إقـــــرار

أنا الموقع أدناه مقدم الرسالة التي تحمل العنوان:

التشغيل المثالي لمحطة ضخ مياه عادمة باستخدام التحكم التنبئي المبني على النموذج الرياضي

Optimal Operation of a Wastewater Pumping Station by Model-based Predictive Control

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Student's name:	اسم الطالب/ة:أحمد محمود محمد شحادة
Signature:	التوقيع:
Date:	التاريخ: 13/ 03 / 2016

The Islamic University Gaza
Higher Education Deanship
Faculty of Engineering
Electrical Engineering dep.

الجامعة الإسلامية – غزة
عمادة الدراسات العليا
كلية الهندسة
قسم الهندسة الكهربائية

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Optimal Operation of a Wastewater Pumping Station by Model-based Predictive Control

“A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science in Electrical Engineering.”

Submitted by:
Eng. Ahmed M. Shehada

Supervised by:
Prof. Dr. Mohamed Abdelati

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The Islamic University - Gaza

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نتيجة الحكم على أطروحة ماجستير

بناءً على موافقة شئون البحث العلمي والدراسات العليا بالجامعة الإسلامية بغزة على تشكيل لجنة الحكم على أطروحة الباحث/ أحمد محمود محمد شحادة لنيل درجة الماجستير في كلية *الهندسة* قسم الهندسة الكهربائية – أنظمة التحكم وموضوعها:

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وبعد المناقشة العلنية التي تمت اليوم الاثنين 18 جمادى الأولى 1437هـ، الموافق 2016/02/29م الساعة الواحدة والنصف ظهراً بمبنى القدس، اجتمعت لجنة الحكم على الأطروحة والمكونة من:

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د. إياد محمد أيوب/ أبو هدروس	مناقشاً خارجياً	....

وبعد المداولة أوصت اللجنة بمنح الباحث درجة الماجستير في كلية *الهندسة*/ قسم الهندسة الكهربائية – أنظمة التحكم.

واللجنة إذ تمنحه هذه الدرجة فإنها توصيه بتقوى الله ولزوم طاعته وأن يسخر علمه في خدمة دينه ووطنه.

والله ولي التوفيق،،،

نائب الرئيس لشئون البحث العلمي والدراسات العليا

أ.د. عبدالرؤوف علي المناعمة

DEDICATION

To my family members who have been a constant source of motivation, inspiration, and support.

To the soul of my brother Raed who was martyred before receiving his Master degree in Civil Engineering.

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ملخص الدراسة

في هذه الرسالة، تم تطوير متحكم مثالي مبني على النموذج الرياضي للتحكم في محطة ضخ مياه عادمة متوسطة الحجم. تم استخدام قوالب برمجية مكتوبة بلغة Simscape المتوفرة في برنامج الماتلاب لبناء نموذج رياضي مفصل للمحطة باستخدام بيئة Simulink. يتكون النظام من خمس مضخات يتم تغذيتها من خزان للمياه العادمة لضخها عبر خط أنابيب يوصلها لمحطة المعالجة. تم تشغيل النموذج الرياضي مرات عديدة لمحاكاة وفحص والتأكد من سلوك النظام في الأوضاع المختلفة. تم تطوير واستخدام نموذج رياضي من نوع ARX ذاتي التصحيح للتنبؤ بكمية المياه الوافدة إلى خزان المحطة وقد تم تقسيم هذا النموذج إلى جزأين منفصلين، الأول يقوم بتقدير كمية المياه الوافدة في الجو غير الماطر بينما يقوم الآخر بالتنبؤ خلال فترات هطول الأمطار. تم توليد بيانات عشوائية لفحص ذكاء هذا النموذج وتم الحصول على نتائج مقبولة. من أجل الوصول إلى التشغيل المثالي للمحطة، تم استخدام النموذج الرياضي للمحطة لتصميم استراتيجيات التشغيل الأولية والتي تم استخدامها لاحقاً لبناء مسألة التحسين. تم استخدام محطة ضخ المياه العادمة في شمال غزة كدراسة حالة، وقد وجد أنه من الأفضل تشغيل المضخات بسرعة ثابتة وليس سرعات مختلفة. تم استخدام الخوارزمية الجينية لتقرر برنامج تشغيل المضخات آخذة في الاعتبار التحسين في تكاليف الطاقة والصيانة، وكذلك حجم المياه العادمة القصوى في الخزان كمعامل بيئي وذلك بأوزان مختلفة. محددات الخوارزمية هي عدم امتلاء خزان المحطة وعدم تفريغه بالكامل. تم فحص المحسِّن وأعطى نتائج جيدة. أخيراً، تم تشغيل المتحكم التنبئي لمدة 48 ساعة للحصول على خطة التشغيل خلال هذه الفترة تحت ظروف مختلفة. تم تزويد الرسالة برسومات بيانية كثيرة لشرح وتفسير سلوك النظام في كل مراحل العمل في هذه الرسالة.

ABSTRACT

In this thesis, Model-based Predictive Controller for a midscale wastewater pumping station is developed. We used MATLAB Simscape blocks to build a full detailed model in a Simulink environment. The system consists of five pumps fed by a buffer tank and deliver sewage to a treatment plant through a pipeline. This model is run many times to simulate, check and validate the behavior of the system. A recursive auto-adaptive ARX model is developed for inflow rate prediction. The predictor is separated into two independent models, one for dry weather and the other for run-off weather. Stochastic data is generated to check the smartness of the predictor and an accepted result is achieved. To optimize the operation plan of the system, the detailed model is used to design a preliminary control strategy which is used later to set the optimization problem. North Gaza Terminal Pumping Station is taken as a case study. Fixed speed pump scheduling is found more efficient. A GA optimizer is used to decide the operation plan of the pumps taking into account power, maintenance, and sewage volume in the tank as an environmental factor with different weights. Upper and lower limits of the water level in the tank is constrained by the GA. The optimizer is tested and gave explainable results. Finally, the MPC is tested with 48 hour time horizon and an accepted operation plan is resulted. Detailed plots and charts are generated using MATLAB to explain what is going on through all levels of work in this thesis.

CONTENTS

LIST OF ABBREVIATIONS

LCC	Life Cycle Cost
MPC	Model-based Predictive Control
APC	Advanced Process Control
NTPS	New Terminal Pumping Station
WWTP	Wastewater Treatment Plant
GA	Genetic Algorithm
ARX	AutoRegressive with eXogenous
PID	Proportional Integral Differentiation
PS	Physical-to-Simulink
SP	Simulink-to-Physical
BEP	Best Efficiency Point
KWH	Kilo Watt Hour
SISO	Single Input Single Output
EA	Evolutionary Algorithm
rpm	revolution per minute

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1 Introduction

1.1 Motivation and Goals

A general wastewater pumping station consists of a main reservoir (a suction chamber and an emergency overflew bond), a group of parallel pumps, pipes, and a control system. The main task of a wastewater pumping station is to pump a suitable wastewater volume from a reservoir to a treatment plant or terminal pools through a transmission pipeline. In normal situations, inflow sewage is directly pumped and no sewage is allowed to be buffered in the emergency overflow bond. However, due to power constrains, developing regions, such as the Gaza Strip, used to sacrifice a little of the environmental aspects of sewage buffering for facing many other serious challenges. **Figure 1.1** shows schematic of NTPS pumping station at north Gaza studied by (Abdelati) [2].

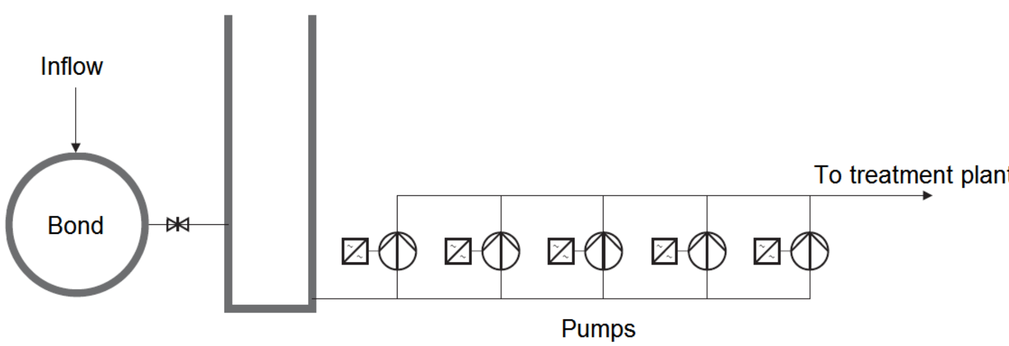


Figure 1.1: Pumping station basic model

In general, pumping systems account for nearly 20% of the world's electrical energy demand, the initial purchase price usually does not exceed 10% of total Life Cycle Cost (LCC) for high usage pumps [1]. Although the electrical energy is the highest pumping cost part, maintenance takes the second place of the total LCC, See Figure 1.2. The *other cost* shown in Figure 1.2 includes the operation, environmental, down time and disposal costs.

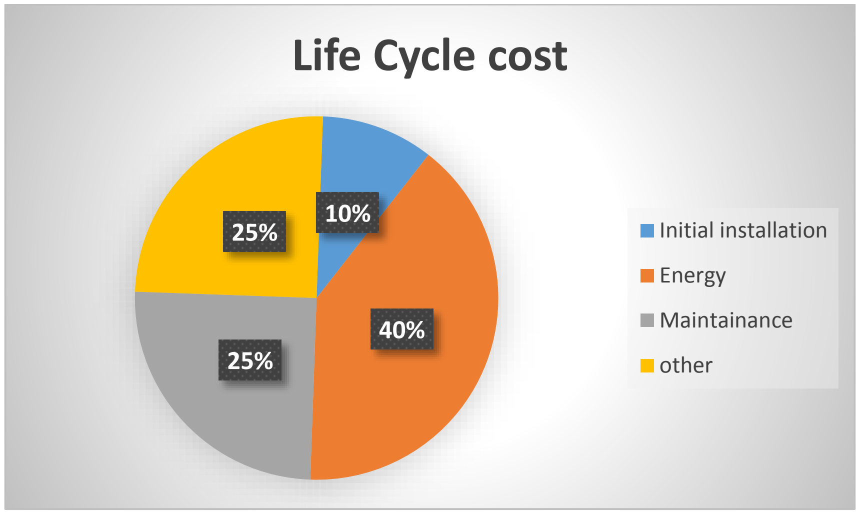


Figure 1.2: Typical life cycle costs for a medium-sized industrial pump

Pumping Life Cycle Cost: A guid to LCC analysis for pumping systems [1]

For an existing pumping station, a multilevel smart controller can optimize the operation of a wastewater pumping station to achieve minimum energy and maintenance costs, which are the major costs of LCC.

No conventional controllers will work properly to reach the optimal operation status, due to the complexity of the system. For example, what is the reference signal to be controlled? Is it the water level in the main reservoir? And even if the answer is "Yes", what is the set value to be tracked. What is the relation between this value and the long-term energy or maintenance cost? What about the safety, full capacity, and water pattern curves? Which pumps must work at an instance of time? And what about the variation in electrical energy cost during a day and a night. Many other questions need to be answered.

For such complicated optimal control problems, modern optimization techniques are used to achieve the optimal operation plan, this problem can be solved in the advanced control level, where the terminal slave controller will implement the control plan in the phase of conventional control theory.

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. Such controller is called Model-based Predictive Control (MPC).

In this thesis, the author aims to design and simulate an MPC controlled mid-size pumping station. Genetic Algorithm (GA) is used for optimization and an AutoRegressive with eXogenous (ARX) prediction model is used to estimate station inlet flow.

1.2 Model-based Predictive Control

For a complex large-scale system (pumping station) with a large number of time-varying elements and high nonlinearities, there are usually numerous operating modes specially when there are high uncertainties due to changes in external conditions (weather or inlet flow) and operational constraints. In these cases, conventional control systems are not enough to achieve an acceptable robust and effective control system, Advanced Process Control (APC) is useful in such cases.

1.2.1 Advanced Process Control

APC refers to a broad range of techniques and technologies implemented within process control systems. Figure 1.3 shows the layers of process control system.

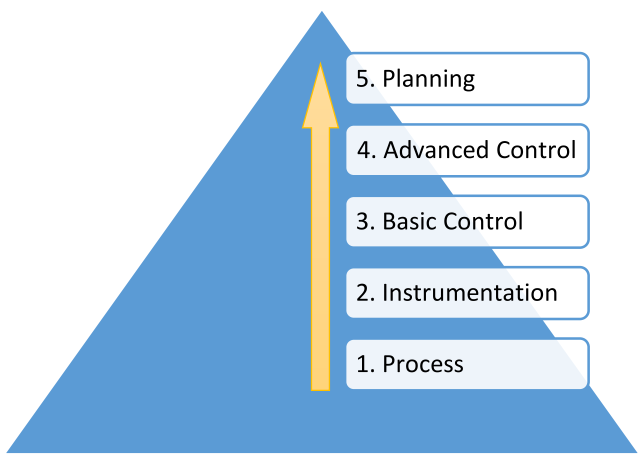


Figure 1.3: Levels of process control system

Process level refers to the system itself needed to be controlled. Actuators and sensors are classified to be in the instrumentation layer, it includes connections and Input/output ports. The third level is the basic control which is responsible for basic functionality and safety operations, it facilitates basic operation, control and automation requirements by implementing the control strategy given from a higher control level named *Advanced Process Control* (APC). Planning level is in the top of the pyramid which sets the main polices for many sub processes often based on economical and statistical analyses. The author is interested in the fourth layer (APC) in this section.

APCs are typically added to the control systems subsequently, often after some years, to address particular performance or economic improvement in the process. It includes advanced functionalities, optimization and coordination of basic control loops by manipulating their set-points based on static or dynamic optimization.

The main goal of APC is to ensure the optimal operation of the plant under a given condition with some constrains and limited resources. MPC is a good candidate to occupy the APC layer in the control pyramid.

