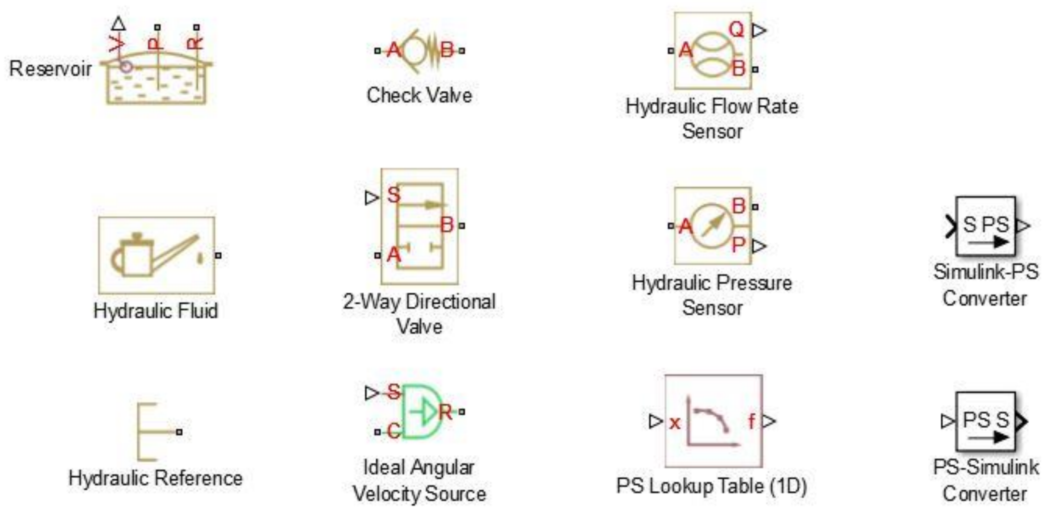



**Figure 2-10: Simscape blocks used in building the model**

The *2-way Directional Valve* block simulates a 2-way directional valve as a data sheet-based model. The block positive direction is from port A to port B. Positive signal at port S opens the valve. It is used for the On-Off operation of the pumps.

The *Ideal Angular Velocity Source* block represents an ideal source of angular velocity that generates a velocity differential at its terminals proportional to the physical input signal. It is used in the model as a prime mover for the pump driver shaft, rotating at constant speed (rpm).

The *PS Lookup Table* block represents a physical signal converter whose input-output relationship is specified by a lookup table. It is used to represent the network demand signal in the model.

Hydraulic measurement blocks are used for measurement of flow and pressure and finally *Simulink-to-PS* and *PS-to-Simulink* blocks are used to convert signals to be read or written to physical simulation domains.

## 2.4 Case Study

### *2.4.1 Vlites Pumping Station Operation*

The Vlites pumping station is located at the area of Vlites in Souda, at an elevation of 83m. It is fed with water from the water drillings in Myloniana and the springs in Meskla. The station is composed of two pumping groups, the inside and the outside. From Myloniana the water is led to the inside pumping group at Vlites by natural flow. From there, it is forwarded to the water supply tank in Korakies, at a 214m elevation. The pumping to Korakies tank is done by 4 pumps, but during the operation of the pumping station only two pumps can be working at the same time, while the third is used as backup. Each of the 4 pumps has 250 kW (340 HP) power and 350 $m^3$/h flow. The useful capacity of the Korakies water supply tank is 4000 $m^3$.

In the outside pumping group, 3 underwater booster pumps (190 kW or 260 HP each) are used, which are positioned on the M.Chorafia-Vlites irrigation pipeline and pump water from Zourbos springs. This pumping group is used only in the summer, when the demand for water supply is higher, while during the winter, the irrigation demand is covered by 2 more pumps (85 kW or 115HP and 50 kW or 70HP) in the inside pumping group that send the water to the Korakies irrigation tank.

All the information about the Vlites Pumping Station is taken from OAK AE and from [9], [23].

### *2.4.2 Simscape System Modelling*

Based on the data from OAK AE, an initial Simulink model was designed for observation and experimentation. It consists of a reservoir, which acts as a water source for this simplified water network and a pump station which feeds a tank at a different elevation. Pipe blocks are used for the transferring of water from and to tanks and sensor blocks are used for monitoring. The network demand in this initial design, is modelled as a variable area orifice which changes the output flowrate, depending on a lookup table which matches the time of simulation to the corresponding demand rate. Another tank is used to measure the total volume of water consumption. The 24-hour demand profile used and further details about the design of the model and its revised version will be discussed in Section 4.

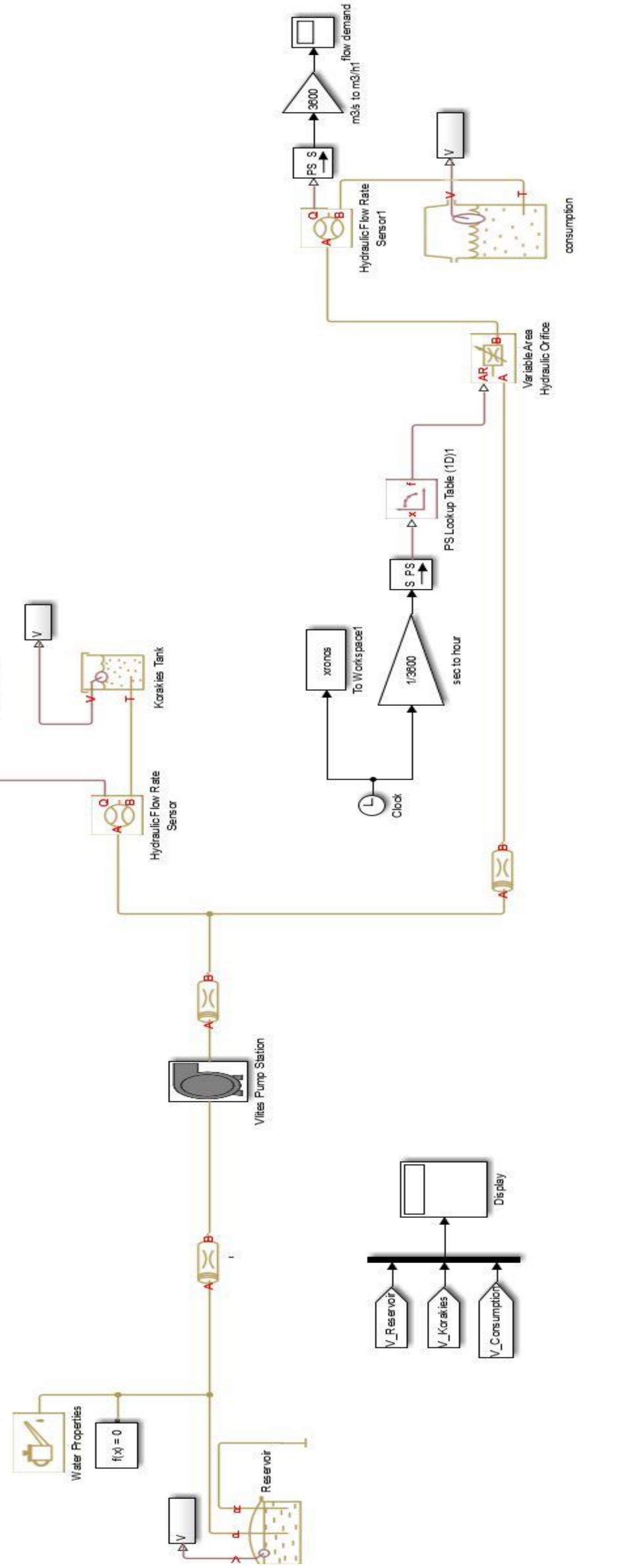



**Figure 2-11: Overall Simulink initial model of water distribution system**

# CHAPTER 3. MATHEMATICAL MODELLING AND MODEL PREDICTIVE CONTROL IN WATER NETWORKS

Model Predictive Control is a methodology that uses a mathematical model of the controlled process to produce predictions of future plant behaviour by using an optimization algorithm, while taking physical and operational constraints into account.

While there is a large variety of MPC algorithms, they all share the following main components:

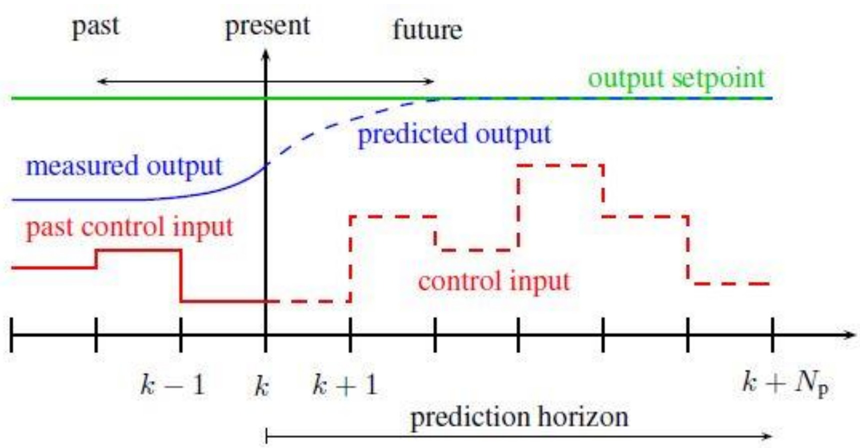



**Figure 3-1: MPC Receding Horizon Concept taken from [24]**

- An *internal model* which describes the dynamics of the system. The model is used to predict at time step $k$, the future process output of the system $y^{k+1|k}$ for $i=1,...,H_p$ over a finite prediction horizon $H_p$. The optimal future output depends on the current measured value of $y^k$ and the predicted or a priori known disturbances and the predicted future control input.
- The consideration of physical and operational *constraints* of the process. The constraints are formulated as equality or inequality constraints and can be applied to states and control variables.
- An *objective function* (or cost function). The objective function is used to express the trade-off between the different (often competing) objectives that the controller tries to achieve. As it is outlined in [24] the most common approach solving multi-objective control problems is to form a scalar cost function, composed of a linearly weighted sum of expressions associated with each objective. An optimization algorithm is used to minimize the objective function, in order for the controller to make the best decision. The result of the optimization is the optimal control sequence, which is a sequence of optimal control inputs over the prediction horizon

that satisfies the constraints. The values of the weights can be used to balance the priority and the importance of conflicting objectives. These weights can be adjusted to tune the controller depending on the application.

- *Receding Horizon Control*. The optimal sequence of control steps $u^{k+1|k}$ for $i = 0, ..., H_p - 1$ is calculated at every time step $k$, but only the first value is applied and the rest of the trajectory is rejected. At the new time step $k+1$, new measurements and current states information is available and the optimal sequence is computed again for the next $H_p$ steps. The basic idea of the Receding Horizon Control is shown in Figure 3-1.

### *3.1.1 Internal Model*

In Model Predictive Control, a mathematical model of the system is needed for the optimization. The model should be formulated in a way that the dynamics of the system are adequately represented. A simplified model is often used though, as a very detailed model is more computationally expensive.

For the purposes of this thesis, a simplified model of a water system is being used (Figure 3-2). While several modelling techniques for water networks have been presented in literature, see [3], [10], [25], [26], the modelling approach used in this thesis is based on a *flow-only* model, where only the control variables are required to compute the change in the state of the networks produced by a control action. An extension of the model would be to include the non-linear relations between flow and pressure for instance, however this would lead to a non-linear model. This thesis examines the linear model of the controlled process, which is often described as a linear discrete-time system, represented by a state-space model [27].

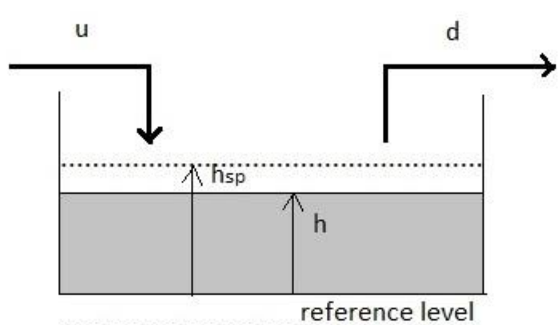



**Figure 3-2: Simplified linear tank schematization**

**Table 3-1: Parameters of simplified tank model**

| Parameter | Value | Unit |
|---|---|---|
| $T$ | 3600 | s |
| $A_s$ | 1075.2 | $m^2$ |
| $h_{sp}$ | 5 | m |
| $h_{min}$ | 0.5 | m |
| $h_{max}$ | 5.8 | m |
| $u_{min}$ | 0 | $m^3/s$ |
| $u_{max}$ | 0.1527 | $m^3/s$ |

The model consists of a single linear tank with an uncontrolled outflow (due to consumer demand) and a controlled inflow that is being used to keep the water level close to a desired setpoint $h_{sp}$ by pumping. It is assumed that the water level in the tank is horizontal, which means that any changes in inflow and outflow cause an instantaneous change in water level over the storage area. The basic equation for tank routing is based on the conservation of mass and it reads:

$$u - d = \frac{\partial V(h)}{\partial t}, \tag{2.1}$$

where $V(h)$ is the storage volume [$m^3$] in the tank as a function of the water level $h$ [m], $A_s$ is the storage area of the tank [$m^2$], $u$ is the controlled inflow [$m^3/s$] and $d$ is the uncontrolled outflow or *disturbance* [$m^3/h$]. The tank has a linear level-volume relation, which means that $A_s$ is constant over the vertical and $\partial V / \partial t = A_s \partial h / \partial t$ , hence the name linear tank. By applying a forward-difference approximation for the time derivative, we obtain the following state-space model:

$$h^{k+1} = h^k + \frac{T}{A_s}(u^k - d^k), \tag{2.2}$$

where $k$ is the index of the time step [-] and $T$ is the control length step [s]. The physical constraint related to the tank volume is expressed as:

$$h_{\min} \le h(k) \le h_{\max}, \tag{2.3}$$

where $h_{\min}$ and $h_{\max}$ denote the minimum and maximum water level, respectively [m]. The parameters of the linear tank model are summarized in Table 3-1.

