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Testing minimum cost strategies of pumping systems with scheduled electric tariffs in a lab scale plant

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Abstract: This paper describes the development and testing of a lab plant that emulates a water supply pumping system with the objective of testing optimal pumping strategies based on standard solvers. The emulated system consists of two tanks that supply the water to two districts in a town. There are two pumps, that can fill the tanks through a reconfigurable hydraulic system with several valves. The automatic controller determines the valves and pumps that are active at each instant of time in order to minimize the operation cost, taking into account the electric tariff periods. Some aspects on the development of the lab plant are first discussed, including hydraulic aspects and real time control implementation issues. Then, a mathematical model is proposed to be able to formulate, in matrix form, the cost index and the constraints, such that, standard solvers as Mosek or CBC can be used. The full optimization proposal is tested on several experiments, and compared to some simulations, to demonstrate the validity of the plant and the optimization approach.

Keywords: pumping optimization, electric tariff, pumping scheduling, lab pumping plant.

1. INTRODUCTION

The main part of the energetic cost in the operation of water supply systems is due to the power consumed by the pumping stations. The water is served to consumers from tanks that are recharged from wells. The energy cost depends on the periods of time when the pumps are on, because the electricity prices vary along the day, according to known tariffing periods.

A review of different approaches to the optimization of water pumping systems is presented in Ormsbee (1994). The approaches cover different configurations of the system and different mathematical models. In the case of filling the main supply tanks, the mass-balance model is the most common. The cost function includes the energy consumed in most of the works, but the electricity tariffing periods are not considered. Besides, the decision variables are defined as the ratio of operation time of each pump in some fixed intervals.

A more recent work, Bunn (2009), also reviews different strategies, with the focus on using real-time dynamic optimization and data mining. This work describes a commercial optimization software for water distribution systems. This software can solve the proposed optimization problem and other that are even more complex, but no details about the algorithms are given.

In recent works, as Fang (2010), detailed models of the hydraulic systems and complex optimization algorithms are used, as genetic algorithms, simulated annealing or particle swarm. The computer cost of those strategies is very high, especially for large systems.

A linear programming approach is used in Pasha (2009), but is only applicable for the optimization of a single tank system.

The use of MINLP is proposed in Dai (2015) for the pump scheduling, taking into account a constraint in the number of pump commutations, but the closed loop is not considered.

Ormsbee (2009) presents three different explicit formulations of the optimal pump scheduling problem. It considers the electric tariff periods, but the decision variables are the start and stop times of the pumps. Non linear algorithms, genetic algorithms, or semi heuristic ad hoc algorithms are needed to solve the resulting optimization problem. Moreover, when the system has some valves that can reconfigure the network, the proposed formulations cannot be applied. In Sanchis (2020) the optimization problem is formulated such that standard solvers can be used. The decision variables are also explicit, but are defined by which of the possible combinations of active pumps and valves must be applied at each instant. The proposed mathematical formulation allows to solve the optimization problem by means of standard parsers (as Yalmip) and solvers (as Mosek or CBC). However, the proposed approach is only tested through simulations. In this paper, the approach proposed in Sanchis (2020) is tested and verified in real time in an experimental plant that emulates a real system scaled in space and time. In section 2 the general problem of optimal pumping operation is introduced. Section 3 describes the experimental plant. In section 4 the mathematical model of the problem is developed. In section 5 the optimization problem, derived from the mathematical problem, is formulated. Section 6 describes the output flow prediction strategy. Section 7 shows the application to the lab plant and the comparison with simulations, and section 8 summarizes the main conclusions.

2. GENERAL PROBLEM

In this paper, we develop an experimental setup to test strategies for the optimal operation of a water pumping system. The system has a predefined structure, with several wells, pumps, tanks and valves. The main objective is to minimize the overall operational cost, that depends on the individual energetic pumping cost of each well (kWh per cubic meter) and on the electric tariff periods prices (€/kWh). The controller must decide the valves and pumps that are operated at every instant throughout the day to minimize the overall cost, while at the same time, some constraints are fulfilled. The main constraint is, of course, to serve the demanded water flow from each tank. Despite this flow is time varying and uncertain, it can be predicted due to its approximate daily pattern. Another important constraint is the maximum and minimum level of the tanks. Some other constraints that may be taken into account include limiting the number of daily starts and stops, and forcing the tank levels to be as high as possible to maintain the service to users in case of failure.