1.2.2 MPC control scheme

"MPC is a set of control methodologies that use a mathematical model of the 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". [3]

A model of the plant is used to predict the future evolution of the process to dynamically (on-line) optimize the control signal. The main role of the MPC is to solve for the optimal set point ($u(t)$ in Figure 1.4) to be tracked by the basic controller over a finite future time horizon. Figure 1.4 is a simple block diagram shows the MPC system.

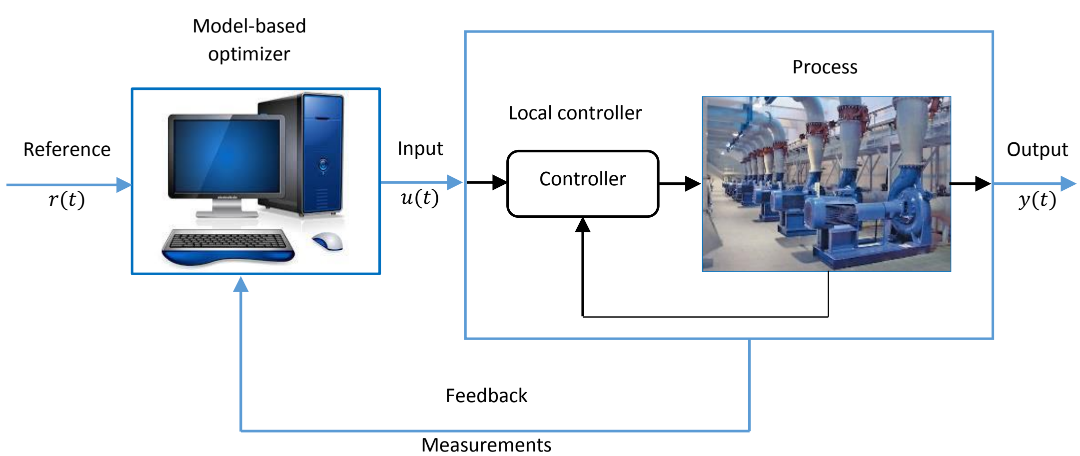


Figure 1.4: MPC diagram

The MPC solves the optimization problem taking into account the current state at the moment and the estimated future values of the uncertainties (inflow, power availability) and the predictive response of the system in the future through a time horizon.

Although the answer of the optimizer is an operation plan for the pumping station in the future horizon, the control system will perform this plan only for one time slot. The optimizer will resolve the problem again taking into account the variations in the system. So, optimization takes place every one time slot. This is the mean of dynamic real time optimization solution.

One can ask, what is the new in MPC if the full model is available? Is not conventional controllers (e.g. PID) can achieve equivalent performance? The answer is: there are many differences between conventional and MPC controllers, (1) MPC is a type of optimal controllers, (2) complicated systems have varying models along the time, it is said: "Satisfying control specs and walking on water is similar, both are not difficult if frozen". The prediction of the future is a continuous process depending on the system presumed model, the measured values, and other influential conditions, where equations of the model can be adapted continuously. Moreover (3) system constraints are accepted in the optimization problem to satisfy the global goal.

MPC has gained in popularity because it provides a systematic approach to control the multivariable systems with constraints. The power of this scheme appears when talking about high uncertain systems with some stochastic forecastable disturbances.

In our case, the plant is the pumping system, the incoming wastewater flow rate needed to be predicted using a smart predictive model (Auto-Regressive) and the optimization technique is (GA). The optimized control signal will schedule the operation of the pumps and an approach to select the time horizon and time slot will be introduced.

1.3 Case Study

The New Terminal Pumping Station (NTPS) modeled by (Abdelati and F.G. Frey) in [4] will be taken as a case study, where some modifications will be done in the model to check the capabilities of the new MPC control.

1.4 Literature Review

Many published papers studied MPC applied on pumping systems. (P.J. van Overloop, R.R. Negenborn, B. De Schutter, and N.C. van de Giesen) introduced MPC for national water flow optimization in The Netherlands, they drive a complicated model includes river levels, pipes, reservoirs. About 20 thousands euro were saved per year compared with the previous control system [5].

(C. Ocampo-Martinez, V. Puig, G. Cembrano, R. Creus and M. Minoves) reached an optimal control for a drinking water management in urban areas, a prediction model is derived and a case study was applied [3].

An optimal control tool developed in the context of a European research project is described and applied on the city of Sintra in Portugal by (G. Cembrano, G. Wells, J. Quevedo, R. PeHrez, and R. Argelaguet). The optimal control values are sent through the SCADA as set points to the local controllers in the remote stations [6].

Many other published researches studied implementing MPC to drinking water network systems, irrigation systems, wastewater treatment systems and others to optimize the process, where a little talking about wastewater pumping.

A good examples for water demand forecasting are introduced by (M. Bakker, J.H.G. Vreeburg, K.M. van Schagen, L.C. Rietveld) in [7] and (House-Peters and Chang) in [8] and some others.

(J. Lindqvist, T. Wik, D. Lumley and G., Äijälä) in [9] developed and tested an AutoRegressive with eXogenous (ARX) prediction model to estimate inflow of wastewater and achieved an accepted results. This model is reformed in this thesis to suit PMC requirement.

(Beckwith, S.P, Wong, K.P.) used GA to schedule the operation of pumps in water supply systems. They considered efficiencies of different pumps in the system and concluded an optimized pumping solution [10].

1.5 Thesis structure

There are five chapters in this thesis. Chapter 1 is an introduction, chapter 2 concerns building a full wastewater pumping station using MATLAB Simscape language in the SIMULINK modelling environment. Chapter 3 re-derives the conventional Auto-Regressive prediction model to be suitable for MPC purposes to estimate the inflow rate at dry and run off weather conditions. Chapter 4 proposes building up the optimization problem with a brief introduction to (GA). Completing the problem and getting the overall controller results also are included in chapter 4. The final chapter will conclude the thesis and suggest a future work.

2 Wastewater Pumping Station Model

2.1 Introduction

Pumping station is a building with machinery for pumping large amounts of water [11]. In wastewater pumping stations, pumps driven by induction motors are used to transport a specific amount of collected effluent to the treatment plants. It is basically consisted of a suction chamber, booster pumps, junctions, pipes, and control system.

To implement an MPC to a pumping station, a full mathematical model must be built to help the controller to optimize the operation decisions taking in to account the prediction of the future of the system.

MATLAB Ready-made blocks are used to simulate the pumping operation and to be used later in the optimization problem in the next chapter.

2.2 Modelling Environment

MATLAB is a high-level language and interactive environment for numerical computation, visualization, and programming. Using MATLAB, one can analyze data, develop algorithms, and create models and applications. It can be used for a range of applications, including signal processing and communication, image and video processing, control systems, test and measurement, computational finance, and computational biology. More than a million engineers and scientists in industry and academia use MATLAB, the language of technical computing [12].

MATLAB provides a block diagram environment for design and simulation purposes, called Simulink. It supports system-level design, simulation, automatic code generation, and continuous test and verification of embedded systems. Simulink provides a graphical editor, customizable block libraries, and solvers for modeling and simulating dynamic systems [12].

Simulink can employ two different computational approaches in solving system networks:

1. The standard Simulink modeling approach: where blocks represent basic mathematical operations. When standard Simulink blocks are connected together, the resulting diagram is equivalent to the mathematical model of the system.
2. The physical network approach: where blocks are represented as consisting of functional elements that interact with each other by exchanging energy through their ports. These blocks are called Simscape blocks.

The two approaches can be used to build a multi-domain model (pumping station), but Simscape network is more suitable for simulating systems that consist of real physical components because the resultant model will match the structure of the system we are studding.

Fortunately, Simscape provides libraries enriched with plenty of blocks for modeling and simulating multi-domain physical systems (electrical, hydraulic, magnetic, mechanical, pneumatic, thermal, thermal liquid). These libraries contain fundamental blocks (electrical resistor, hydraulic resistance…etc.) and integrated high-level blocks (Induction motor, centrifugal pump…etc.). New Libraries or even new domains of Simscape blocks can be built by using the MATLAB based Simscape language. Simscape hydraulics block library is shown in Figure 2.1.

2.3 System Components

Since we are concentrating in this thesis on the control system of a pumping station as an optimization problem, detailed equations are not the beef when a group of ready-made blocks are available. These blocks are accurate enough to predict the system behavior in the MPC time horizon, where full formulation is explained in the help of MATLAB. A general description for the major used blocks explained in this section, where the complementary blocks are tabulated only. The reader is advised to visit MATLAB help documentations for full details and mathematical models of these blocks.

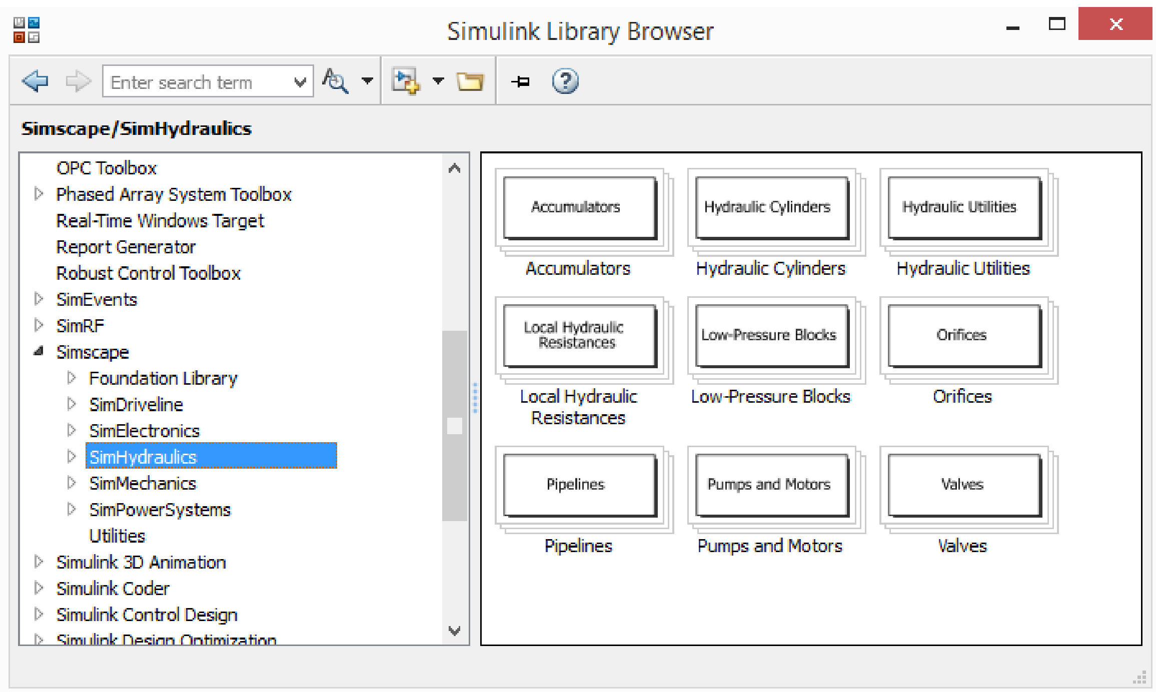


Figure 2.1: Hydraulics Simscape block library

2.3.1 Three-phase induction machine

An induction motor is an AC machine in which AC current is supplied to the stator winding directly and to the rotor winding by induction from the stator. The rotor of the induction motor may be either of two types:

a. A wound rotor carries three windings similar to the stator windings.
b. A squirrel-cage rotor consists of a conducting bars embedded in slots in the rotor magnetic core and these bars are short circuited at each end by conducting end rings.

An induction machine can be approximately modelled by its equivalent circuit shown in Figure 2.2.

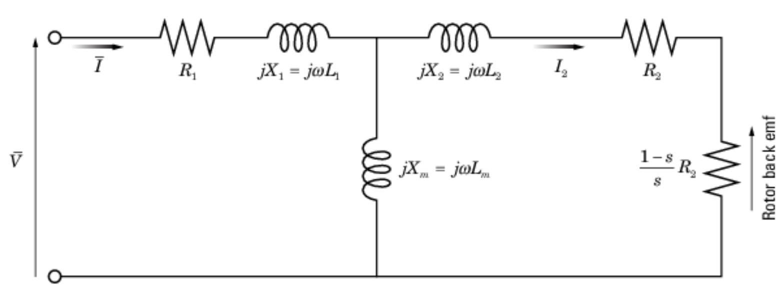


Figure 2.2: Induction motor equivalent circuit

where V is the stator terminal voltage per phase, R_1, L_1, L_m, R_2, L_2, are the characteristic parameters of the equivalent circuit. R_2, L_2 can be transformed to be related to the stator winding using the formulas:

$$R_r = R_2 \left(\frac{N_1}{N_2}\right)^2, L_r = L_2 \left(\frac{N_1}{N_2}\right)^2 \qquad 2.1$$

where N_1, N_2 are the stator and rotor windings number of turns respectively.

The parameters of the equivalent circuit of the induction motor can be estimated by three standard tests which are No-Load Test, DC Test, and Blocked-Rotor Test. Detailed explanation for these tests are proposed in [13].

The synchronous speed (electrical speed) n_s of the motor depends on the operating frequency f and the number of poles p

$$n_s = \frac{120f}{p} \qquad 2.2$$

where the rotor speed (mechanical speed) n_r depends on n_s and the mechanical loads on the motor shaft. The relative difference between the two speeds is called the slip

$$s = \frac{n_s - n_r}{n_s} \qquad 2.3$$

The delivered mechanical power by the machine is function of slip s which is a function of the mechanical loads on the motor shaft.

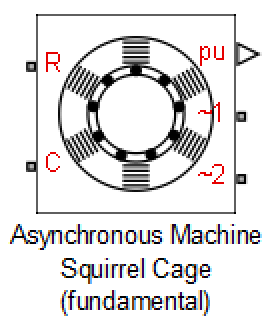


Figure 2.3: Three-phase induction machine block

Simscape libraries provide a block (Figure 2.3) to simulate the induction motor. This block solves the equivalent circuit of the motor which will be used as a pump driver in this thesis.