### *3.1.2 Linear MPC*

The model described in Section 3.1.1 is a linear system. The MPC model used in this thesis is constrained with measured disturbances (known demands), so it can be described as a linear discrete-time system, represented by a state-space model:

$$x(k+1) = Ax(k) + B_u u(k) + B_d d(k), \tag{2.4}$$

$$y(k) = Cx(k), \tag{2.5}$$

where $x \in \mathbb{R}^{n_x}$ is the state, $u \in \mathbb{R}^{n_u}$ the control input, $d \in \mathbb{R}^{n_d}$ the a priori known disturbance, $y \in \mathbb{R}^{n_y}$ the output of the system, at time step *k*, $A$ the system matrix, $B_u$ the control input matrix, $B_d$ the disturbance matrix and $C$ the output matrix. The state-space model (3.4) can be extended over a finite prediction horizon $H_p$ from $k+1$ to $k+H_p$. When the initial state $x(k)$ and all disturbances and control inputs are known, all future output variables $x(k+i\,|\,k)$ for $i = 1,...,H_p$ can be computed. The $k+i\,|\,k$ denotes the sequence of $k+i$ future values that are evaluated at the current time step $k$.

Following the considerations in Section 3.1.1, system constraints are related to bounds in system states and measured inputs expressed by the inequalities:

$$u_{\min} \le u(k) \le u_{\max}, \tag{2.6}$$

$$x_{\min} \le x(k) \le x_{\max}, \tag{2.7}$$

where $u_{\min}$ and $u_{\max}$ are vectors containing the lower and upper limits of the actuator (pump). Hence, using (3.4), (3.5), (3.6) and (3.7), the constrained model of the system for MPC design purposes is expressed as:

$$\begin{cases} x(k+1) = Ax(k) + B_u u(k) + B_d d(k), \\ y(k) = Cx(k), \\ u_{\min} \le u(k) \le u_{\max}, \\ x_{\min} \le x(k) \le x_{\max}. \end{cases} \tag{2.8}$$

### *3.1.3 Control Objectives*

The various MPC algorithms propose different cost functions for obtaining the control law. The general aim is that the future output (y) on the considered horizon should follow a determined reference signal (r) and, at the same time, the control effort (Δu) necessary for doing so should be penalised [8].

A drinking water network has multiple objectives that can assume different priorities. The main goal of the control law is to satisfy the demands, while at the same time taking into account the optimization of the system performance considering different operational criteria. The most common objectives, in general, are related to the physical bounds of the elements, in terms of their safety, or to the operational constraints aimed to satisfy economic goals.

In further detail, the criteria which should be considered are:

- **Security**: maintaining the volume in the tank over a threshold to avoid infeasibilities.
- **Stability**: avoiding continuous and abrupt set-point variations in the actuators to ensure that all treatment plants and actuators operate as smoothly as possible. This criterion is important to avoid damage in valves and pumps.
- **Quality**: especially important when several sources exist with a different water quality, which could depend on the level or concentration of some element that decays in time.
- **Cost**: the electrical cost (price) in the network type consisting of the water cost in the source and the electrical cost necessary for the pumping. The water cost could change at different sources with different elevation or treatment, while the electrical cost for pumping changes depending on the hour of the day (electricity tariff).
- **Conservation**: water sources such as rivers and reservoirs are usually subject to operational constraints to maintain water levels, ecological flows and sustainable water use.

The aforementioned objectives can be included into a single-objective optimization problem with a scalar-value objective function in the form of a weighted sum of the functions $f_i$ , which represents every objective that has to be optimized:

$$F(k) = \sum_{i=1}^{r} w_i f_i(k) \tag{2.9}$$

where $r$ is the number of objectives present in the problem and the priority of the objectives is reflected by the weights $w_i$. For an evaluation over the entire optimization horizon, the performance index must be summed as:

$$J = \sum_{k=1}^{H-1} F(k) \tag{2.10}$$

where H is the optimization horizon in a number of sampling periods.

This thesis will focus on two main objectives of the MPC, where the objective function to be minimized at each time step $k$ is formed as follows:

$$\min_{\Delta u} \quad J = \sum_{i=0}^{H_p} W_e (e^{k+i|k})^2 + \sum_{i=0}^{H_p - 1} W_{\Delta u} (\Delta u^{k+i|k})^2, \tag{2.11}$$

where:

$$e^k = \tilde{x}^k - x_{sp} \tag{2.12}$$

$$\Delta u^k = u^k - u^{k-1} \tag{2.13}$$

and $\tilde{x}$ is the predicted plant state, $x_{sp}$ is the setpoint, $\Delta u$ is the predicted change in control value, $W_e$ and $W_{\Delta u}$ are penalties on water level deviation from setpoint and change in control input respectively. This quadratic objective function penalizes the squares of deviations from setpoint $x_{sp}$ of the simulated states $\tilde{x}^k(u^k, d^k)$ and control input. With a linear process model and a quadratic objective function, the optimization problem can be written as a convex QP problem [28], that has to be solved at every discrete time step *k*.

### *3.1.4 Application to Linear Tank Model*

Rewriting the above equation 3.2 in the shape of equations 3.4, 3.5, with $x^k = h^k$ , $A^k = 1$, $B_u = T / A_s$ and $B_d = -T / A_s$ , we have:

$$x^{k+1} = A^k x^k + B_u^k u^k + B_d^k d^k, \tag{2.14}$$

$$y^k = x^k. \tag{2.15}$$

When the water level is bounded between $h_{\min}$ and $h_{\max}$ , this can be expressed in the inequality constraint of the quadratic programming problem.

$$h_{\min} \le Ax(k) + B_u U + B_d D \le h_{\max} \tag{2.16}$$

$$\begin{bmatrix} B_u \\ -B_u \end{bmatrix} U \le \begin{bmatrix} h_{\max} - Ax(k) - B_d D \\ -h_{\min} + Ax(k) + B_d D \end{bmatrix} \tag{2.17}$$

# CHAPTER 4. VLITES PUMP STATION: THE CASE STUDY

## 4.1 Case Study Description

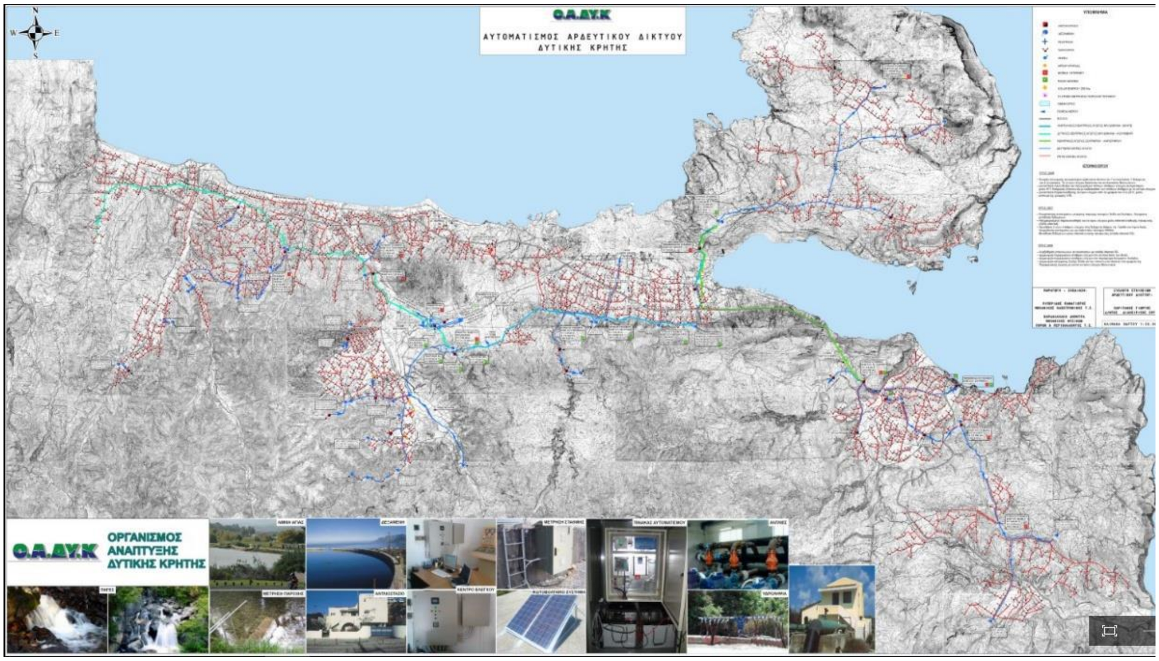



**Figure 4-1: OAK Water Network in Chania**

OAK AE water distribution network extends across Crete, however the focus of this thesis is in the Region of Western Crete, particularly in the part of the Chania network which includes the pumping station of Vlites. The operation of the pumping station was briefly described in Section 2 and an initial model of the water network was presented. In this Section, we will describe a case study based on a real water network derived from the Western Crete water distribution system. Using a revised version of the model presented in Section 2, the MPC techniques and control objectives outlined in Section 3 are applied to the system and their effects are discussed through the analysis of the controller design and simulation scenarios.

### *4.1.1 Simulink Model Description*

The revised model used for the case study is shown below in Figure 4-2. Separate parts of the system will be discussed in more detail.