The moment of inertia of the rotor is not included in this block, and it will be added as a separate block includes the inertia of the motor and the pump.

2.3.2 Machine Inertia

The Machine Inertia block (**Figure 2.4**) models inertia and damping that can be connected to the mechanical rotational port of a three-phase machine. The block has an internal connection to a mechanical rotational reference.

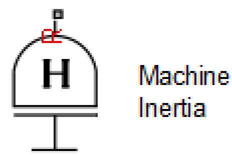


Figure 2.4: Machine Inertia block

This block is used to simulate the inertia of the rotor of the induction machine and the inertia of the rotating part (blades and shaft) of the pump.

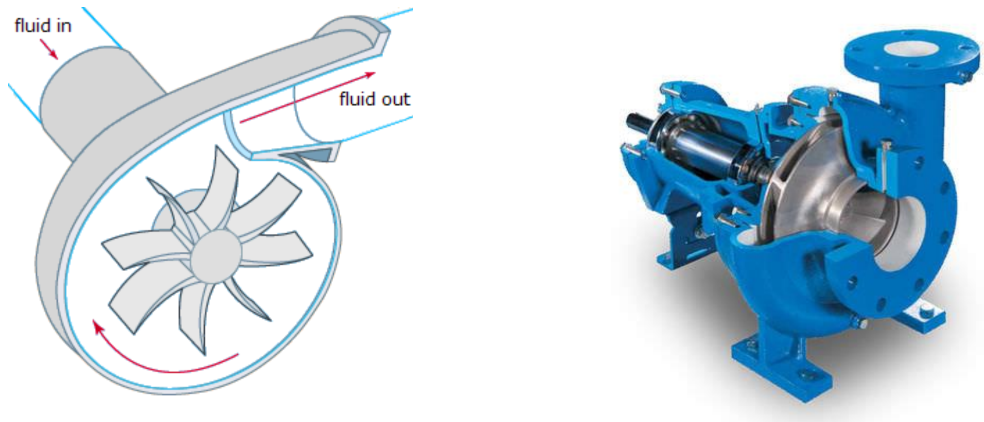
The inertia of the rotating parts affects only the starting and stopping periods of the pump when the speed of the shaft is not constant.

$$\sum \tau - B\omega = J\alpha \qquad 2.4$$

where τ is the total torque, B is the friction damping coefficient, ω is the angular speed, J is the rotor moment of inertia, and α is the angular acceleration. τ includes the generated torque by the motor and the opposite torque generated by the pump because of the stresses of the fluid mechanics.

2.3.3 Centrifugal pump

A Centrifugal pump is a machine used for the purpose of transferring quantities of fluids from one place to another. It consists mainly by impeller rotating freely inside a special casing which is driven by means of a coupled motor. (Figure 2.5) shows a general view of the centrifugal pump.



(a) (b)

Figure 2.5: Centrifugal pump

When the shaft rotates, the hydraulic design of the impeller generates a pressure deferential between the inlet and outlet, so that, the liquid flows from the outlet.

Mathematically, a centrifugal pump can be identified by its characteristic curves, which declare the relationship between the total output pressure (or head) and liquid flow at different speeds.

The efficiency of the pump is characterized by iso contours connecting between the equal efficiency points as shown in Figure 2.12 (section 2.4). These iso curves can be formulated using surface fitting tools (available in MATLAB). Figure 2.6 shows an example of 3D plot of efficiency (EFF) as a function of head (H) and flow rate (Q). The designer is mainly asked to let the pump operates at the Best Efficiency Point (BEP).

The hydraulic pressure and flow of the liquid around the impeller blades generate an opposite torque which is directly proportional to the square of the angular speed of the driving shaft as shown in equation 2.5.

$$\tau = Kn^2 \qquad 2.5$$

The torque τ_{max} (K N.m) at maximum speed can be approximated by equation 2.6

$$\tau_{max} = \frac{30P}{\pi n} \qquad 2.6$$

where P is the pump power (KW), and n is shaft speed (rpm). If the pump is working at zero efficiency operating point (no liquid flow), then the torque is 30% to 50% of the torque when working at BEP.

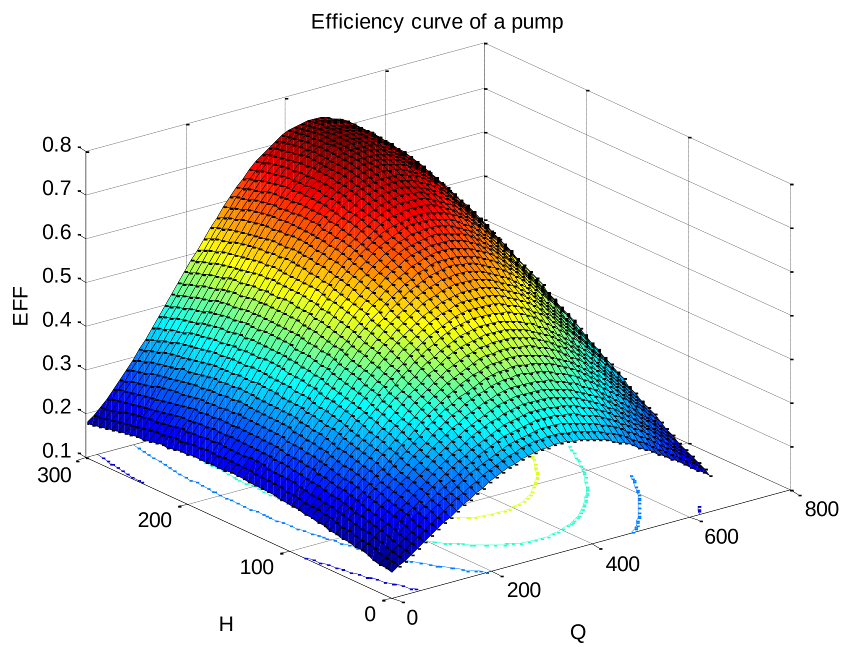


Figure 2.6: Typical centrifugal pump characteristic curves

Datasheet-based Simscape centrifugal pump block (**Figure 2.7**) is available, and the hydraulic torque on the shaft will be calculated separately and applied to the shaft by Torque source block shown in **Figure 2.10** (Section 2.3.6).

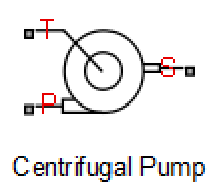


Figure 2.7: Centrifugal pump block

2.3.4 Pipe

The pipe line can be modelled basically by the pressure difference between the two terminals and the flow of the liquid in the pipe. The pressure difference is caused by the static difference in the level between the two terminals (static head) and the pressure loss due to friction and flow turbulences (dynamic head). Pressure loss is proportional to the square of the flow rate of the liquid in the pipe and can be calculated using Darcy equation,

$$p = \overbrace{f \frac{L}{D_H} \frac{\rho}{2A^2} q.|q|}^{\text{Dynamic head}} + \overbrace{\rho g (z_B - z_A)}^{\text{Static head}} \qquad 2.7$$

where f is friction coefficient, q is the flow rate, L is pipe geometrical length, D_H is pipe hydraulic diameter, A is cross sectional area, ρ is liquid density, g is gravity acceleration, and z_B, z_A are the elevations of the ports of the pipe with respect to a hydraulic reference.

Friction coefficient is computed using Haaland approximation which varies rapidly when passing the critical Reynolds number. More details about pipe line formulation is available in [14].

Simscape block libraries provides two blocks to simulate liquid propagation in pipe lines, the first is *Resistive pipe LP* block which solves using Darcy and Haaland approximations, and the other is *Segmented pipe LP* block which uses the same equation with additional equations to compute the effect of liquid inertia. The first block is more computational effective in simulating the steady flow of the liquid, where the second (Figure 2.8) can solve accurately in transient periods. We used the *Resistive pipe LP* block in our project because it is more computational efficient.

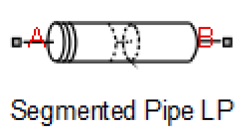


Figure 2.8: Pipe line block

2.3.5 Tank

Variable Head Two-Arm Tank represents a pressurized tank, in which fluid is stored under a specified pressure (atmosphere). The block accounts for the fluid level change caused by the volume variation, as well as for pressure loss in the connecting pipes that can cause some local resistance. Figure 2.9 shows the tank block.

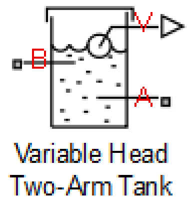


Figure 2.9: Tank block

2.3.6 Other parts

Many other parts are used to fully model a pumping station, these parts are tabulated below:

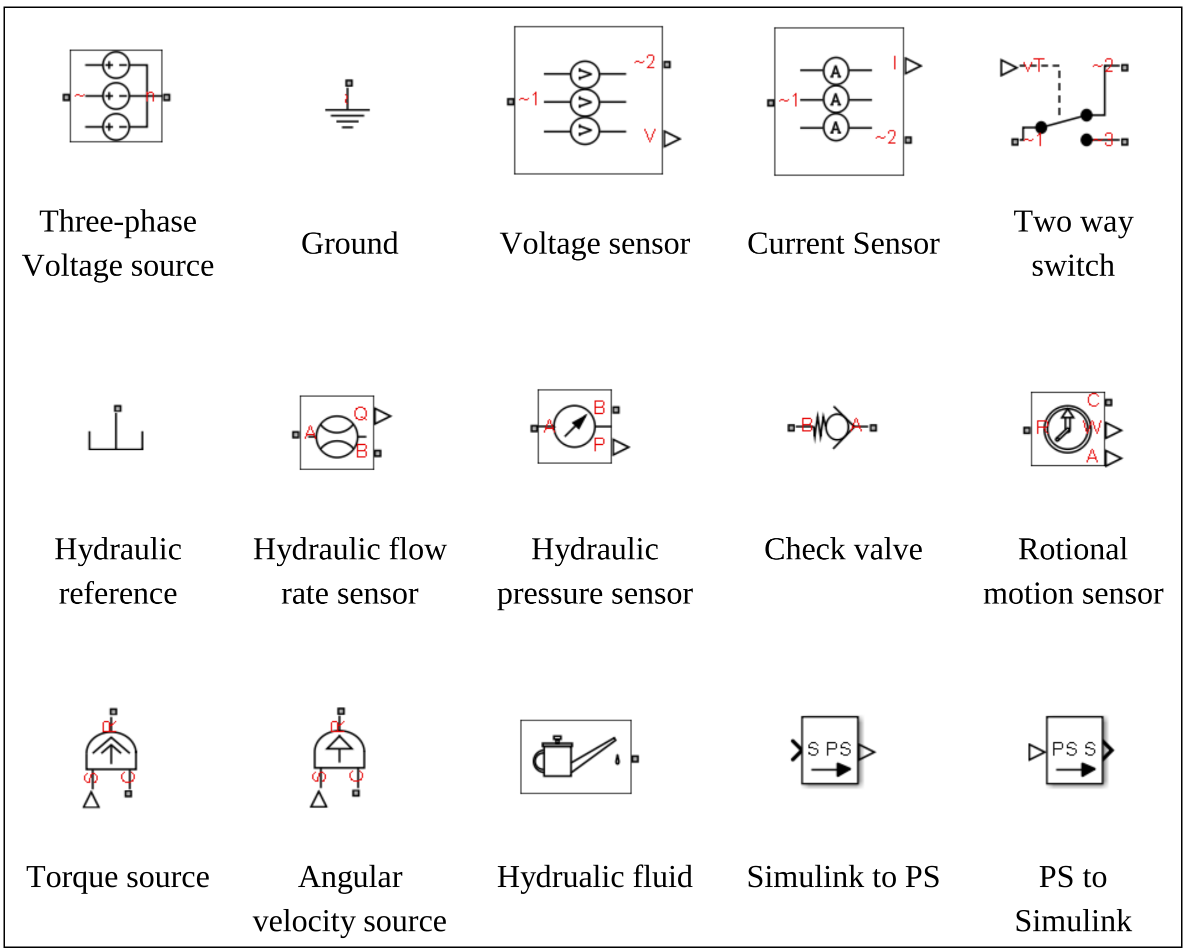


Figure 2.10: Used Simscape components in building the model

Two *three-phase voltage source* blocks are used to simulate the main line and the generator which have different cost of energy, and the *two-way switch* is used to change over between the two sources. The *ground* component is used as an electrical reference to complete the calculations.

The *hydraulic fluid* block is used to specify the type of hydraulic fluid. It provides the hydraulic fluid properties, such as kinematic viscosity, density, and bulk modulus, for all the hydraulic blocks in the loop.

The *hydraulic reference* block represents a connection to atmospheric pressure. It can absorb any amount of fluid under a constant pressure. This matches the ground in electrical circuits which always has a constant zero potential.

The purpose of the *check valve* block is to permit flow in one direction and block it in the opposite direction. This will prevent the liquid from flowing back through OFF pumps.

Torque source is use to simulate the mechanical loads on the pump/driver shaft which depends on pump speed and pressure in the hydraulic circuit, where *angular velocity source* is used to maintain a specific angular speeded regardless with mechanical torques.

The purpose of electrical, mechanical, and hydraulic measurement blocks are clear from its captions in the tabulated Figure 2.10, and finally, *Simulink-to-PS* and *PS-to-Simulink* are used to convert signals to be read or written to physical simulation domains.

2.4 Case study

Five 315 kW booster pumps from ABS have to pump 15000 m^3 of partially treated wastewater from the New Terminal Pumping Station (NTPS) located at northern Gaza to the new Wastewater Treatment Plant (WWTP) per a day. At an expected head of 38m (3.7 bar), pump can deliver about 360 Kg/s while running at maximum speed.

The transmission pipe has 7.6 km length, 80 cm diameter and 26 m static head. 20000 m^3 pond near the pumping station is used to buffer and partially treat the wastewater collected from northern Gaza. All detailed information about the operation of this pump station is from [2]. The overall Simscape model for NTPS is shown in Figure 2.11.

Two power sources are used to supply up to five induction motors, the output mechanical ports of the motors are coupled with the corresponding mechanical ports of the pumps.

The impedances of the equivalent circuit of the induction motor described in section 2.3.1 are $R_1 = 0.118\ \Omega$, $L_1 = 0.148$ mH, $R_r = 0.007\ \Omega$, $L_r = 0.067$ mH, $L_m = 8.4$ mH.

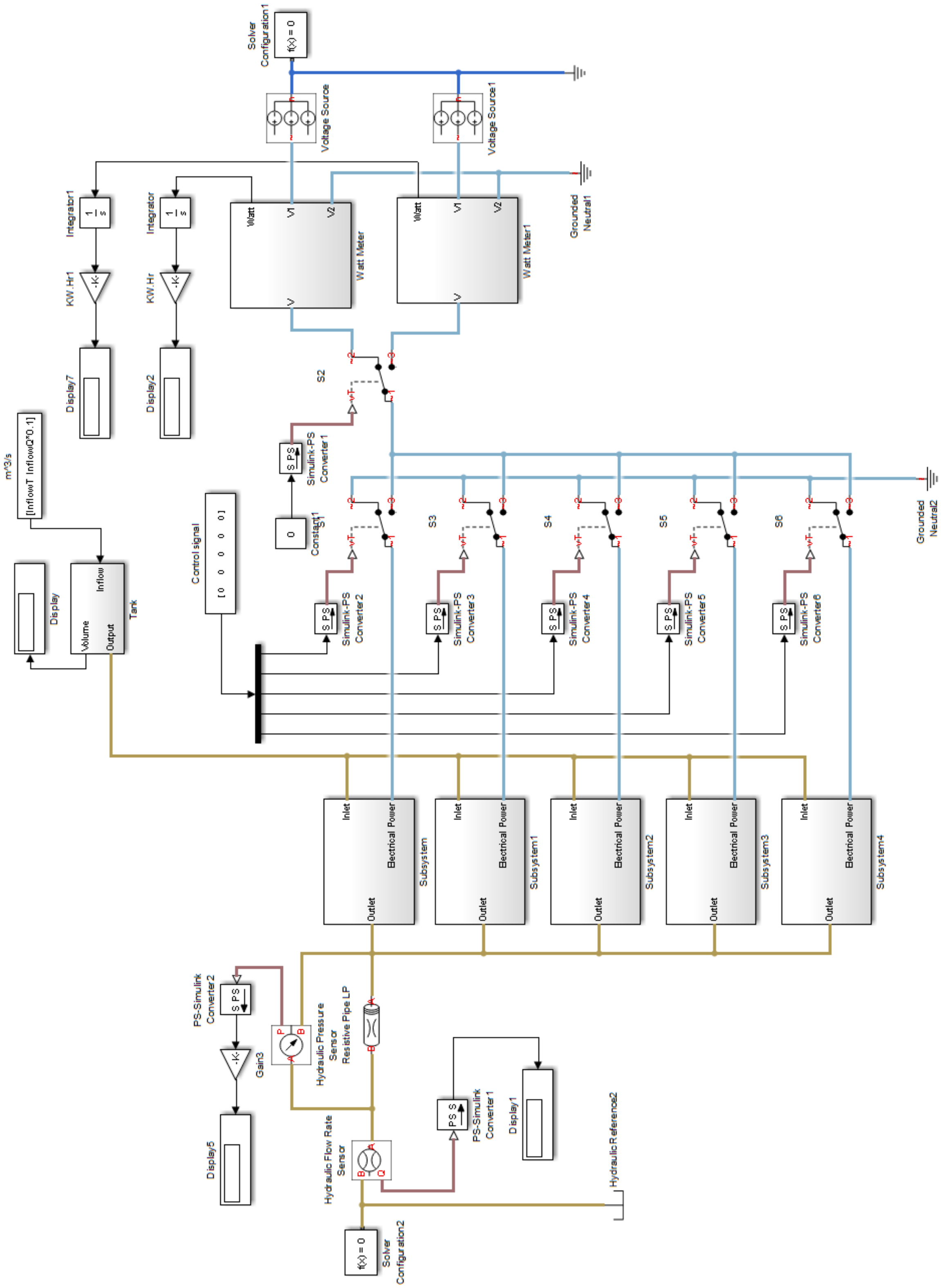


Figure 2.11: Wastewater pumping station overall system

These parameters are chosen to match the performance described by Abdelati in [2] and [4]. On the other hand, these parameters are tuned carefully to ensure that the motor accepts the specifications of the Rotating Electrical Machines IEC60034 standards [15]. The slip will not exceed 5%, and efficiency is not less than 95% (96% in our case).

For the pumps, no data is available from the manufacture (ABS) and these pumps are no more supported by the manufacture, instead, a typical characteristic curves are used to simulate the centrifugal pump with 71% max efficiency at (400 Kg/s, 30 m head) operation point. Figure 2.12 is plotted to show the system curve with respect to the pump curves. System curve is obtained by measuring the pressure across the pipe line while changing the flow through the pipe. It is found that maximum flow is about 1 m^3/s when all 5 pumps are working simultaneously, and the head reaches 44m (26m static head + 18m dynamic head). It is also noted that this is totally inefficient case.

Figure 2.13 shows the pump unit, the induction machine is connected to 3-phase power line, and the output mechanical port (named R) is connected to the centrifugal pump through a block named (Shaft). Shaft block is used to calculate and load the hydraulic torque on the driving shaft as well as the angular moments of inertia. Finally, a check valve is used at the pump output port to allow flow in one direction only.

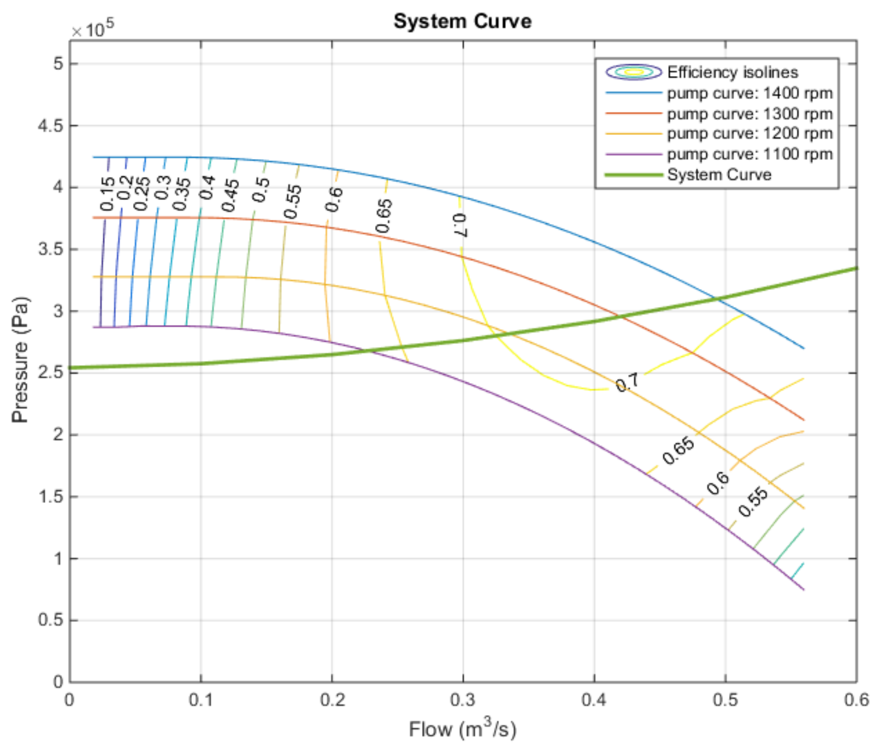


Figure 2.12: System curve plotted on the characteristic curves of the pump

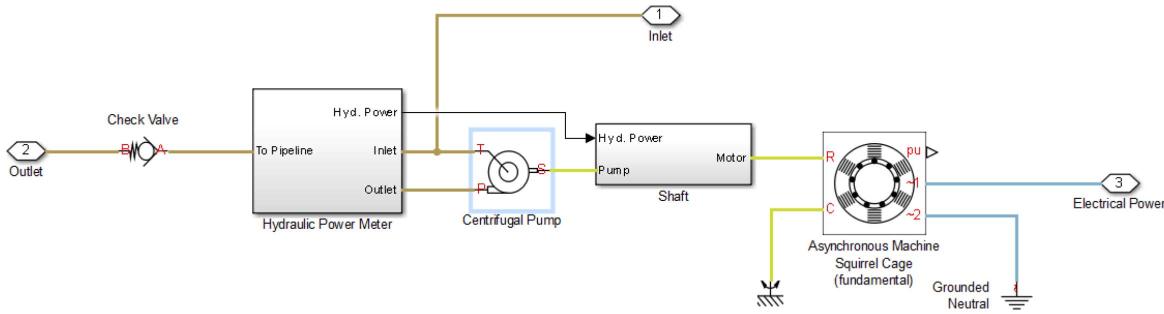


Figure 2.13: Pump unit

2.5 Model validation

This section is used to make some tests on the model before getting directly into the optimization operation, this will check the performance of the model and push us to the next step safely.

2.5.1 Induction motor characteristic curve

Plotting the developed torque as a function of motor speed is shown in Figure 2.14. An accepted pattern is shown when compared with typical curves. In our case, peak torque is 5.95 KN.m at 140 rad/sec (1320 rpm).

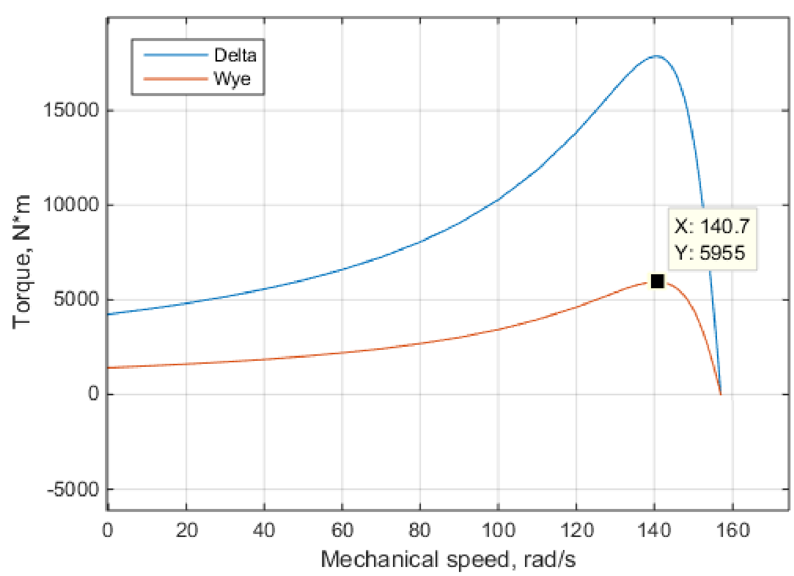
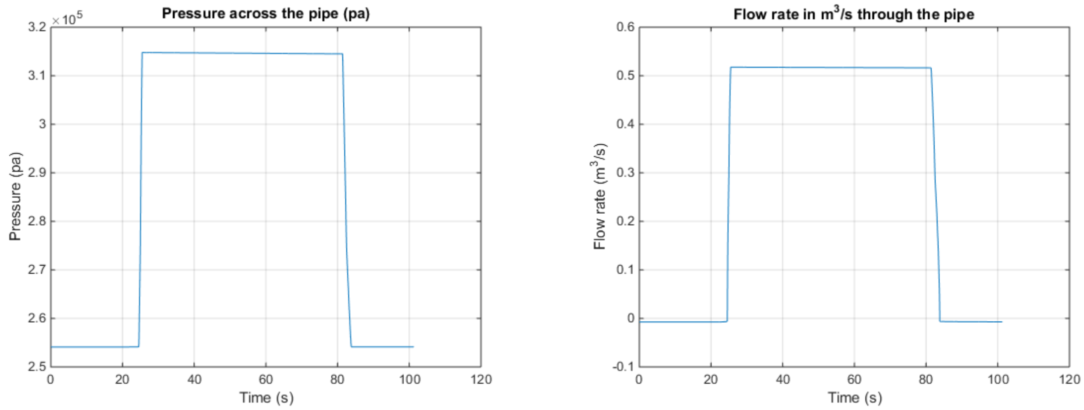


Figure 2.14: Induction motor torque-speed characteristic carve

2.5.2 Flow and pressure across the pipe

Turning one pump on, the induction motor will start rotating tell reaching the max speed. Water will start propagation as a response to the rotation of the blades of the centrifugal pump while the pressure across the pipe will increase due to the dynamics of the fluid and the friction of the pipe surface.



(a) (b)

Figure 2.15: Flow rate and pressure across pipeline when one pump is running

Figure 2.15(a) shows that the static pressure of the system which is about 2.54e5 (pa), this value represents the elevation difference between the terminals of the pipe (26 m head). When pump number one started up, the flow rate increased rapidly to reach 0.517 m^3/s as shown in Figure 2.15(b), at the same time, the pressure across the pipe increased from 2.54e5 to 3.15e5 because of the friction (dynamic pressure). These results are matched with our case study.

2.5.3 Power and efficiencies

To get an idea about power and efficiencies of a pump, pump one is started up for about one minute, the electrical power absorbed by the induction machine is converted to mechanical power, which is converted to hydraulic power by the pump.

Figure 2.16 shows that at steady phase, there is a little losses in electrical power when converted to mechanical power by the induction machine. The efficiency is about 96%, this value matches the specifications stated by IEC standard [15] for the efficiency of the large scale induction motors (>95%). This means that the characteristic impedances of the approximate model of the induction motor are chosen accurately, see section 2.3.1.