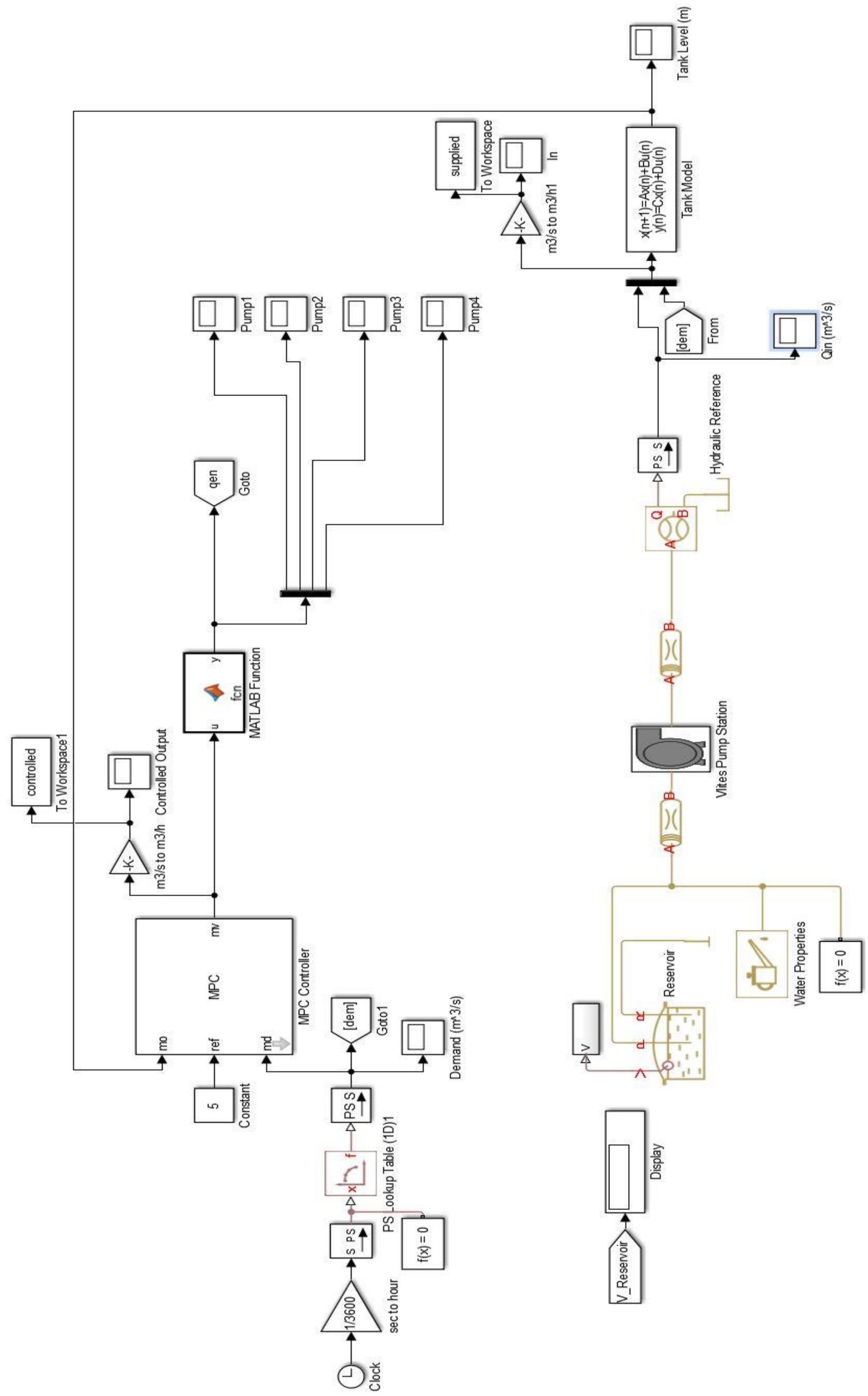



**Figure 4-2: Basic Simulation Model of Vlites Pump Station and Korakies Tank**

Although a system can be extensively modelled in order to include the physical laws of the system, many of the restrictions and constraints, as well as the randomness that appears within the system, that would result to an increased complexity that would require significant computing effort and time in order to be compiled. Following a standard modelling technique, the basic laws and limitations of the system are represented in the model, while some parts of the system have been omitted and others approximated. Simulink allows us to approximate several behaviors of the system that would be too complex to be calculated, by using Simscape library blocks, or by grouping parts that show great complexity and replacing them with a generic block that has similar effects.

The current model definition was designed based on a simple approach, where there is a water source, represented by a reservoir, with enough water to supply a water system with average consumption. The source supplies another tank with the use of a pump station which pumps water from the source to a tank with different elevation. The pump station consists of 4 pumps, each of which has its specific pressure-discharge curve stored inside the block, together with several blocks that are necessary for its operation, measurement and operating point calibration. A state-space model block has been used for the tank, which represents a linear tank with an inflow from the pump station and an outflow which stands for the water network demand. An MPC Controller block is present to control the level of the tank, by ordering the on-off switching of the pumps. Finally, a custom Matlab function block contains the logic with which the enables of the pumps are turned on or off, based on the controller output.

In Figure 4-2 above, we see the basic simulation model. Some of the blocks used are from the Simscape Hydraulic library and are necessary for the basic hydraulic relations and operation of the model. The Hydraulic Fluid and Solver Configuration blocks are used to set fundamental model properties. Each physical network represented by a connected Simscape block diagram requires solver settings information for simulation. The

Hydraulic Fluid block lets us specify the type of hydraulic fluid used in a loop of hydraulic blocks.

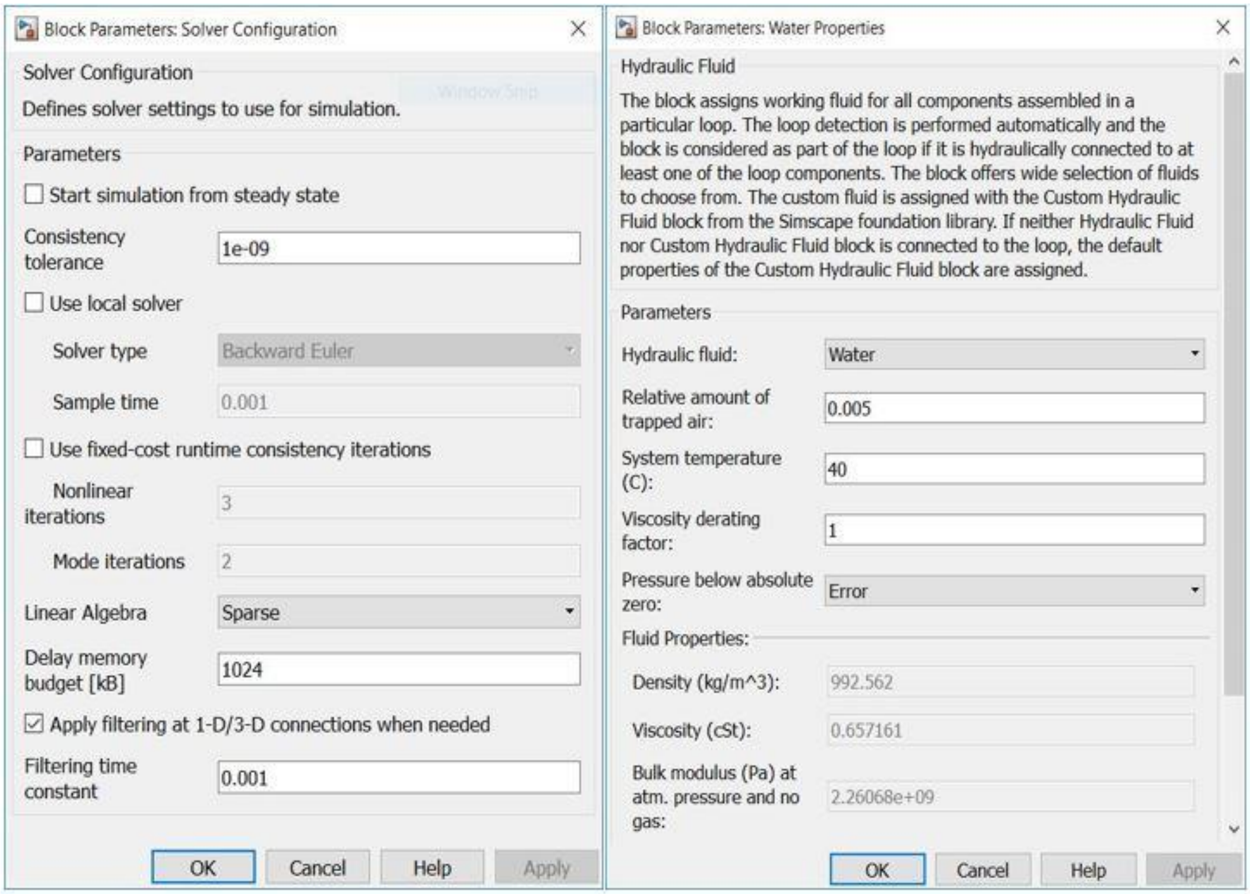



**Figure 4-3: Simulink Model Parameters**

Water is transported from the reservoir to the Vlites pump station and Korakies tank, through pipes. Their dimension, length and other values are set as shown in Figure 4-5.

### *4.1.2 Pump Station*

The pumps were grouped in a subsystem, which is depicted in Figure 4-8.

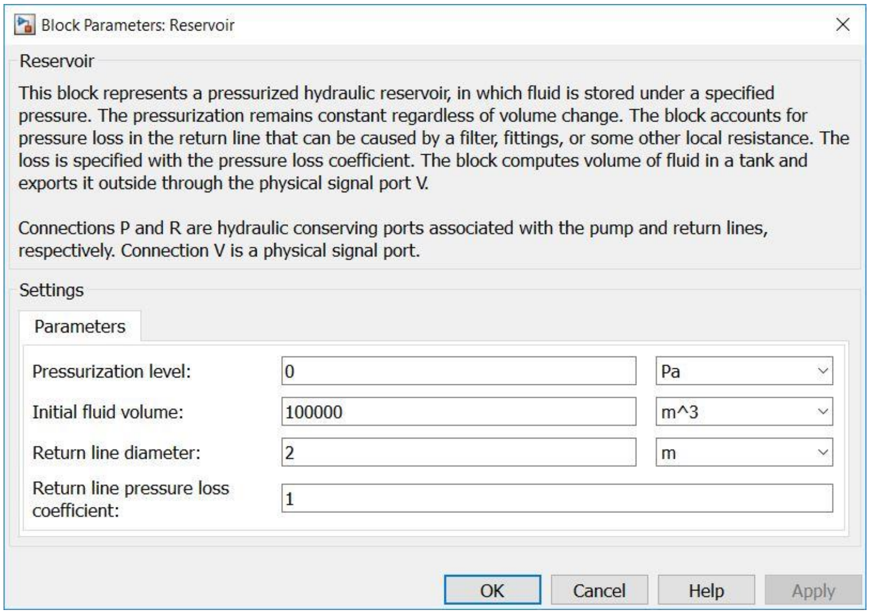



**Figure 4-4: Reservoir parameters**

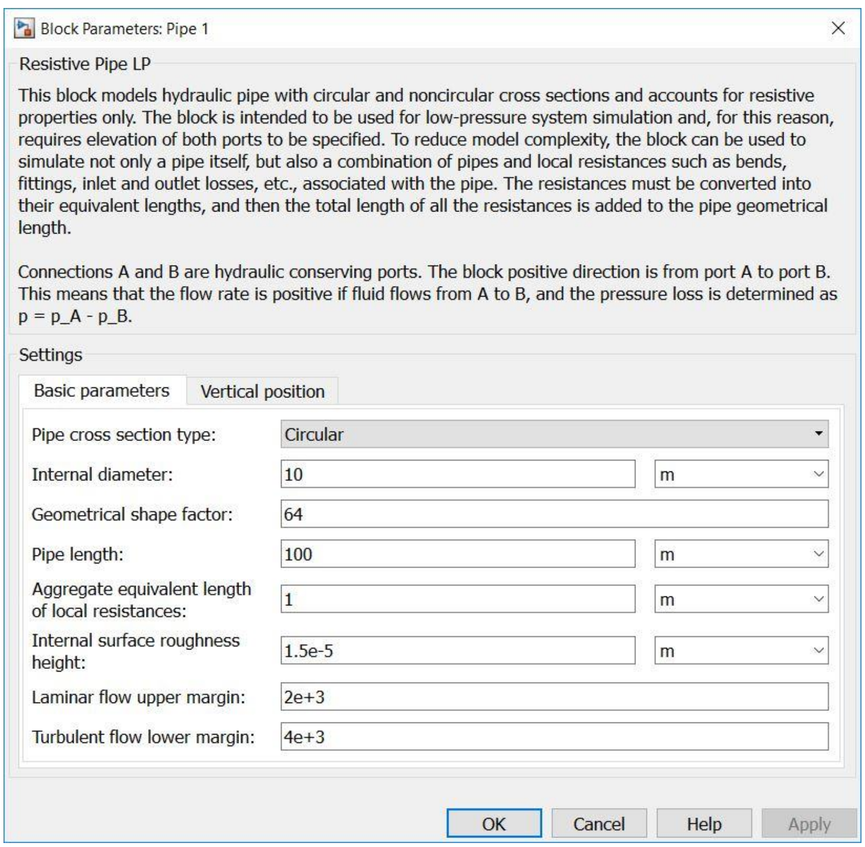



**Figure 4-5: (a)**

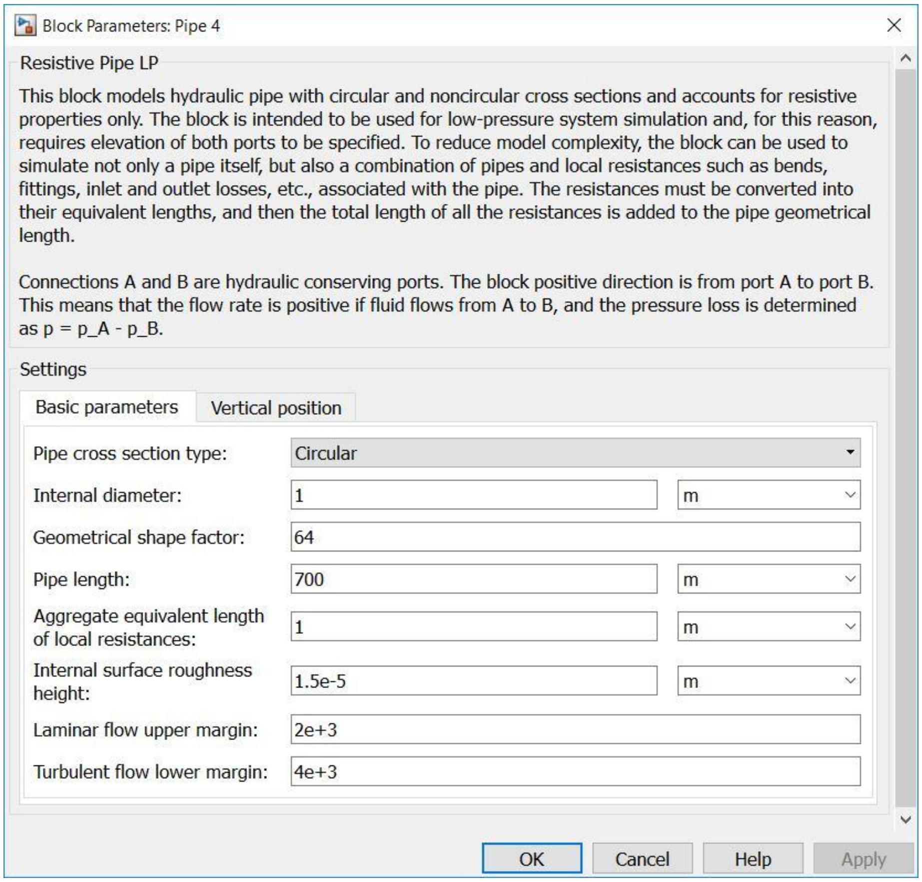



**Figure 4-5: (a) and (b) Pipe parameters**

The pump parameters were set according their Efficiency curves and Pressure-Flow curves (Figure 4-6). From the data from OAK AE, the nominal operating point was located, then, the specific flow value was located on the Pressure-Flow curve in order to find the corresponding pressure value. This specific pressure value for each curve was used in the pump model to calibrate the model to the nominal operating point.