On the other hand, the efficiency of the centrifugal pump is 60.3% only, it is noted here that the maximum efficiency of the pump is 71%. That means that the pump is not working on the Best Efficiency point (BEP). Efficiency is measured by calculating the ratio between the simulated input and output power.

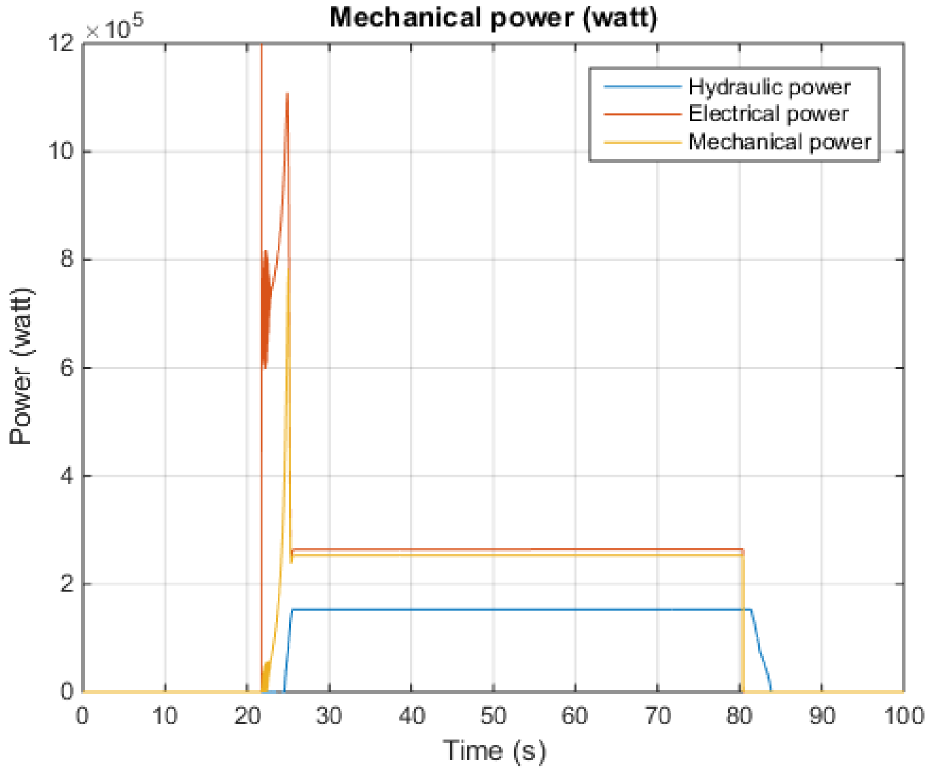


Figure 2.16: Power transformation through the system

Sharp sparks appeared on the transient phase are acceptable because the model does not include soft starters or variable speed driver blocks, because we interested in the steady phase operation (not the transient). When the pump is turned on, a huge starting current is absorbed for a moment. When the shaft of the pump started to rotate, hydraulic torque is generated which affects the speed of the motor, this process is repeated many times with some damping causes the oscillation appeared in the transient phase.

When the pump is turned off, the electrical and mechanical powers are cut, while the hydraulic power continued for few seconds, the rotating shaft inertia caused the rotor to continue rotating and the blades continued delivering power to the hydraulic system for a moment.

3 Auto-adaptive Inflow Prediction Model

The purpose of prediction is to estimate future values of the flow input to the pumping station. (J. Lindqvist, T. Wik, D. Lumley and G., Äijälä) in [9] developed and tested an AutoRegressive with eXogenous (ARX) prediction model to estimate inflow of wastewater and achieved an accepted results. In this chapter, the author reformed their work to make the estimation suitable for MPC with 48 hour time span (not only for one time slot).

The time slot is chosen to be 30 minutes to sense the sharp peaks of the flow witch is belonged to the human activities. Also the 30 minutes must be enough to solve the optimization problem. On the other hand, the time span must be large enough to be about infinity with respect to the time slot. It is noted that enlarging the time span will rapidly increase the complexity of the optimization problem and the solver may not be able to solve every time slot.

3.1 ARX model:

ARX is a mathematical model used to predict the future output of a system depending on the history information and some other inputs. It is classified as a polynomial-based input-output model. Basically, a linear Single-Input-Single-Output (SISO) ARX model structure has the following formula:

$$\begin{aligned} y(k) + a_1 y(k-1) + a_2 y(k-2) + \cdots + a_{na} y(k-na) \\ = b_1 u(k-nk) + b_2 u(k-nk-1) + \cdots \\ + b_{nb} u(k-nk-nb+1) + e(k) \end{aligned} \tag{3.1}$$

Equation (3.1) implies that the current output $y(k)$ is predicted as weighted sum of past output values and past input values with an error $e(k)$.

$y(k-1),\ y(k-2),\ \ldots,\ u(k-nk),\ u(k-nk-1),\ u(k-nk-nb+1)$ are the delayed output and input variables, called regressors, nk is the dead time which sets the response delay from input to output, that's mean that nk is the number of input samples that occur before the input affects the output, and $a_1,\ a_2\ \ldots\ a_{na},\ b_1,\ b_2\ \ldots\ b_{na}$ are the weights. By separating $y(k)$ and reforming equation (3.1) in vector form, $\hat{y}(k)$ can be presented as

$$\hat{y}(t) = [-a_1, \ldots, -a_{na}, b_1, \ldots, b_{nb}] * [y(k-1), \ldots, y(k-na), u(k-nk), \ldots, u(k-nk-nb+1)]^T \quad (3.2)$$

where the *hat* ($\widehat{\ }$) notation tells that $\hat{y}(k)$ is an estimated value.

When calling a function implementing equation (3.2) once, it can predict only the current output value $\hat{y}_m(k)$ which is not enough when talking about MPC Control system. Predicted future samples number must at least equal the number of MPC time horizon samples, and the inputs may be a future forecasted variables (inputs from weather forecasting).

[*Lubomír Baramov and Vladimír Havlena*] in 2005 reformulate the traditional ARX model to be suitable for MPC real-time control systems [16]. They wrote equation (3.1) in a discrete matrix form by replacing $\hat{y}(k)$ with $Y_f(k)$, $y(k-i)$ with $Y_p(k)$, and split $u(k-nk-i)$ into $U_p(k)$ and $U_f(k)$, where

$$Y_p(k) = \begin{bmatrix} y(k-na) \\ \vdots \\ y(k-1) \end{bmatrix}, Y_f(k) = \begin{bmatrix} \hat{y}(k) \\ \vdots \\ \hat{y}(k+N) \end{bmatrix},$$
$$U_p(k) = \begin{bmatrix} u_r(k-nk-nb) \\ \vdots \\ u_r(k-nk-1) \end{bmatrix},\ U_f(k) = \begin{bmatrix} u_r(k) \\ \vdots \\ u_r(k+N-1) \end{bmatrix} \quad (3.3)$$

It is clearly noted here that N is the number of future outputs needed to be predicted (MPC time horizon). So, equation (3.2) could be mapped to equation (3.4) to expect future output vector $Y_f(k)$.

$$Y_f(k) = \left(\tilde{A}_f\right)^{-1}\left(-\tilde{A}_p Y_p(k) + \tilde{B}_p U_p(k) + \tilde{B}_f U_f(k)\right) \quad (3.4)$$

where

$$[\tilde{A}_p|\tilde{A}_f] = \left[\begin{array}{ccc|ccccc} a_{na} & \cdots & a_1 & 1 & & & & \\ & \ddots & \vdots & a_1 & \ddots & & & \\ & & a_{na} & \vdots & \ddots & 1 & & \\ & & & a_{na} & \cdots & a_1 & 1 & \\ & & & & \ddots & & \ddots & \ddots \end{array}\right] \quad (3.5\ a)$$

$$[\tilde{B}_p|\tilde{B}_f] = \left[\begin{array}{cccc|cccc} b_{nb} & \cdots & b_1 & & & & & \\ & \ddots & \vdots & \ddots & & & & \\ & & b_{nb} & \cdots & b_1 & & & \\ & & & \ddots & \vdots & \ddots & & \\ & & & & b_{nb} & \cdots & b_1 & \\ & & & & & \ddots & & \ddots \end{array}\right] \quad (3.5\ b)$$

The $\tilde{A}_f$ weight matrix is appeared here (no corresponding gain parameter in equation (3.2)) to let the values of the far future depends on the near predicted future values with the same criteria implemented in the past measured output values. In other words, the predicted output value $\hat{y}(k+N-1)$ is considered as a past value with respect to $\hat{y}(k+N)$, and the prediction of $\hat{y}(k+N)$ must be affected by the predicted output value of $\hat{y}(k+N-1)$ even both are in the future.

To avoid bugs later in programing and testing, the dimensions of the above matrices are tabulated in Table 1, and equation (3.4) has to be dimensioned carefully according to the dots notation (…).

Table 3.2: Prediction equation matrices dimensions

Matrix	Dimension
$Y_p(k)$	$na \times 1$
$Y_f(k)$	$(N+1) \times 1$
$U_p(k)$	$(nb) \times 1$
$U_f(k)$	$N \times 1$
$\tilde{A}_p$	$(N+1) \times na$
$\tilde{A}_f$	$(N+1) \times (N+1)$
$\tilde{B}_p$	$(N+1) \times (nb)$
$\tilde{B}_f$	$(N+1) \times N$

3.2 ARX recursive parameter Estimation:

As mentioned above, equation (3.4) can be used to predict the value of $Y_f(k)$ which includes values of $y(k)$ for the current value and N future samples. ARX model parameters a_1, a_2 … a_{na}, b_1, b_2 … b_{na} needs to be chosen carefully and updated continuously to satisfy the needs of the MPC controller.

Some famous recursive polynomial model estimation algorithms are explained in details by (*Ljung*) in [17]. These algorithms are *Forgetting factor*, *Kalman filter*, and *Gradient adaptation algorithm*.

After comparing the three algorithms, *Forgetting Factor* is chosen because it allows the user to set λ (explained later) implies that past measurements are less significant for parameter estimation, where the other algorithms need parameters which are difficult to get in this case.

The following set of equations summarizes the forgetting factor adaption algorithm:

$$\begin{gathered}
\hat{\theta}(k) = \hat{\theta}(k-1) + K(k)\big(y(k) - \hat{y}(k)\big) \\
\hat{y}(k) = \psi^T(k)\hat{\theta}(k-1) \\
K(k) = Q(k)\psi(k) \\
Q(k) = \frac{P(k-1)}{\lambda + \psi^T(k)P(k-1)\psi(k)} \\
P(t) = \frac{1}{\lambda}\left(P(k-1) - \frac{P(k-1)\psi(k)\psi^T(k)P(k-1)}{\lambda + \psi^T(k)P(k-1)\psi(k)}\right)
\end{gathered} \tag{3.6}$$

$\hat{\theta}(k)$ is the parameter estimate at time k which is $[-a_1, \dots, -a_{na}, b_1, \dots, b_{nb}]$. $y(k)$ is the measured output at the same time, and $\hat{y}(k)$ is the prediction of $y(k)$ based on observations up to time $k-1$. The gain matrix $K(k)$ determines how much the current prediction error $y(k) - \hat{y}(k)$ affects the update of the parameter estimate. The estimation algorithms minimize the prediction error term $y(k) - \hat{y}(k)$.

ψ^T represents the gradient of the predicted model output $\hat{y}(k|\theta)$ with respect to the parameters θ. Adaption algorithm (3.6) implicates minimizing the following function (equation 3.7) at time k

$$\sum_{k=1}^{n} \lambda^{n-k} \left(y(k) - \hat{y}(k)\right)^2 \tag{3.7}$$

This approach discounts old measurements exponentially. An observation that is τ samples old carries a weight that is equal to λ^{τ} times the weight of the most recent observation. $\tau = 1/(1-\lambda)$ represents the memory horizon of this algorithm. Measurements older than τ typically carry a weight that is less than about 0.3. λ is called the *forgetting factor* and typically has a positive value between 0.97 and 0.995 [18].

3.3 Wastewater inflow prediction

Some adjustments are held to the model developed by [9] to satisfy MPC requirements. The flow during dry weather is very different from rainfall runoff flow, and therefore has to be modelled separately.

3.3.1 Dry weather model:

The dry weather flow depends mainly on the time of day as the human activities vary, and can be described by two components, a mean flow value and a flow pattern (with zero mean).

Flow pattern is a time-series elements which are weighted mean values of the flow shape, sampled with certain time intervals (30 minutes in this study). To describe the complete dry weather flow, the mean value is added to the flow pattern as shown in Figure 3.1. The data plotted in this figure is just an example.

A set of different daily flow patterns according to the day type can stand for the variations in flow during the weekends and holidays periods. Every pattern consists of 24 hour values for each daily pattern and mean. This approach is mentioned in some similar MPC projects like water demand forecasting, for example, [3].