**Table 4-1: Flowrate and Pressure values for model calibration**

| | **Nominal Flowrate [$m^3$/h]** | **Simulink Flowrate [$m^3$/h]** | **Simulink Pressure [bar]** |
|---|---|---|---|
| **Pump Type 1** | 350 | 350 | 15.5 |
| **Pump Type 2** | 125 | 120 | 10.6 |

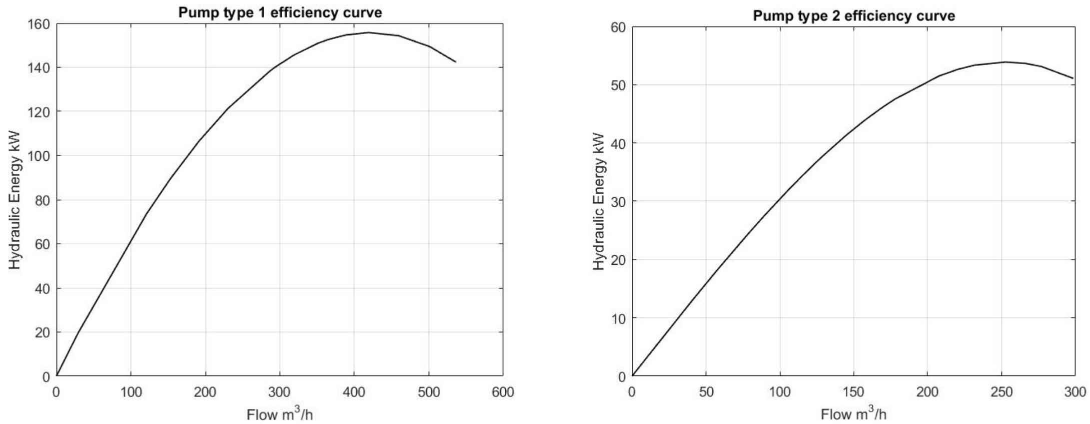



**Figure 4-6: Pump type 1 [350m$^3$/h] and type 2 [125m$^3$/h] Efficiency Curves**

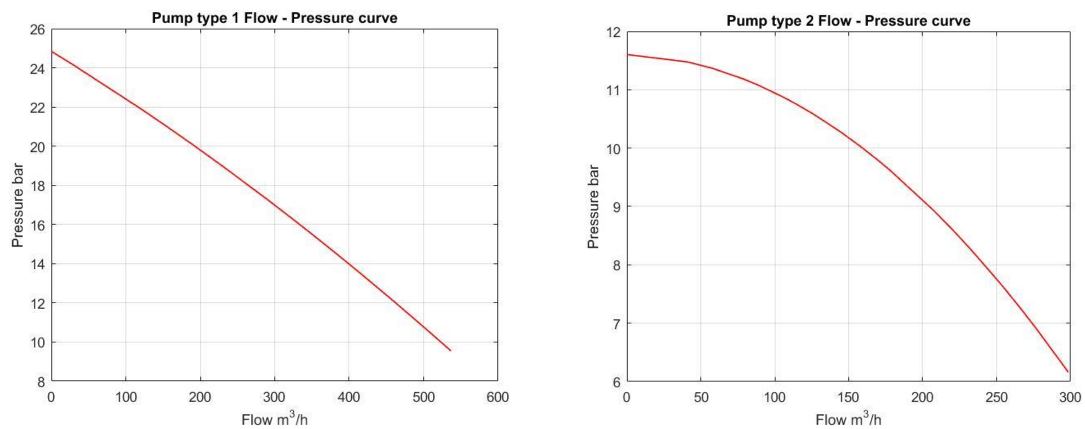



**Figure 4-7: Pump type 1 [350m$^3$/h] and type 2 [125m$^3$/h] Pressure-Flow Curves**

For the centrifugal pump model, the P-Q and N-Q parametrization was selected from the three options and the appropriate parameter table lookups are computed in a Matlab script. The m$^3$/h unit was not an available option for the flow rate, so m$^3$/s was used instead and the values were divided by 3600 (Figure 4-10).

In Figure 4-9, the model for the pump, we can see that a selection switch decides whether there will be 1450 rpm or 0 rpm input in the prime mover of the pump, thus changing its condition between states, on (value of the switch selector is 1) or off (value of the switch selector is 0). Hydraulic Flow Rate and Pressure sensors are used for monitoring and Gains for unit conversion.

Some additional blocks were used for the operation of the pump, which are shown in Figure 4-8. A check valve is necessary to avoid water returns when pump is off or when the network pressure is higher than the pressure generated by the pump. Also, a pipe block is used in order to control the output of the pump by modifying the cross-section of the

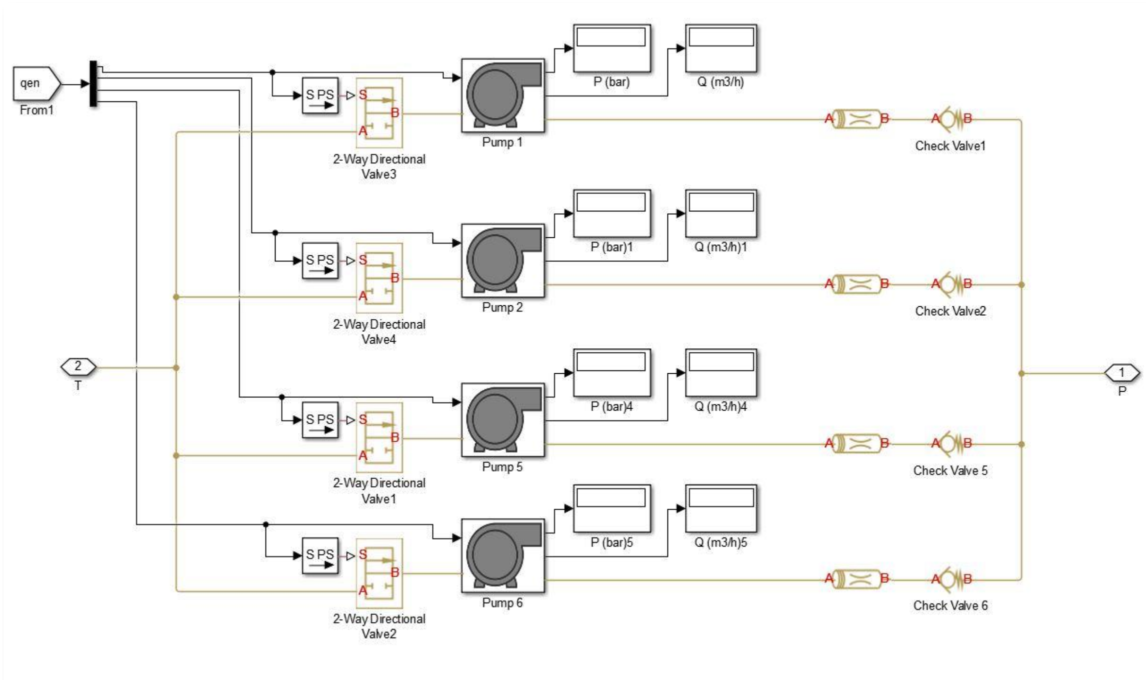



**Figure 4-8: Pump Station Subsystem**

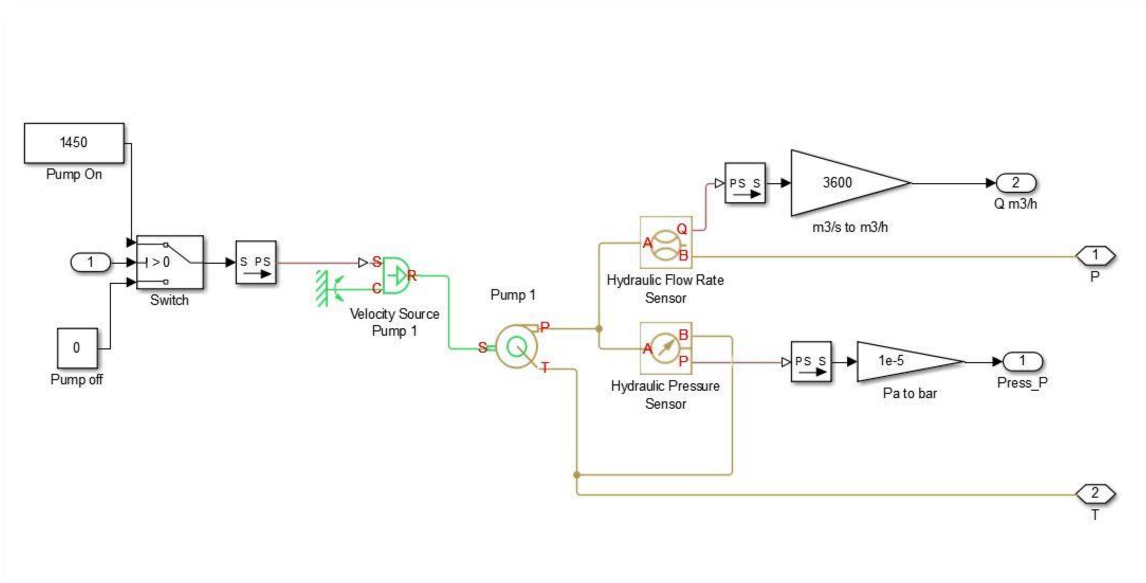



**Figure 4-9: Pump Subsystem**

output orifice. By reducing the cross-section of the orifice, the pressure is increased and the flowrate is reduced. After experimentation, the pipe's cross-section for each type of pump was selected, so that the pressure and the flowrate of the pump would be that of its nominal operation point, as that was located from the pump curves.

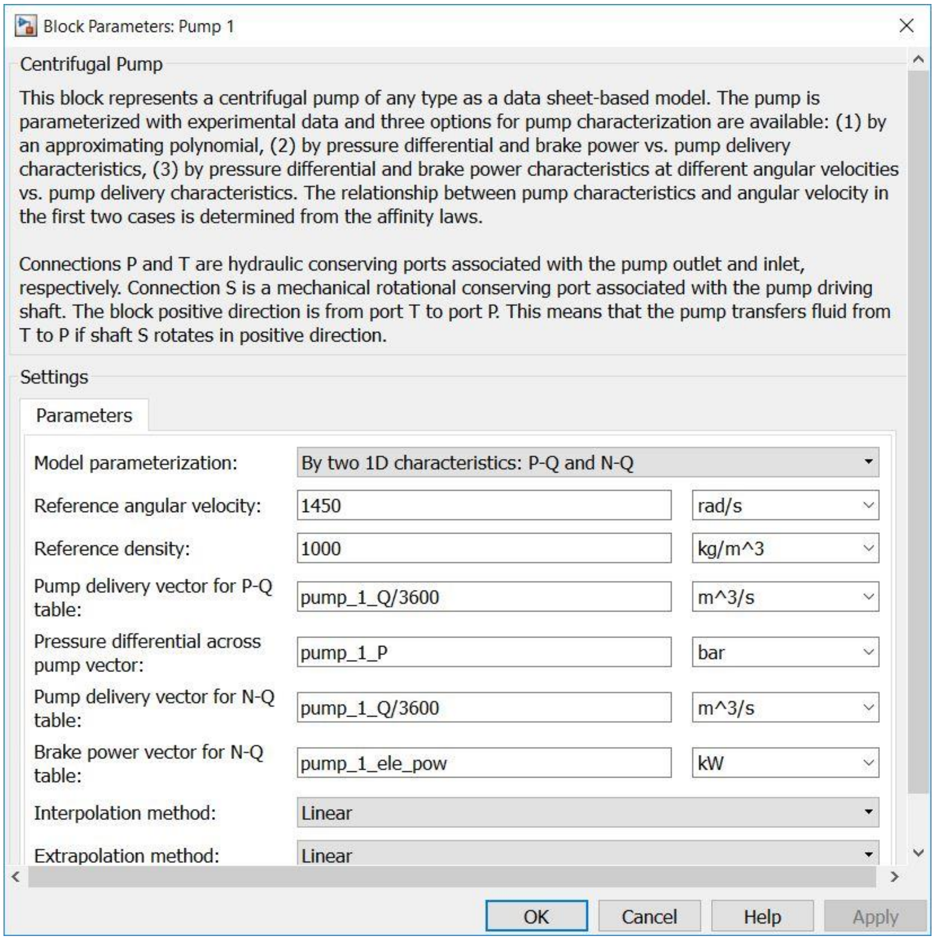



**Figure 4-10: Centrifugal Pump parameters**

### *4.1.3 Tank Model*

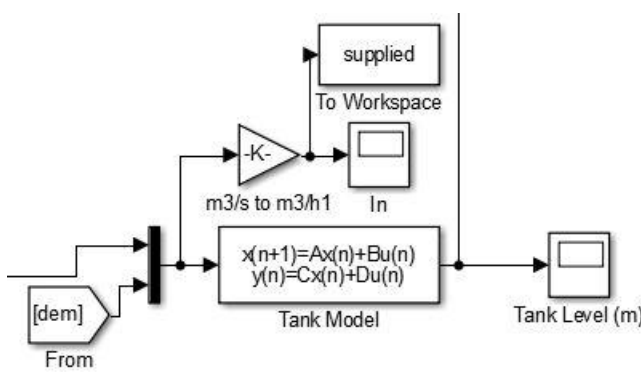



**Figure 4-11: Tank model**

For the Korakies tank model, a state-space model block was used, as shown in Figure 4-11 and 4-12.

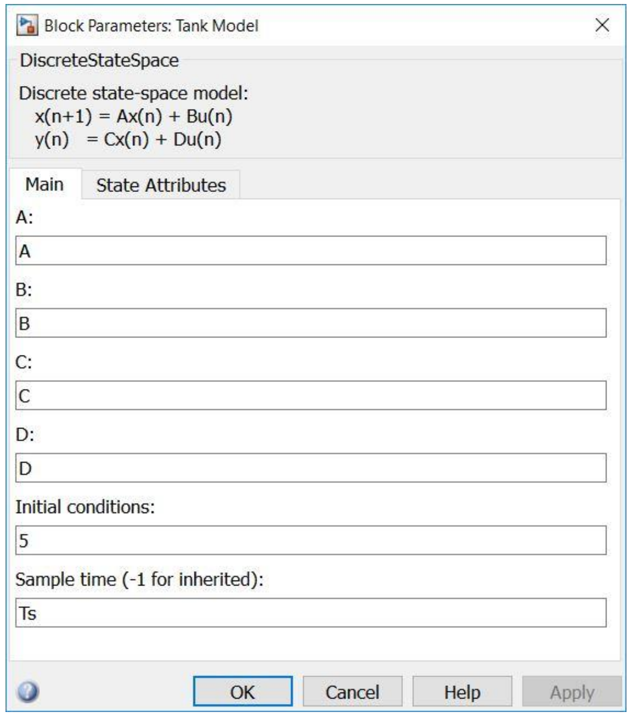



**Figure 4-12: Tank model parameters**

The state-space model parameters are set from a Matlab script, based on the discrete state-space model of the linear tank discussed in Section 3, equation 3.14, 3.15, where Ts=3600 s, A=1, B=[Bu Bd], C=1, D=[0 0] and Bu=Ts/kor_tank_cs, Bd=-Ts/kor_tank_cs, where kor_tank_cs=1075.2 $m^2$ is the tank calculated cross-section area. The inputs are the flowrate from the water flowing from the pump station and the demand (both $m^3/s$), the output is the tank level (m) and the initial condition is the tank level equal to 5 m.

### *4.1.4 Demand*

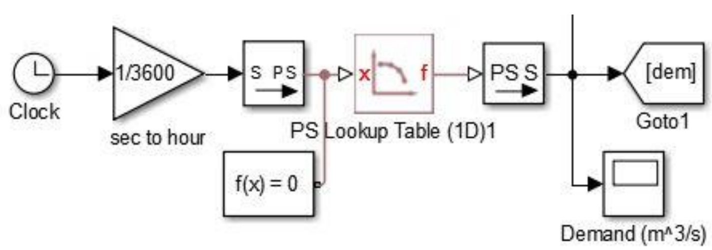



**Figure 4-13: Water Demand representation**

As shown in Figure 4.13, the demand is modelled as a time function. The look up table for the water demand that was used in this study derived from statistical data from the Vlites pump station. The daily demand profile has a similar form throughout the year, where there is a peak during noon and a secondary peak during afternoon hours. Although the form remains the same the average consumption changes from month to month. In this study, two cases of demand will be examined, which will be discussed in further detail in Section 4.3.

### 4.1.5 *MPC Controller*

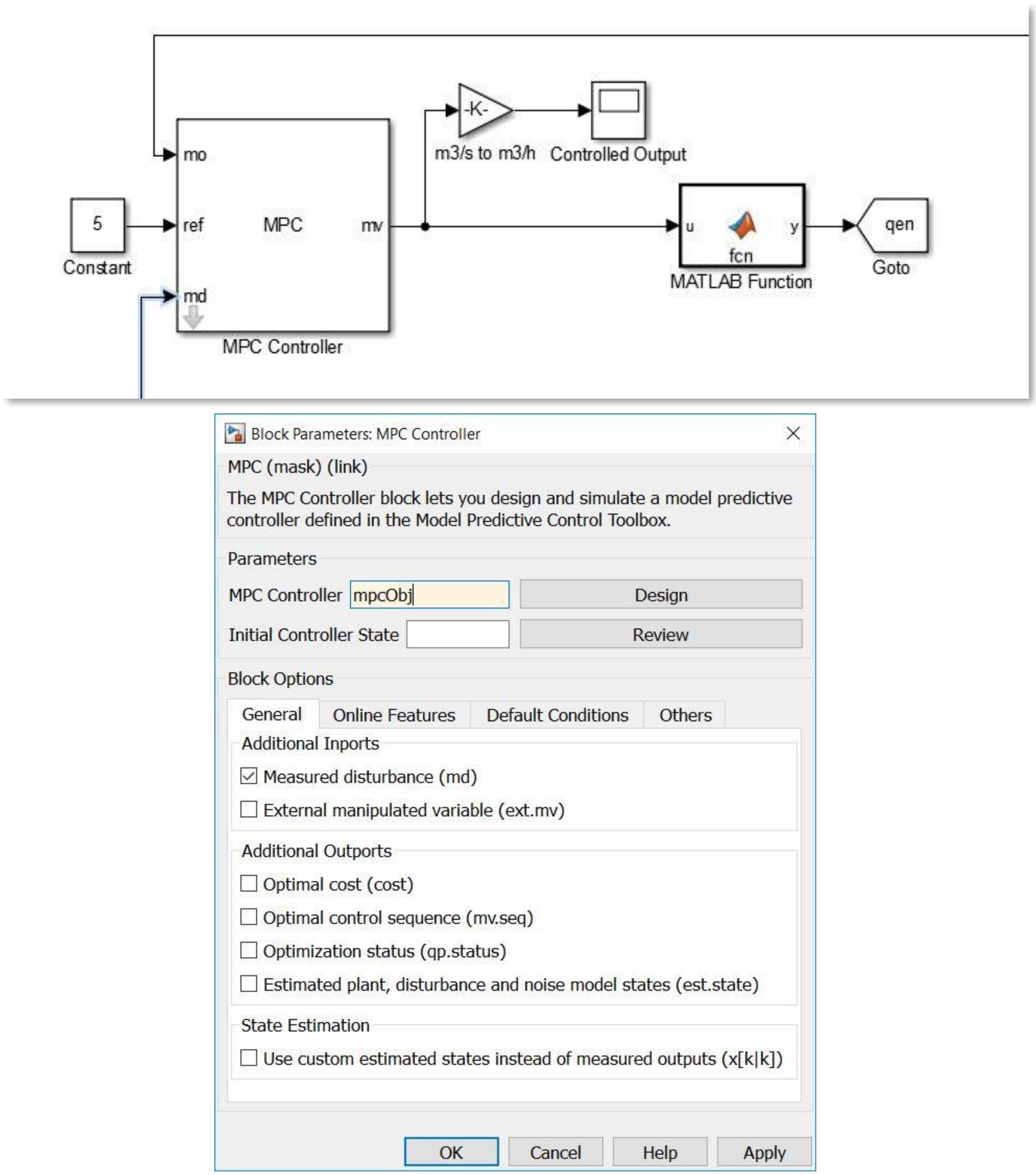



**Figure 4-14: MPC Controller block and parameters**

After the MPC object has been designed and implemented in a MATLAB script (see Appendix), it is used in the MPC Controller block used in the model we study. The MPC object's design and parameters are discussed in detail in Section 4.2 below. The inputs of the MPC block are, first, the tank level feedback signal from the tank model which goes into the controller's measured output (mo) port, second, a constant value signal in the reference (ref) port and third, the demand signal, which goes into the measured disturbance (md) port of the controller. The output, the manipulated variable of the controller, is a flowrate. A gain block is used for unit conversion, for display purposes. The controller computes an optimal inflow value for the tank, then a custom MATLAB function based on this value sets which of the pumps are to be active to achieve the closest to this value, so it sets each pump's enable signal to 0 for off, or 1 for on status. The output of the MATLAB function, qen signal, is input for the pumps' enable switches.

## 4.2 Controller Design

In MATLAB controller design, a model predictive controller uses linear plant, disturbance, and noise models to estimate the controller state and predict future plant outputs. Using the predicted plant outputs, the controller solves a quadratic programming optimization problem to determine optimal manipulated variable adjustments.

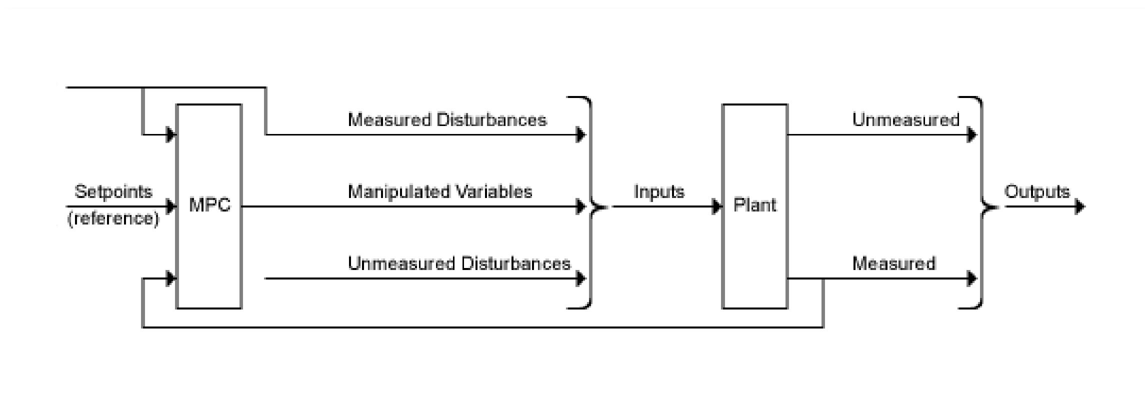



**Figure 4-15: Matlab Controller Design, general MPC structure**

In relation to the simplified tank model, the reference is a constant value, the measured disturbance (MD) is the demand, the manipulated variable (MV) is the tank inflow and the measured output (MO) is the tank water level.

First, a discrete time state-space plant model is defined, based on the linear tank model explained earlier in Section 3, using the ss command, to be used as the controller's internal model. After creating the MPC object, the controller sample time and horizons are defined. Supposing that the current control interval is $k$, the prediction horizon, $p$, is the number of future control intervals the MPC controller must evaluate by prediction when optimizing its MVs at control interval $k$. The control horizon, $m$, is the number of MV moves to be optimized at control interval $k$. The control horizon falls between 1 and the prediction horizon $p$. The default is $m = 2$. Regardless of our choice for m, when the controller operates, the optimized MV move at the beginning of the horizon is used and any others are discarded. With the general MPC controller design guidelines from literature and Mathworks under consideration [29], the controller's sample time $T_s$ is set to $T_s$=3600 s, the prediction horizon is set to $p$=10 and the control horizon is set to $m$=4.