When a new inflow value is sampled, it adapts the flow pattern using equation (3.1) directly because the pattern itself is a predictive tool for future, and no need to estimate future values since the pattern will do that directly. This assumption is approved in [9]. No external inputs affect the pattern, and equation (3.1) can be used in its simplest form as follows:

$$y(k+1) = a_1 y(k) + a_2 y(k-1) \tag{3.8}$$

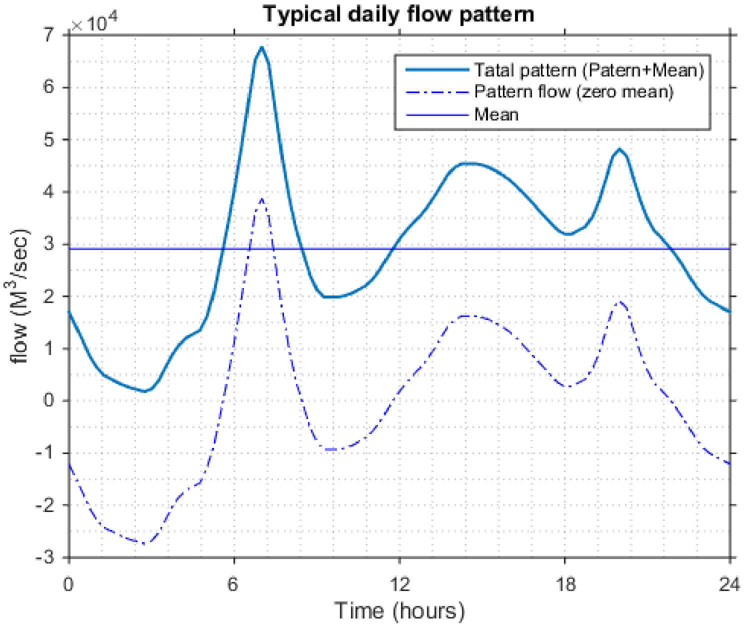


Figure 3.1: Daily wastewater flow pattern disassembled into mean and pattern

where $y(k)$ is the new sampled value, and $y(k-1)$ is the value of the pattern at that time and the pattern will be adapted by replacing $y(k-1)$ with $y(k+1)$. This simplification is acceptable because the pattern has built-in information about many history reading. $a_1 + a2$ must equal 1. Higher value of a_1 gives a stronger weight to old values and thereby a slower adaptation to changes.

To avoid high frequency variations in the flow pattern and mean flow caused by rapid changes in inflow (like rain runoff or troubles in the swage net), a limit is set and if exceeded no change is made to the output values. The mean flow value which is based on the average flow over 24 hours is adapted daily exactly in the same way.

To validate dry weather model, a simple MATLAB program written to simulate the adaption of the pattern during 7 days from the worst case that no pattern is available. Figure 3.2 shows the adaption process with $a_1 = 0.6$ and $a_2 = 0.4$ for both pattern curve and mean value. In real cases, a_1 must be large enough to avoid disturbing the flow pattern rapidly.

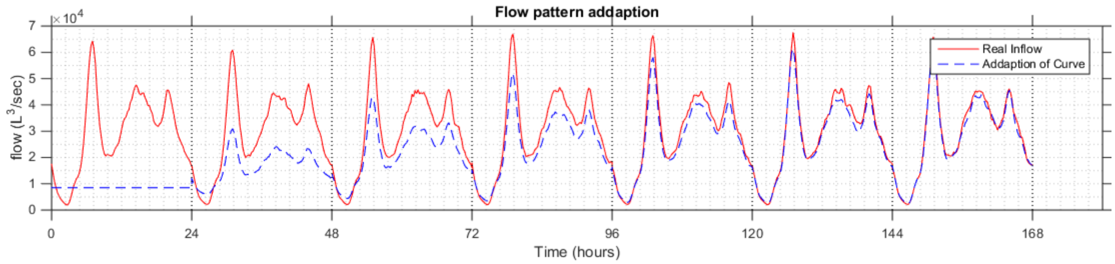


Figure 3.2 Flow pattern adaption

The real flow (drawn in red) is generated from a suggested flow pattern with Gaussian noise distribution (variance=5%). The system reads the flow every time slot (30 minutes) and adapt the pattern continuously. After about 6 days, the system developed an accurate pattern to be used later in MPC.

3.3.2 Storm water runoff model:

In runoff days, runoff inflow can be calculated by subtracting the dry weather pattern from the incoming flow to remove the periodic base (dry weather flow). This methodology of separation between wet and dry weathers is used by [9] to study every case alone.

The model derived in equation (3.4) can be used to estimate the runoff flow with precipitation forecasting for the future period as inputs (mm/hour), and the predicted inflow due to the precipitation in the time horizon as outputs. $nk \neq 0$ because there is an obvious delay between rain (mm/hour) and water inflow (m^3/hour) value.

To validate the runoff model, MATLAB code is written to generate a random forecasted precipitation (mm/hour) stepped every 6 hours for 144 hours. It is noted here that weather forecasting institutes usually provide precipitation in 6 hour intervals for 1 week future period, an example is [19] .The true precipitation and the corresponding inflow (m^3/hour) is generated in the same way with some random process based on the forecasted precipitation curve. Figure 3.3 shows these data.

Every time step (30 minutes), the model reads the new sample of precipitation and uses the ARX model with 12 measured past samples and 12 future precipitation values to estimate the inflow through the future 48 hours.

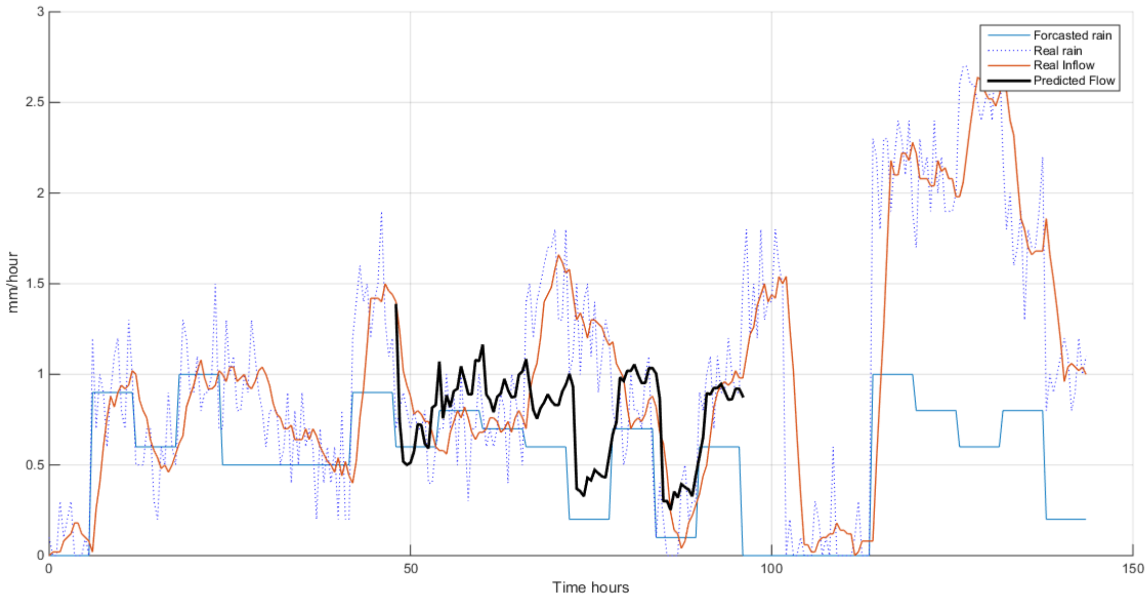


Figure 3.3: Forecasted and true precipitation, predicted and true inflow

After 48 hour of training using the recursive algorithm (equations 3.6), It is seems that the model improved the accuracy to be useful in MPC controller.

As shown in Figure 3.3, at the first 48 hours, the forecasted precipitation is little underestimated compared with the real precipitation. This leads the model to over expect the inflow and depends on the current flow rate more than the forecasted precipitation. For the next 12 hours, the real precipitation is much closed to the forecasted, which maintained the confidence with the forecasted data which leads to a problem in the next 12 hours.

Finally, one more time, the smart predictor lost the confidence with the forecasted data and tracked the real current precipitation which improved the model expectation. This predicted inflow curve will be adapted every 30 minutes to be more smart and accurate. To overcome the unexpected inflow in the storm days, the optimizer must be asked to minimize the volume of liquid in the tank as a safety requirement.

4 Pumping Optimal Operation

Many nonconventional optimization techniques could be used to solve our problem. GA is selected due to its power for high nonlinear problems with multi objectives and constraints, where others have more probability to be trapped on local minima solutions. The full random processes are the source of power of GA. A brief overview about GA is expressed in this chapter and the pumping problem is solved.

4.1 Genetic Algorithm:

Genetic algorithms (GA) belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover.

In GA, a population of candidate solutions to an optimization problem is suggested. Each individual solution is represented in binary or other encodings, the encoded candidate solution can be considered as a chromosome carrying the properties of this individual.

The GA starts from a population of individuals which are generated randomly (the first generation), the fitness of every individual is evaluated by substituting in the objective function of the optimization problem. The better individuals have higher probability to live and be modified to form the new generation, so that they have a good chance to inherit its properties to the next generations. The properties of the new generation are improved and the algorithm continue improving the generations tell some stopping criteria is matched.

The repetitive improvements through generations is done by natural evolution operations like mutation, crossover, inversion and selection as shown in Figure 4.1.

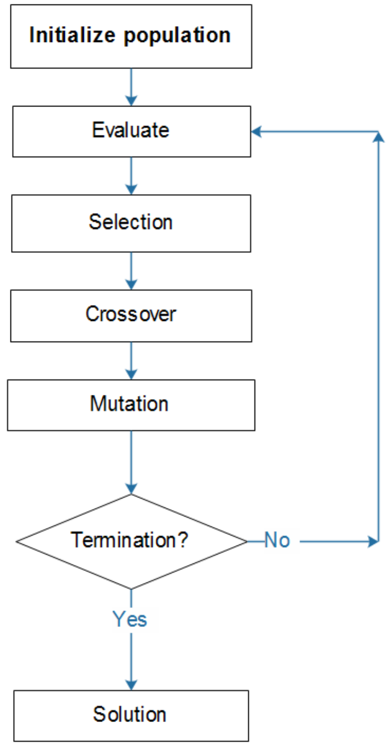


Figure 4.1: GA standard algorithm chart

4.1.1 Why GA?

Wastewater pumping station is a very complicated system because it is affected by water income pattern and weather conditions. It is a multi-objective problem. That means optimization must take into account the power, maintenance, and environmental issues. The system also related to some constraints.

The author traced on the non-conventional optimization techniques and selects GA because:

1. GA searches parallel for a population of points, so it avoids being trapped in a local optimal solution, this is suitable for our problem because of the huge number of available solutions (4^{96}) as will be discussed later.
2. GA Selects the next population by computation which uses random number generators with significant probabilities, where most of optimization techniques calculated the next point by deterministic computation.
3. GA is applicable to solve problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, non-differentiable, stochastic, or highly nonlinear.
4. GA accepts nonlinear constrains and integer searching which both are needed in pumping scheduling.

4.1.2 Selection

For a specific generation, the quality of the individuals are evaluated using the fitness function. The mean fitness of the population is calculated. All individuals with a fitness at the average and bellow will be died out. On the other hand, the individuals with high rating will be copied times proportional to its fitness value. Some other individuals can be selected randomly to the new generation. This criteria guides the properties of the generations to be improved iteratively. Some other algorithms could be implemented in the selection module.

4.1.3 Crossover

Some of the selected individuals will be mated in pairs, a crossover point will be chosen and the information after this point will be exchanged. Some other methods also used, for example, a famous used criteria for cross over operation is to give every gene in the chromosome a random probability to be exchanged with the counterpart in the other gene. **Figure *4.2*** shows an example of a crossover operation.

4.1.4 Mutation

The implementation of Mutation is fairly trivial, where each bit in every gene has a defined probability to get inverted.

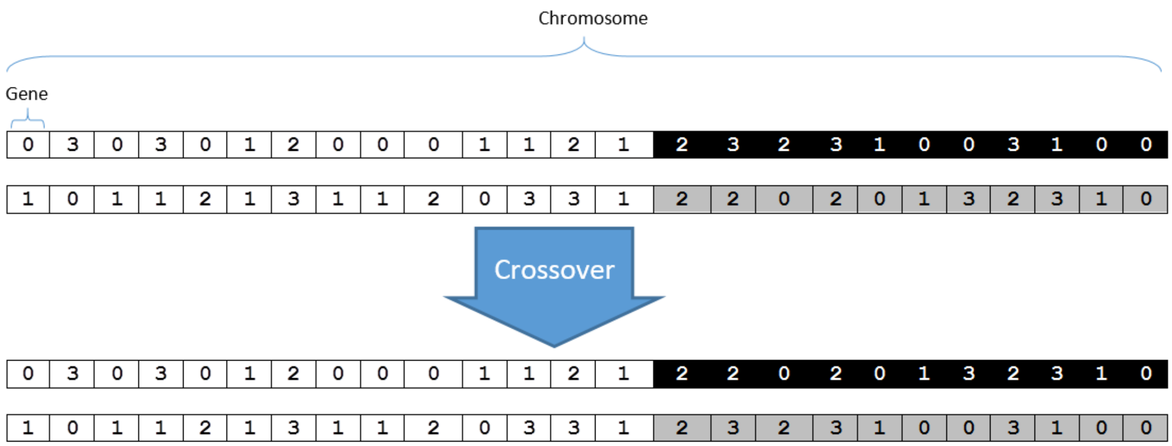


Figure 4.2: Genetic crossover operation

4.1.5 Termination

Just like any other iterative optimization techniques, GA continues until reaching a termination condition which may be:

1. Satisfying an accepting solution.
2. Fixed number of iterations.
3. Celling computer processing time.

4. Specific tolerance between solutions

4.2 Simplifying the problem

Typical optimization methods cannot deal with such types of problem. In this case, it may be necessary to forgo an exact evaluation and use an approximate fitness that is computationally efficient. It is apparent that GA may do hard computations for a huge number of suggested solutions. MPC is a dynamic optimizer, and the dead time for computing everything is the time slot (30 minute in our problem).

To guide the optimizer to start correctly, it is important to reduce the range of searching depending on analyzing the system behavior in different cases. In this section, the author will answer two questions:

1. Fixed or variable speed pumping?
2. How many pumps may be running simultaneously?

4.2.1 Fixed or variable speed operation?

Figure 2.11 (section 2.4) shows the system curve plotted on the pump characteristic curve (Pressure vs. Flow rate) at different speeds. Because of the high static pressure (26m head), a little decrease in pump speed (from 1480 rpm to 1000 rpm) will reduce the pump efficiency from (70% to 0%). This is because the liquid will not flow any more, and output power of the pump is zero.