Having specified the controller sample time and horizons, we then specify the required constraints. The specified upper and lower bounds for the values of plant outputs and manipulated variables and also for the rate of change of manipulated variables are summarized in Table 4-2.

**Table 4-2: Plant input and output upper and lower bounds**

| Parameter | Min Value | Max Value |
|---|---|---|
| **MV** | 0 | 0.2027 |
| **MV.Rate** | -Inf | Inf |
| **OV** | 0.5 | 5.8 |
| **OV.ECR** | 0.1 | 0.1 |

**Note 4-a: (MV = plant manipulated variable; OV = plant output variable; MV.Rate =>MV increment = u(k) – u(k – 1), ECR = value for constraint softening)**

The Model Predictive Control Toolbox also allows us to tune the MPC controller performance by adjusting the cost function penalty weights for plant outputs and manipulated variables, and also for the rate of change of manipulated variables. To understand the impact of weight tuning, it is useful to first discuss the optimization problem and the cost function equations.

Model predictive control solves an optimization problem – specifically, a quadratic program (QP) – at each control interval. The solution determines the manipulated variables (MVs) to be used in the plant until the next control interval. This QP problem includes the following features:

- The objective, or "cost", function — A scalar, nonnegative measure of controller performance to be minimized.
- Constraints — Conditions the solution must satisfy, such as physical bounds on MVs and plant output variables.
- Decision — The MV adjustments that minimize the cost function while satisfying the constraints.

In MPC Toolbox, the standard cost function is the sum of four terms, each focusing on a particular aspect of controller performance, as follows:

$$J(z_k) = J_y(z_k) + J_u(z_k) + J_{\Delta u}(z_k) + J_\varepsilon(z_k) \quad (3.1)$$

where

$z_k$ is the QP decision and each term includes weights that help balance competing objectives.
The first term, $J_y(z_k)$ , refers to Output Reference Tracking, regarding the tank water level,
the second term, $J_u(z_k)$ , refers to Manipulated Variable Tracking, regarding the tank inflow,
the third term, $J_{\Delta u}(z_k)$ , refers to Manipulated Variable Move Suppression, that is the change in control action regarding the tank inflow and
the fourth term, $J_\varepsilon(z_k)$ , refers to Constraint violation regarding constraints to plant input and output.

The MPC controller toolbox provides default weights and by adjusting them the controller can be tuned for each application. Keeping general MPC controller design and Mathworks guidelines under consideration [30], the weight values used for this study are summarized in Table 4-3.

**Table 4-3: Tuning Weights**

| Parameter | Value |
|---|---|
| Weights.MV | 0 |
| Weights.MVRate | 0.1 |
| Weights.OV | 1 |
| Weights.ECR | 100 |

The MATLAB script used for designing and setting the parameters of the MPC controller can be found in Appendix A.

## 4.3 Scenarios

As it was briefly mentioned previously, the daily demand profile for the water network examined in this study is similar throughout the year. While the form remains the same, with a peak in noon and a second peak during the afternoon hours, the average consumption changes from month to month. The average consumption is lower during the winter months while during the summer months, there is an increase in consumption, due to touristic accommodation activity and increased irrigation needs. Below, we can see this yearly behaviour in a chart based on data from OAK AE.

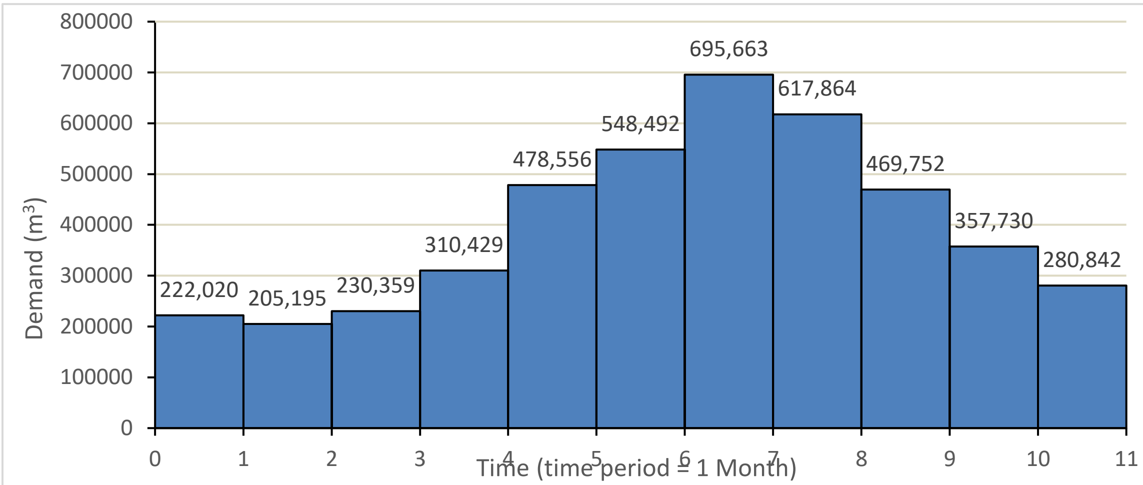



**Figure 4-16: Vlites monthly demand from OAK AE**

For this study, based on this information, two profiles were developed, one for medium demand, with a total daily consumption of 7780 $m^3$ and one for high demand, with a total daily consumption of 11745 $m^3$. The multipliers and hourly demand values can be found in Appendix A. Below, the 24-hour demand profiles for both scenarios are shown.

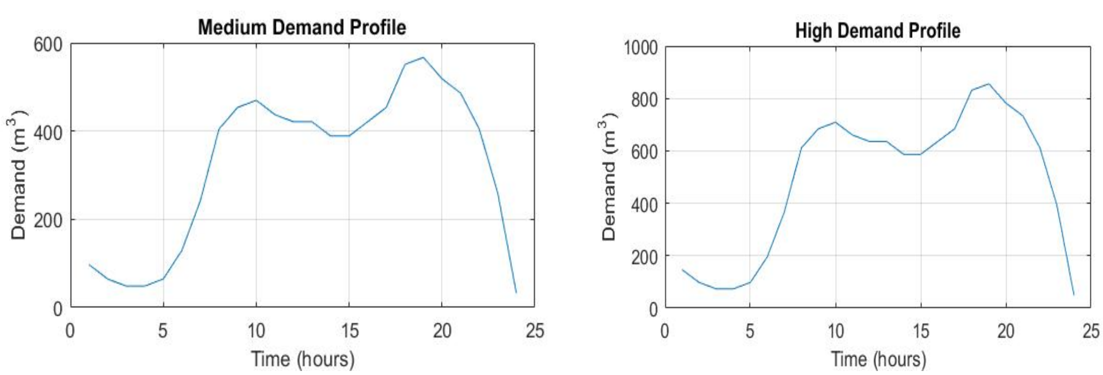



**Figure 4-17: Daily Demand Profiles**

One parameter of the model which is significant for the outcome of the simulation is the controller's reference signal. With this signal we can set the setpoint for the tank level. We examine two cases, one where the setpoint has a high value of 5 m, close to the upper security level and one where the setpoint has a much lower value of 2 m. This second setpoint level is more realistic, because it is required to keep the tank volume as low as possible, while at the same time satisfying the demands.

Combining the above, four scenarios are developed as follows:

i. Medium demand, setpoint = 5
ii. Medium demand, setpoint = 2
iii. High demand, setpoint = 5
iv. High demand, setpoint = 2.

## 4.4 Simulation

For all scenarios, all the parameters of the model except from the controller setpoint, are kept the same. The lower and upper bound of the tank level, the initial state of the tank (80% of its maximum capacity) and the duration of the simulation are summarized in Table 4-4.

**Table 4-4: Simulation parameters**

| Parameter | Value |
|---|---|
| $h_{min}$ | 0.5 m |
| $h_{max}$ | 5.8 m |
| Initial tank state | 4.8 m |
| Simulation time | 86400 s (24h) |
| Fixed step size | 3600 s |

### 4.4.1 Scenario 1: Medium Demand Case, setpoint=5

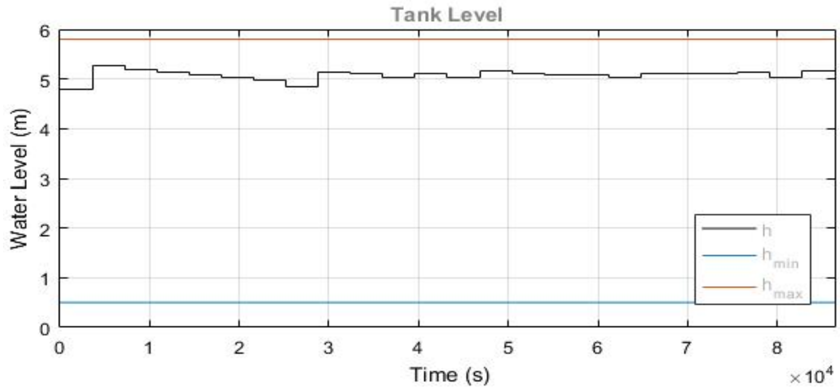



**Figure 4-18: Water Level in Korakies Tank, Scenario 1**

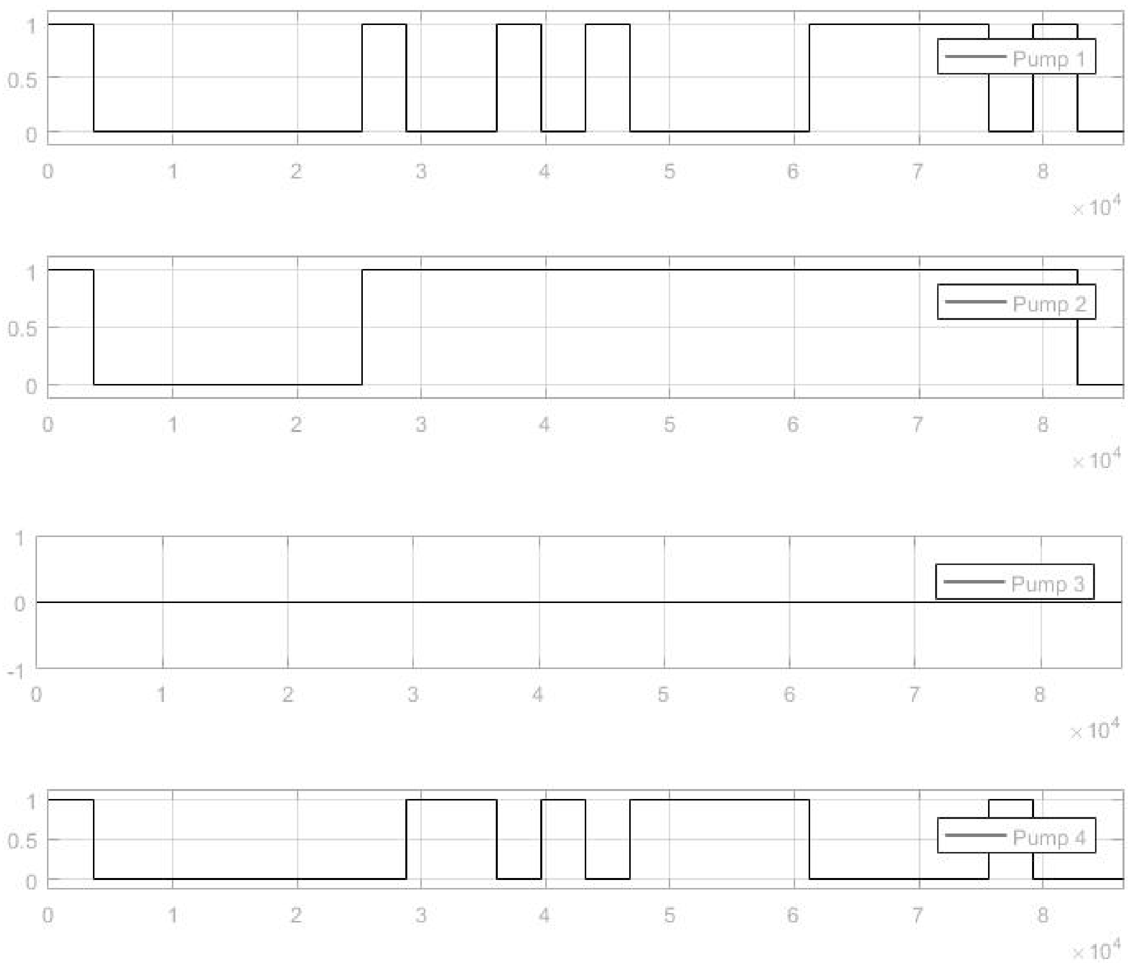



**Figure 4-19: Pumps Operation in 24-h simulation, Scenario 1, 0="off" and 1="on"**

### *4.4.2 Scenario 2: Medium Demand Case, setpoint=2*

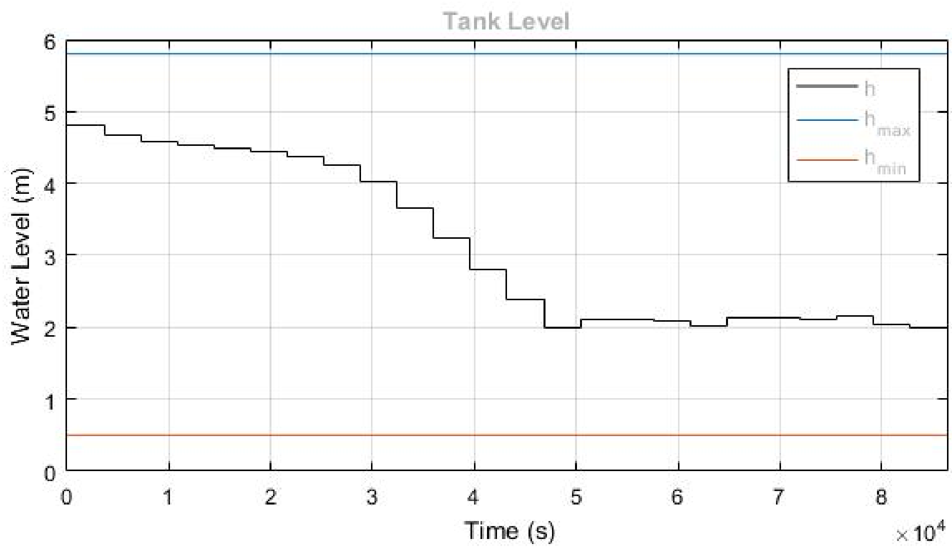



**Figure 4-20: Water Level in Korakies Tank, Scenario 2**

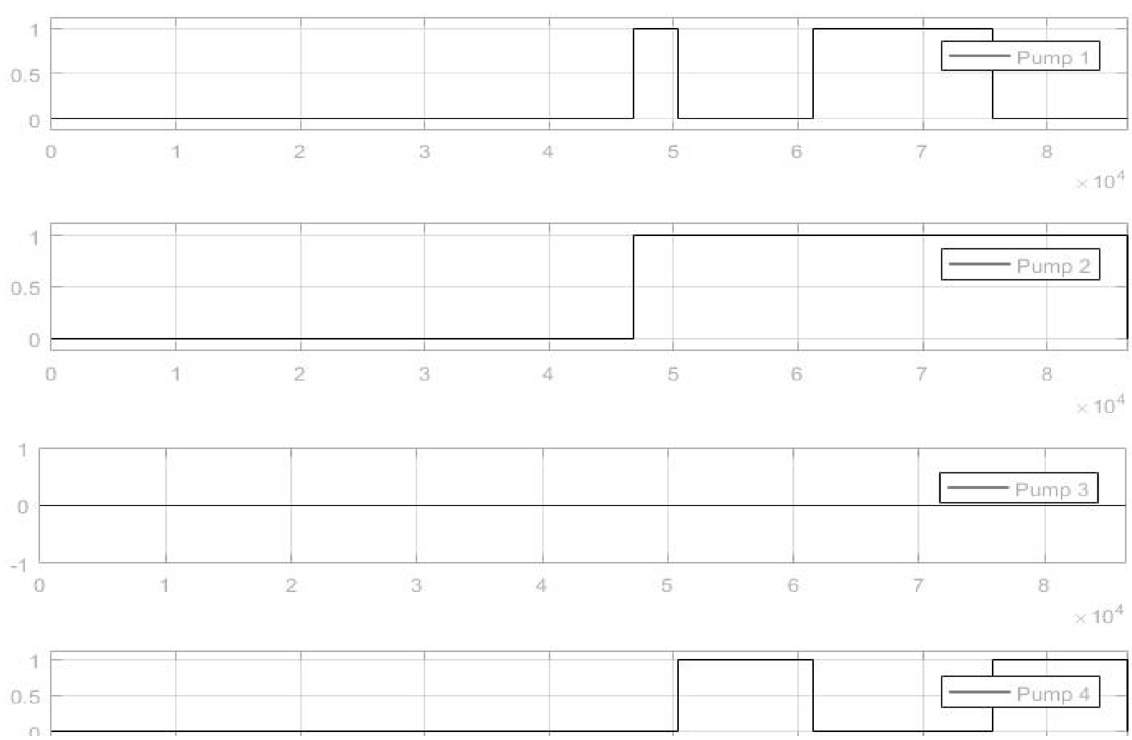



**Figure 4-21: Pumps Operation in 24-h simulation, Scenario 2**

### 4.4.3 Scenario 3: High Demand Case, setpoint=5

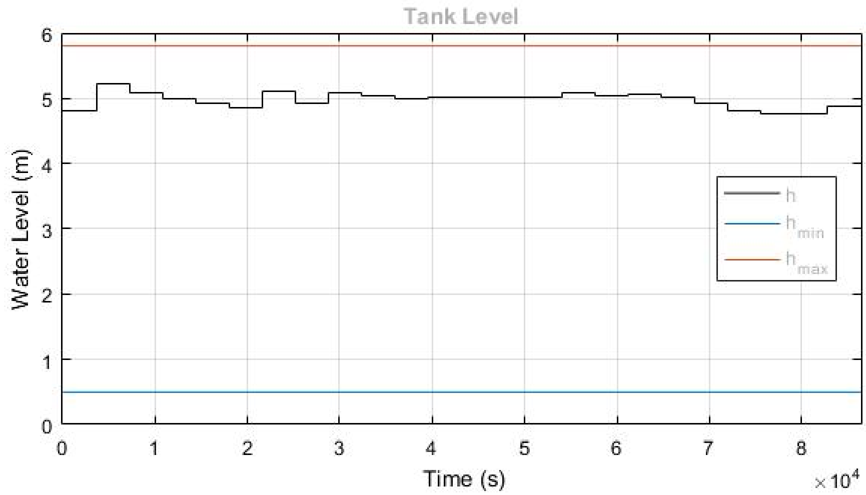



**Figure 4-22: Water Level in Korakies Tank, Scenario 3**

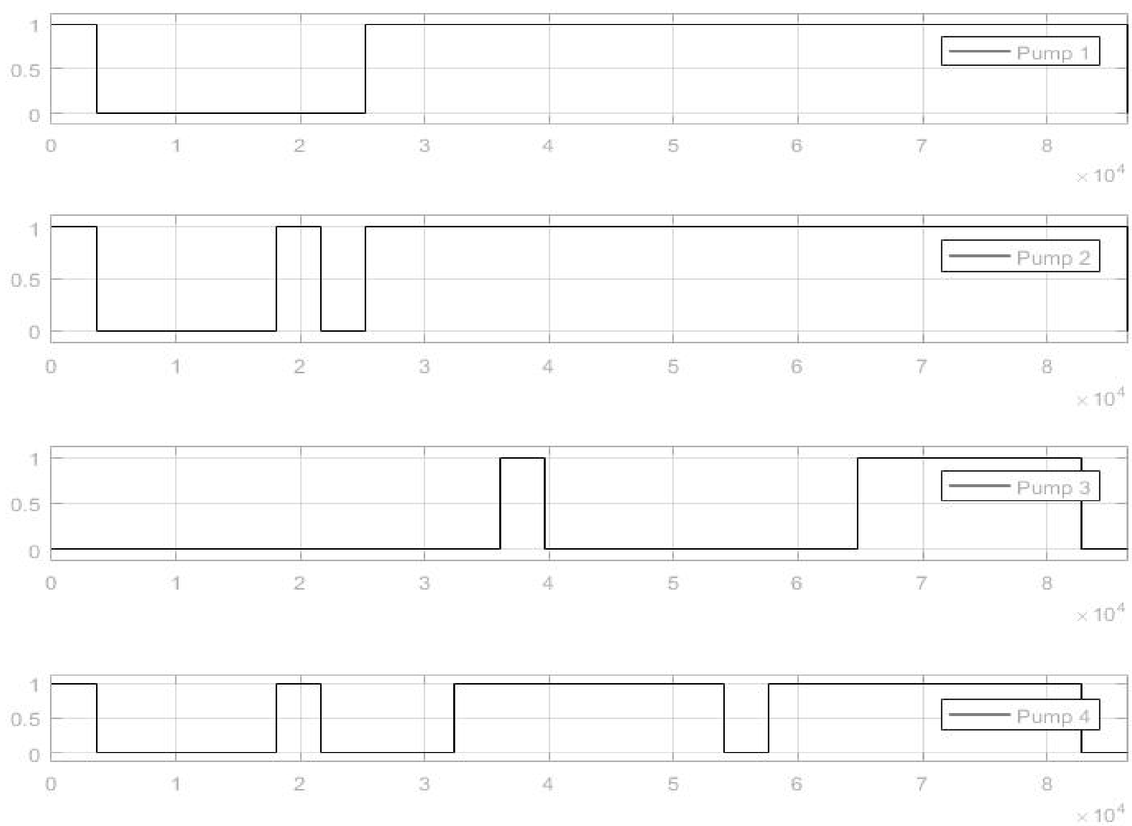



**Figure 4-23: Pumps Operation in 24-h simulation, Scenario 3**

### 4.4.4 Scenario 4: High Demand case, setpoint=2

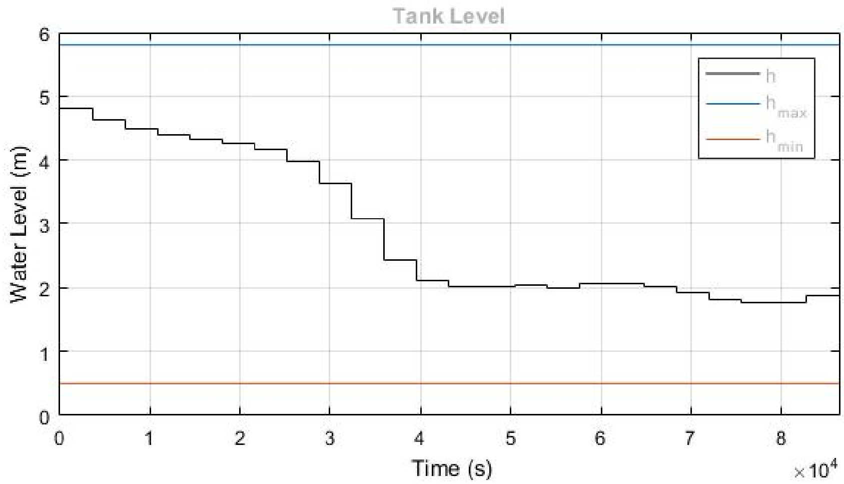



**Figure 4-24: Water Level in Korakies Tank, Scenario 4**

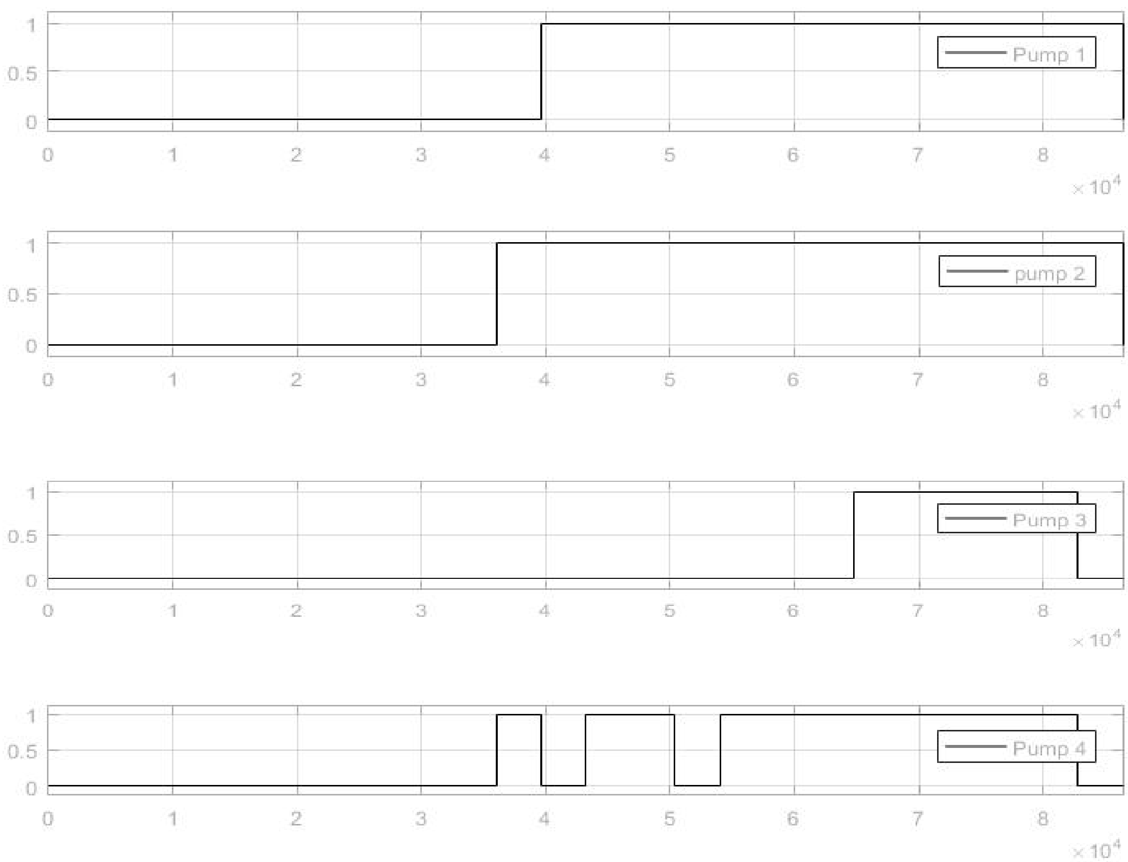



**Figure 4-25: Pumps Operation in 24-h simulation, Scenario 4**

### *4.4.5 Results*

From the simulation results, it is observed that the controller manages to keep the tank level well within the safety limits at all cases, while satisfying the consumer demands.