The *'Variable Speed Pumping, a guide to successful applications'* manual [20] states: "The ratio of static to friction head over the operation range influences the benefits achievable from variable speed drivers".

Decreasing the efficiency of the pump not only affects the power losses, it also decreases the reliability of the pump and then increasing the maintenance costs. The power losses in the pump is converted to vibration and heat in the pump, and this will damage the bearings, seals, and the impeller.

Figure *4.3* illustrates the effect of operating the pump out of BEP. The reliability of the pump is inversely proportional to the number of failures in a specific time (for example one year).

For our case study, we can conclude that it is a must to operate the pumps at a fixed speed around its BEP to improve power efficiency and maintenance cost.

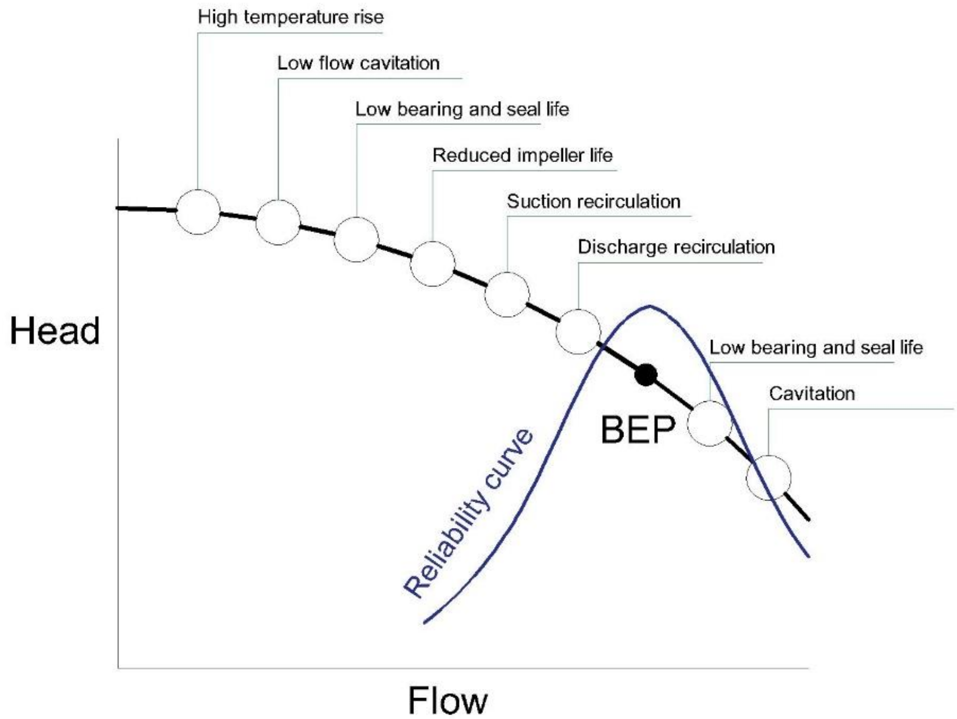


Figure 4.3: Typical pump reliability curve

4.2.2 Number of concurrently running pumps:

Getting data out from the overall model, it appears that the relation between number of running pumps and flow rate is not linear, it converges to a maximum flow value and this makes sense. It is known that the dynamic head of the pipeline is directly proportional to the square of the flow rate through the pipe. Increasing the dynamic pressure of the pipeline and joints will push up the pump to reach the shut off pressure. At this moment, the pump will no more cause any flow and efficiency will be destroyed.

On the other hand, the power absorbed by the pumps stills more linear with some concavity. This also make a reasonable sense. When the efficiency of a pump decreases, the torque practiced on the pump blades by the liquid dynamics decreases. Consequently the driving motor mechanical power declines.

Figure 4.4 illustrates the difference in the slops of Power and flow curves as a function of number of running pumps.

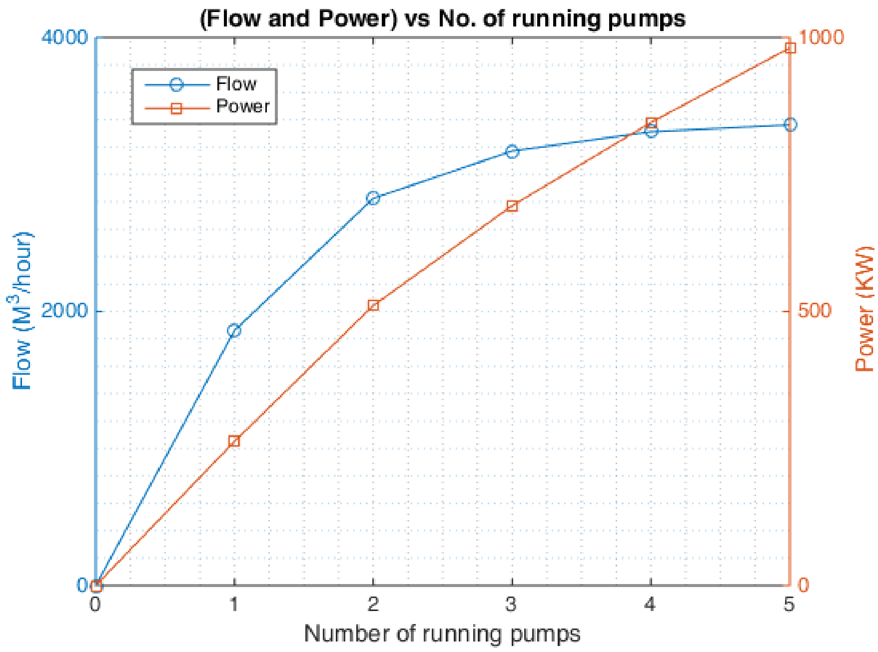


Figure 4.4: Flow and power vs. number of running pumps

As a result of this discussion, we can conclude some points:

- The optimizer must be advised to run minimum number of pumps concurrently to get most efficiency.
- The max number of concurrent running pumps is 3 and the other two can be considered as standby pumps.
- A new parallel pipeline is needed to allow all five pumps to run at the same time.

4.3 Cost function and constraints:

4.3.1 Power cost:

Two sources of electrical power are available: main line and generator. The KWH cost for the main line is about 0.6 NIS and it is constant. For a generator, the cost of KWH is function of the size of the generator and the load at which the generator is operating at.

Usually, generators' manufacturers provide approximate fuel consumption charts to help the customers optimize their operation. These charts are much closed for standard generators. A Typical chart from *Diesel Service & Supply* cover generators form 20 to 2250 KW at different operation loads is available in [21]. For 1000KW generator (Our case study), the KWH cost is as follows:

Table 4.1: Cost estimate for power from 1000 KW generator

	1/4 Load	1/2 Load	3/4 Load	Full Load
Output power (KW)	250	500	750	1000
Fuel consumption (liter/hr)	82	138	197	269
Cost per liter (NIS/liter)	5			
Cost per hour (NIS/hr)	410	690	985	1345
Cost per KW.hr (NIS/KWH)	**1.64**	**1.38**	**1.31**	**1.35**

The average cost is 1.4 NIS which is much higher the cost from the main line.

4.3.2 Maintenance cost:

Although it seems very complicated to formulate maintenance cost of pumping processes, maintenance cost can be approximated as a function of number of starts for a fixed speed running pump. The effect of liquid circulations, vibration, high surge starting currents, and the influent of water shock occur at the starting time increases the maintenance cost and decreases the reliability of the pump.

For this reason, pumps manufacturers often limit the number of starts per hour. In many cases, scheduled maintenance programs are belonged to the number of starts as well as operation duration. Therefore, we will minimize the number of starts of the pumps during the time interval of operation as an approximation of minimizing the maintenance cost.

4.3.3 Water level in tank:

Water level in tank could be classified under environmental cost. Keeping this level down appeared to be more needed at storm days to overcome any inaccurate weather forecasting.

4.3.4 Fitness function:

Table 4.2 shows the power absorbed by the pumps, during every time slot (30 minutes) which is got from the full model. It is possible to run zero, one, two, or three pumps simultaneously.

The cost of the total power consumed during the time span (48 hours) is

$$E_c = \sum_{t=1}^{96} 0.5 C_t P(n_t) \tag{4.1}$$

Table 4.2: Power vs. number of concurrent running pumps

Number of running pumps n	Power $P(n)$ (Kw)
0	0
1	263
2	511
3	693

where C_t is the electrical energy cost (NIS/KWH), and P is the pumping power at time t, n_t is the number of running pumps at time t. The value is multiplied by 0.5 because the duration is half an hour. C_t equals 0.6 (NIS) for main line source and 1.4 (NIS) for generator source as discussed above.

Number of starts noted as NOS is obtained by counting changes of number of running pumps during the operation, where the maximum liquid volume in the tank is computed by equation 4.2.

$$V_T = \max\left(V_0 + \sum_{t=1}^{t<96} Q_{in}(t) - Q_{out}(t)\right) \tag{4.2}$$

Q_{in} is the input flow. Abdelati studied the pattern of the NTPS pumping station in [2]. He estimated the average of wastewater flow depending on the average of water consumption per capita. The population of the area under study is about 260,000 having access to the swage network each with 134 liters per day. This results in a daily average flow of about 35000 m^3.

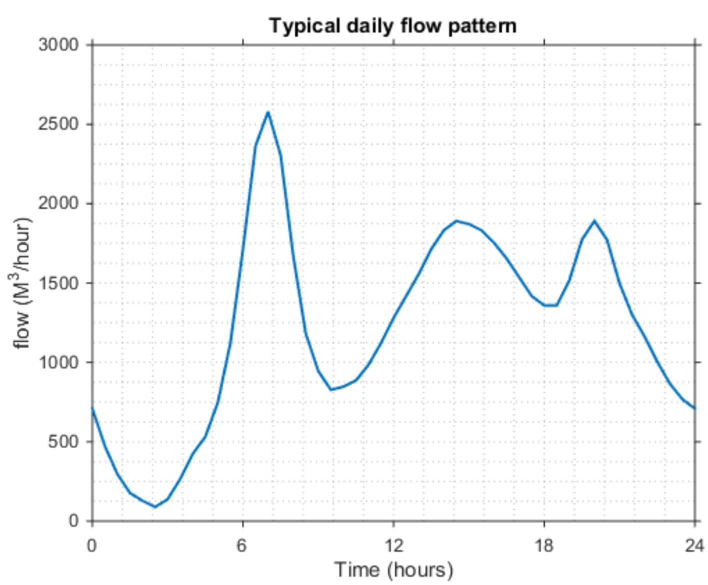


Figure 4.5: NTPS Inflow pattern

Moreover, he used a questionnaire about the frequency of use per capita per day to distribute the average value on the 24 hours in a day. The result value is shown in Figure 4.5.

Finally, Q_{out} is the out flow from the station which is a function of number of pumps running at time t. Table 4.3 shows the data got from the model for flow vs. number of running pumps.

Table 4.3: Flow vs. number of running pumps

Number of running pumps n	Out flow (m^3/hr)
0	0
1	1861
2	2826
3	3171

Now, Equation 4.3 is ready as a fitness function for GA to be minimized. A, B, and C are weights could be selected to satisfy the needed operation behavior.

$$\text{Total cost} = \mathrm{A} * E_c + B * NOS + C * V_T \tag{4.3}$$

4.3.5 Constraints

For environmental issues, the wastewater in the tank must not exceed a limited value. In our case study, the upper limit value is 20000 m^3, and the lower limit is 200 m^3 of the liquid. This can be easily satisfied using the inequality 4.4

$$200 < V_0 + \sum_{t=1}^{1<T<96} Q_{in}(t) - Q_{out}(t) < 20000 \tag{4.4}$$

4.4 Results and discussion:

The GA algorithm is set up as shown in table 4.4.

Table 4.4: GA setup parameters

GA parameter	Value
Population size	1000
Number of generations	150
Elite count	200
Tolerance	1e-6

Main line power availability is scheduled to be eight hours ON and eight hours OFF as it is now in Gaza strip.