In scenarios 1 and 3, we can see that the water level is kept very close to the setpoint value throughout the simulation. Almost the whole demanded volume is provided by water pumped from the pump station, so the water that is pumped goes to consumption and the tank level is kept almost the same as the initial condition, since it very close to the setpoint value.

However, in scenarios 2 and 4, where the setpoint value is quite lower than the initial condition, at first the consumer demand is covered by the water that is already stored in the tank, so we see the tank level getting lower. The pumps are scheduled to start working when the tank level approaches the setpoint value and while the demand is about to start increasing before it reaches a peak. In this way the controller tries to satisfy the consumer demands using a minimal quantity of water, which means less pumping and electricity costs.

**Table 4-5: Total Time of Operation for each pump during 24-h simulation of different scenarios**

| | Scenario 1 | Scenario 2 | Scenario 3 | Scenario 4 |
|---|---|---|---|---|
| **Pump 1** | 9 h | 5 h | 18 h | 13 h |
| **Pump 2** | 17 h | 11 h | 19 h | 14 h |
| **Pump 3** | 0 h | 0 h | 6 h | 5 h |
| **Pump 4** | 9 h | 6 h | 15 h | 11 h |

By analysing the resulting pump operation times from the simulation of the four different scenarios, we were able to compare the pump station operation with the MPC scheduling approach, with that of an empirical pump station operation, using statistic data from Vlites pump station SCADA measurements from the year 2015. The average total energy consumption per day is calculated for the simulated model for both high and medium demand case. Below, it is compared with the calculated average total daily energy consumption of Vlites pump station for the same demand cases. It is noted that the medium demand scenario corresponds to the water consumption data from Vlites for the month of March 2015, while the high demand scenario corresponds to the Vlites consumption data for the month of October 2015.

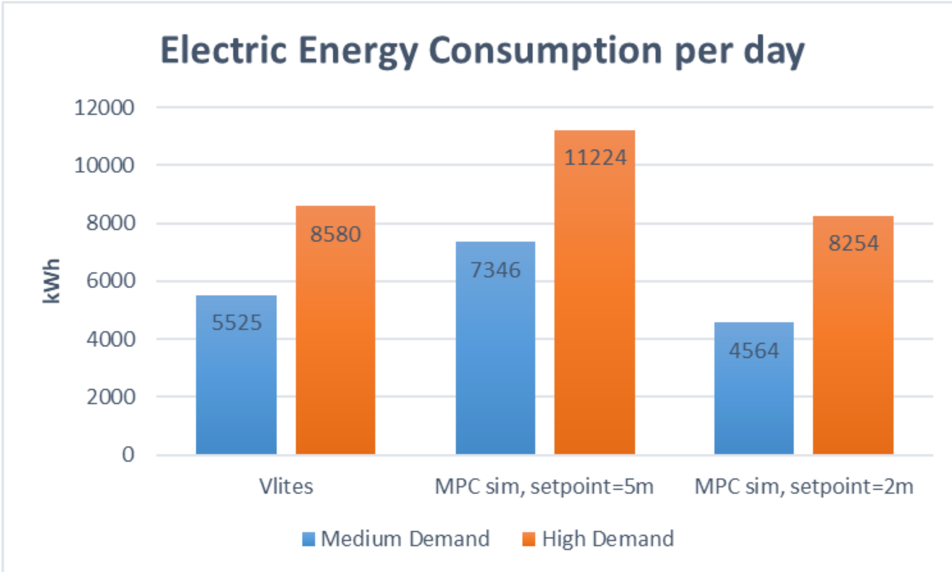



**Figure 4-26: Average daily Electric Energy Consumption comparison of Vlites and model pump station**

As it was observed earlier, in Scenario 1 and 3 the MPC controller tries to satisfy the network demand while maintaining the water level in the tank very high (setpoint = 5m). Thus, the pumps have longer total daily operation times in both the medium and high demand cases. However, in Scenario 2 and 4, where the tank level setpoint is lower (setpoint = 2m), the controller manages to cover the demand using less pumping, with the total daily pump operation times being shorter in both medium and high demand cases.

**Table 4-6: Percentage of difference of MPC in daily energy consumption with change of controller setpoint from 5m to 2m**

| | **High demand** | **Medium demand** |
|---|---|---|
| **Percentage** | -26.5% | -37.9% |

Consequently, the average Electric Energy consumption is smaller in the simulation of scenarios where the setpoint is set lower. In Figure 4-26, we can see that in the cases where the setpoint is set at 2 m, the average total daily consumption in the simulation of our pump station model with MPC scheduling is lower than the actual average consumption of the Vlites pump station, both with medium and with high demand (4564 kWh vs 5525kWh in medium demand scenario and 8254kWh vs 8580kWh in high demand scenario).

**Table 4-7: Percentage of difference of MPC in daily energy consumption compared with Vlites empirical operation**

| | Setpoint = 5 | Setpoint = 2 |
|---|---|---|
| **High demand** | +30.8% | -3.8% |
| **Medium demand** | +33% | -17.4% |

While the simulation of scenarios with high tank level setpoint does not provide better results comparing with the actual pump station, with the lower tank level setpoint the MPC approach shows an improvement of 17.4% in the medium demand scenario and 3.8% in the high demand scenario.

# CHAPTER 5. CONCLUSION

## 5.1 Concluding Remarks

In this study, the basic idea was the design of a Model Predictive Control strategy for a small-scale water distribution system, that would be able to compute an optimal solution for the pump scheduling and flow management of a water network. Based on the literature for MPC in water distribution networks, a model of the system was designed and simulated using the Vlites greek Pump Station as a case study. The analysis of the case study simulation gave us an indicative view on the effects of applying a model predictive control approach to the Vlites pump station and the water distribution network of Akrotiri area (Chania, Crete island, Greece). The results from the simulation of four scenarios indicate that with careful parameterization, the MPC approach proposed in this thesis can result to an improvement of the current operational cost of the pump station of Vlites.

To conclude, the author considers an MPC approach as a fair choice for the control and management of a regional water distribution network such as the one studied in our case study.

## 5.2 Future Work

The objectives of scheduling problems, especially in water distribution systems which include complex dynamics and entail multi-objective optimization, can be various. The focus of the objective function in the optimization process of this study was mainly on controller performance, while optimizing the flow of water into the network tank unit. As future work, the author suggests including the economic cost, for instance the electricity prices and tariffs, in the objective function of the associated optimal control problem, as the economic cost examination and optimization is a major concern in water management related topics.

A further development would be to add the number of pump switches as a constraint, because switching of pumps is assumed to be a key factor for operational reliability and for maintaining the healthiness of pumping systems.

Finally, a further extension of the water network model can be implemented, including the entire region of Western Crete. This thesis focused on the study of a simplified network model, which nevertheless included all the basic elements of a water distribution network and was able to capture the system dynamics. The extension of this model could allow us to further understand and examine the operation of the water distribution network of Western Crete area and propose an MPC approach for optimizing pump schedules and operational reliability.

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# APPENDIX A

**Demand Profiles**

| **hour** | **multiplier** | | **hour** | **demand** (m3) | | **hour** | **demand** (m3) |
|---|---|---|---|---|---|---|---|
| 0.00 | | | 0.00 | | | 0.00 | |
| 1.00 | 0.3 | | 1.00 | 97.2 | | 1.00 | 146.7 |
| 2.00 | 0.2 | | 2.00 | 64.8 | | 2.00 | 97.8 |
| 3.00 | 0.15 | | 3.00 | 48.6 | | 3.00 | 73.35 |
| 4.00 | 0.15 | | 4.00 | 48.6 | | 4.00 | 73.35 |
| 5.00 | 0.2 | | 5.00 | 64.8 | | 5.00 | 97.8 |
| 6.00 | 0.4 | | 6.00 | 129.6 | | 6.00 | 195.6 |
| 7.00 | 0.75 | | 7.00 | 243 | | 7.00 | 366.75 |
| 8.00 | 1.25 | | 8.00 | 405 | | 8.00 | 611.25 |
| 9.00 | 1.4 | | 9.00 | 453.6 | | 9.00 | 684.6 |
| 10.00 | 1.45 | | 10.00 | 469.8 | | 10.00 | 709.05 |
| 11.00 | 1.35 | | 11.00 | 437.4 | | 11.00 | 660.15 |
| 12.00 | 1.3 | | 12.00 | 421.2 | | 12.00 | 635.7 |
| 13.00 | 1.3 | | 13.00 | 421.2 | | 13.00 | 635.7 |
| 14.00 | 1.2 | | 14.00 | 388.8 | | 14.00 | 586.8 |
| 15.00 | 1.2 | | 15.00 | 388.8 | | 15.00 | 586.8 |
| 16.00 | 1.3 | | 16.00 | 421.2 | | 16.00 | 635.7 |
| 17.00 | 1.4 | | 17.00 | 453.6 | | 17.00 | 684.6 |
| 18.00 | 1.7 | | 18.00 | 550.8 | | 18.00 | 831.3 |
| 19.00 | 1.75 | | 19.00 | 567 | | 19.00 | 855.75 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 20.00 | 1.6 | | 20.00 | 518.4 | | 20.00 | 782.4 |
| 21.00 | 1.5 | | 21.00 | 486 | | 21.00 | 733.5 |
| 22.00 | 1.25 | | 22.00 | 405 | | 22.00 | 611.25 |
| 23.00 | 0.8 | | 23.00 | 259.2 | | 23.00 | 391.2 |
| 24.00 | 0.1 | | 24.00 | 32.4 | | 24.00 | 48.9 |
| | | | **Total** | 7776 | | **Total** | 11736 |
| **Average** | 1 | | **Average** | 324 m^3 | | **Average** | 489 m^3 |
| | | | | | | | |

**Matlab Code Sample**

```
%% Initialization
water_dens=1000; %kg/m^3
grav_acc=9.80665; %m/sec^2  0
d=37; %m diameter korakies tank
kor_tank_cs=pi*(d/2)^2;

%% pump type 01 curve 350 m^3/h
pump_1_Q=[0.0 29.2 121.0 153.0 191.3 230.4 287.0 295.2 319.0 350 364.4
388.2 419.0 459.2 501.0 536.5];        % m^3/h
pump_1_H=polyval([-0.0001,-0.2370,253.3063],pump_1_Q);      % m
pump_1_eff=polyval([-0.0005,0.4163,-1.9548],pump_1_Q);      % 100%
pump_1_int_diam=0.039;  %pressure / volume setting          %m


pump_1_P=pump_1_H*grav_acc/100;                             %bar
pump_1_hydr_pow=pump_1_Q.*pump_1_H*grav_acc*water_dens/3600;  %watts
pump_1_hydr_pow=pump_1_hydr_pow/1000;                          % kW
pump_1_ele_pow=pump_1_hydr_pow./pump_1_eff;                    % kW



...



%% specify weights
mpcControllerObj.Weights.MV = 0;
mpcControllerObj.Weights.MVRate = 0.1;
mpcControllerObj.Weights.OV = 1;
mpcControllerObj.Weights.ECR = 100;

%% open simulink model
open_system('case_study_model')
```

**Matlab function for pump "on-off" status**

```
function y = fcn(u)
%#codegen

if (u>50 && u<177/3600)
    y=[0, 0, 1, 1];
elseif (u>=177/3600 && u<367/3600)
    y=[0, 1, 0, 1];
elseif (u>=367/3600 && u<555/3600)
    y=[1, 1, 0, 0];
elseif (u>=555/3600 && u<645/3600)
     y=[1, 1, 0, 1];
elseif (u>=645/3600)
     y=[1, 1, 1, 1];
else
    y=[0, 0, 0, 0,];
end
```