4.4.1 Case 1: Dry weather, A=1, B=1, C=0

Zero weight of the liquid volume in tank is selected, the result is shown in Figure 4.7. Red plot on the upper of the graph represents the availability of electrical power from the

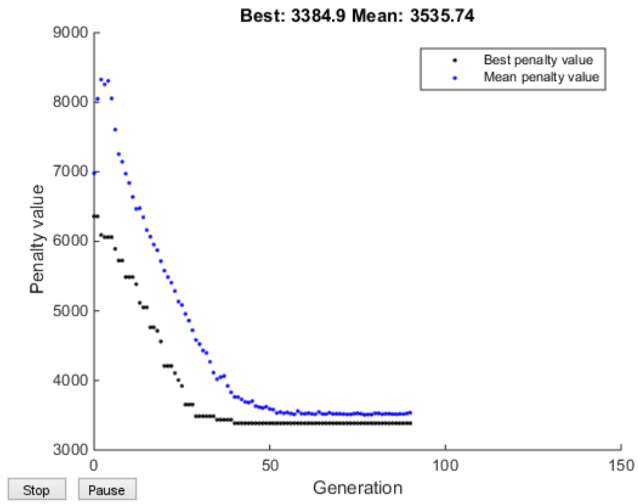


Figure 4.6: Best and mean fitness value through all generations for case 1

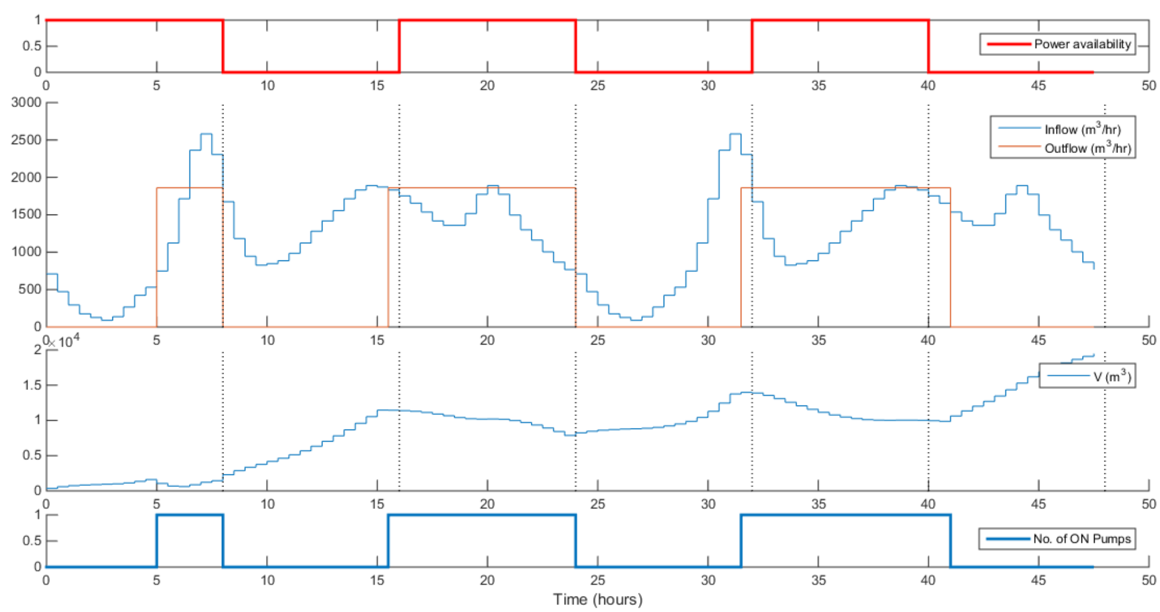


Figure 4.7: Case 1 result

main line, where the blue plot at the bottom is the solved number of pumps to work. An expected operation plan is resulted as follows:

- Only one pump is used, this matches the result of the discussion in section 4.2.2. This means that the optimizer tracked successfully the best efficiency operation to save losses on the pipeline.
- Most of the operating time is within the main power availability, and this shows that the algorithm guides the solution to occupy the cheapest energy intervals.
- Setting C=0 pushed the optimizer to ignore the maximum value at the tank during all the interval, and this leads the tank to be slightly under the upper limit at the end of the 48 hours.
- The number of starts is 3 only. It is clear that this is the minimum number could be achieved.

4.4.2 Case 2: Dry weather, A=1, B=1, C=0.25

When $C \neq 0$, the solver will search for solutions with maximum liquid in the tank less than that in case 1. Figure 4.9 illustrates the behavior of the solver. A near solution is resulted with maximum liquid volume on the tank not exceeds 20% of its capacity compared with about 95% in case 1.

Even the most of the operation periods were during the main line source ON intervals, the pump occupied wider range while main line power OFF compared with case 1.

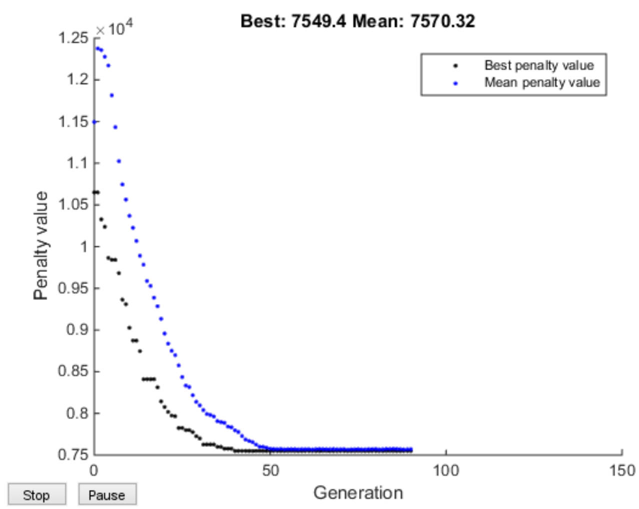


Figure 4.8: Best and mean fitness value through all generations for case 2

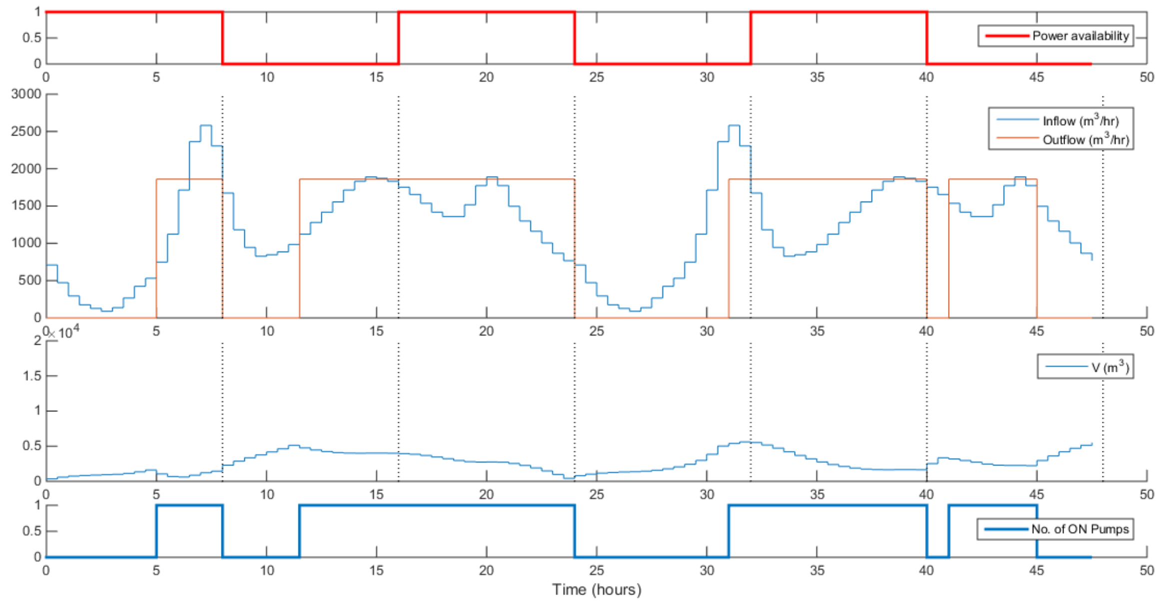


Figure 4.9: Case 2 result

4.4.3 Case 3: Storm weather, A=1, B=1, C=0.5

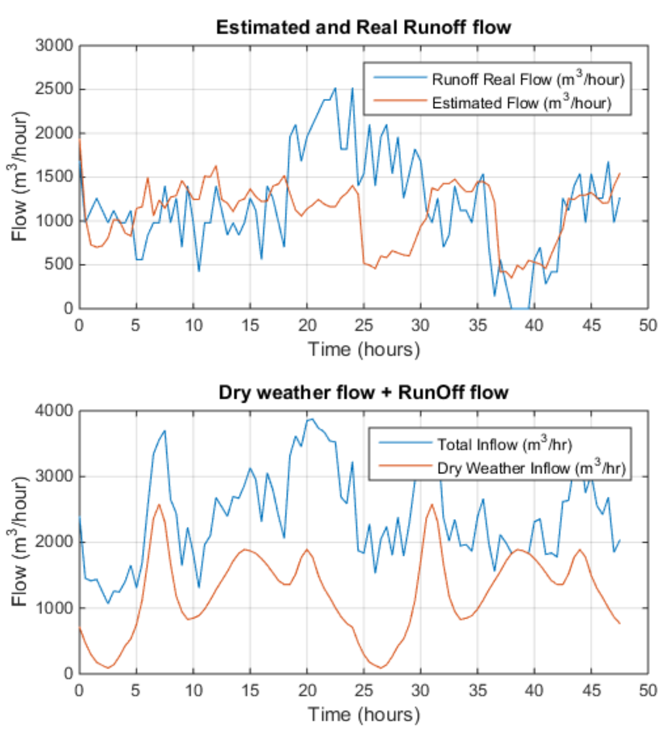


Figure 4.10: Run off and Total Inflow

When the optimizer is asked to solve for pumping operation with C=0.25 as in case 2, the result included an overflow in the tank because of the underestimation of run off in average as shown in Figure 4.10. Data plotted in **Figure *4.10*** is pre generated from a trained ARX filter and integrated directly as an input to the system.

C is doubled to be 0.5, and the number of generations is enlarged to be 450. The results was satisfactory. **Figure *4.11*** shows that the system struggled hard to converge compared with cases 1, 2.

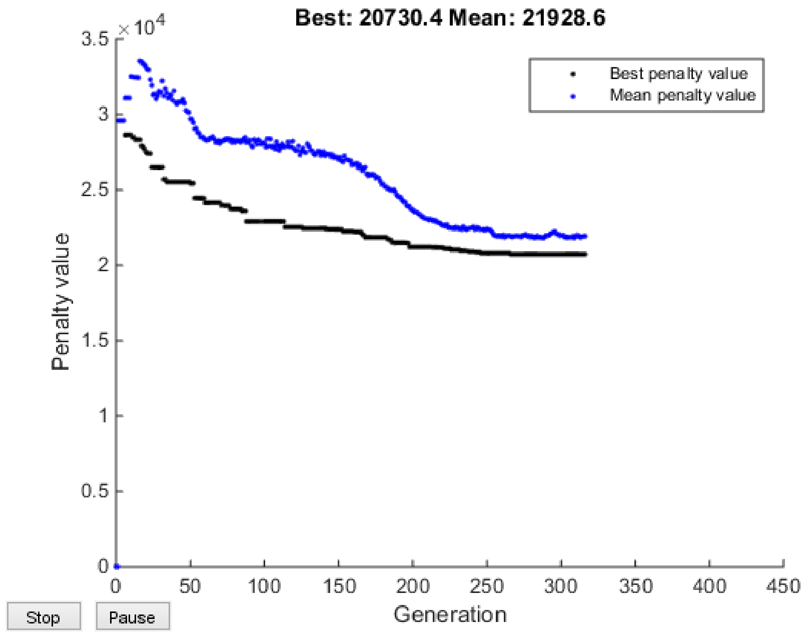


Figure 4.11: Best and mean fitness value through all generations for case 3

Figure *4.12* is the detailed result. One pump continued to be run for about all the time, the second one is run only when the main line in ON. At the same time, the operating scheduling keeps minimum number of starts. Finally, the tank is not overflowed even if there is some underestimate of run off inflow.

Many other cases can be tested to validate the controller, and to tune the optimizer to give better results.

Figures 4.6, 4.8, 4.11 shows the convergence of the solution from a full random solutions to the optimized one.

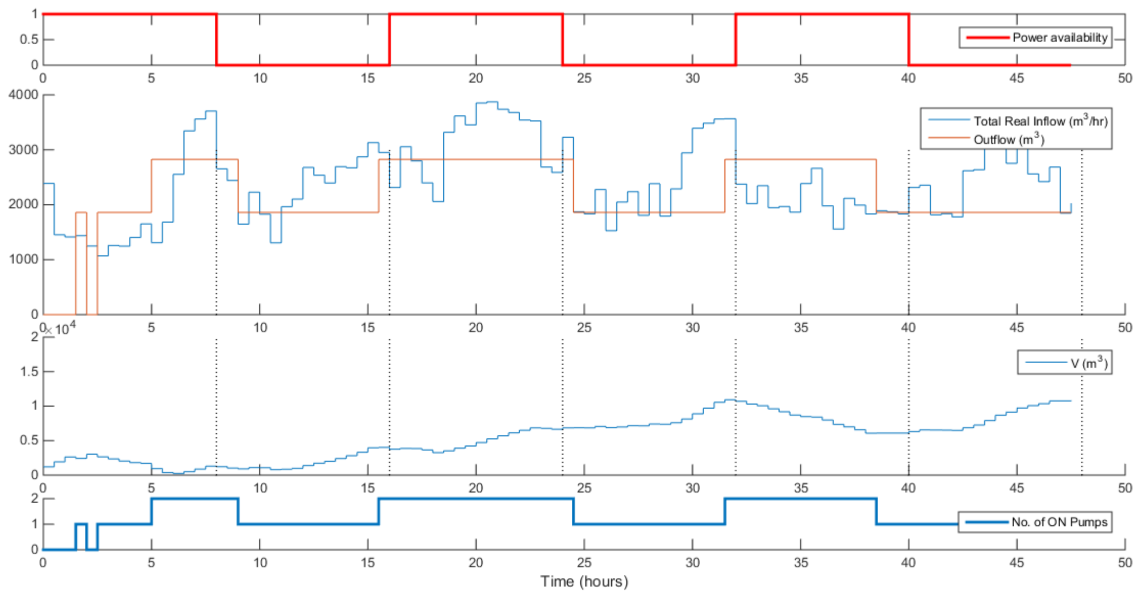


Figure 4.12: case 3 results

5 Conclusion and future work

Model-based predictive controller is a good choice to occupy the advanced process control block in the control levels' pyramid. The approximate steady model for the system is accepted and seems to be more computational efficient, especially when using the nonconventional revolutionary algorithms for optimization. The AutoRegressive with eXogenous filter is upgraded to be suitable for MPC problems, and succeeded to some degree in prediction of pumping station inflow at dray and storm weathers. The controller is simulated for the North Gaza Terminal Pumping Station as a case study. Three different cases were taken and all results were convenient and analyzed clearly. Genetic Algorithm proposed a powerful solver. This was clearly noted when observing the fitness value converges to a satisfactory solution from 4^{96} available ones.

As a future work, we suggest expanding the fitness function to involve all the LCC costs as well as the constraints (not only power and maintenance costs). Reformulating the maintenance cost will add a contribution, that the number of starts only give an indication, and may be not enough in other cases. Also, redesigning the optimizer to work with variable speed pumps on other cases studies is suggested.

Repeating the work to let the optimizer cover both design and operation phases of a pumping stations is our next plan.

The author advices to implement an MPC controller to the NTPS pumping station especially because of the situation of the electrical power in Gaza. It is a good scheme to select the minimum volume of the bond taking into account power, maintenance and environmental costs.

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