3. EXPERIMENTAL PLANT DESCRIPTION

Figure 1 shows the developed experimental plant to test the optimization algorithms in real time.

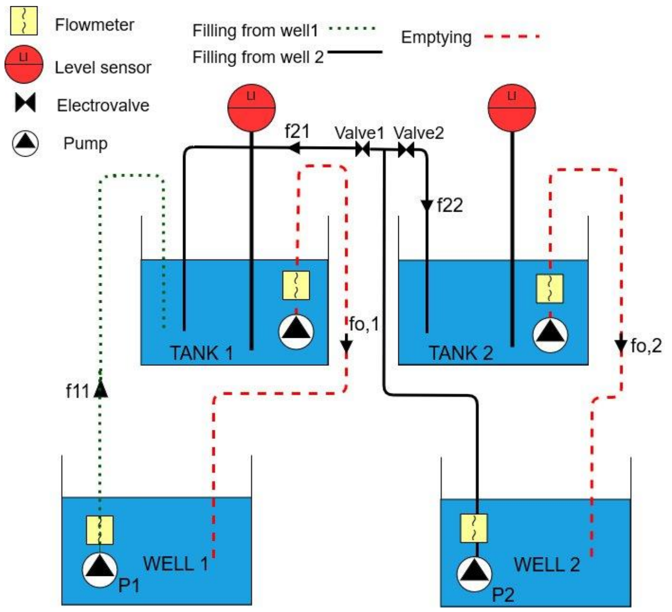

Fig. 1. Experimental plant schematics.

The plant consists of 2 big tanks that act as the supply wells, and 2 smaller tanks that are the storage tanks that serve water to users. Two pumps (with a flowmeter in series) extract water from the storage tanks to emulate the water consumed by users. On the other hand, two pumps move the water from the wells to the storage tanks. Two valves allow to reconfigure the hydraulic system, such that the pump 2 can pump water to either one of the storage tanks. The control actions are the state of the well pumps and the state of the valves. Two flowmeters are located in series with the well pumps, and two level sensors measure the level of the storage tanks.

All the electric elements are connected to a PLC, that communicates via Modbus TCP with a computer running Matlab. The optimization algorithm is run periodically in Matlab, where standard solvers are used (with Yalmip parser).

The emulated flow supplied by the storage tanks to consumers is computed by the PLC following a Fourier series with a random component, and is unknown by the optimization algorithm. The Fourier series defines the set point of a PI flow control loop that controls the outlet flow of each tank.

In order to emulate a large scale system with 500 m^3 tanks, and 200 m^3/h maximum flows, using a small 5 l tank, that is 100000 times smaller, the time is scaled by a factor of 46: this means that 1.3 seconds in the lab plant corresponds to a 60 seconds period in a large scale system. This means that 32 minutes in the lab plant represent one day in a large scale system. With this in mind, the maximum flow in the lab plant should be around 2 l/min. The pumps and flowmeters have been chosen according to these requirements. The pumps are 24V DC submergible water pumps for caravans, with a maximum flow of 10 l/min, and the flowmeters are ultrasonic with a range of 0.1 to 8 l/min. The main drawback of this flowmeter is the sampling period: it delivers a new measurement every 250 ms, that is a long time compared to the flow time constants. This sampling period has been taken into account in the design of the PI controllers that are used to control the flows of each pump. In the case of the filling pumps that emulate the wells, the flow is also controlled in closed loop through a PI, with a constant set point that determines a constant filling flow. Several different experiments can be devised with the same plant by configuring the following parameters:

- Filling flows from well pumps (f_{ij} in (1) and (2)).
- Emulated outlet flows for consumers.
- Electric power of each well pump (P_{ij} in (3)).
- Electric tariff of each well pump.

4. MATHEMATICAL MODELLING OF THE PROBLEM

The system is assumed to have N_t tanks, N_p pumps (one in each well), and N_v valves. The hydraulic system that connects the pumps to the tanks can be reconfigured with the valves. There is a maximum number of possible combinations of 2^{Np+Nv}, but not all the combinations are assumed to be feasible. Let us define the number of valid pumps and valves combinations as N_c. We define a binary matrix, M_c, of size $N_c \times (N_p + N_v)$, where each row corresponds to one of the valid combinations. The elements of each row take the value 1 or 0 depending on the state of the valves and the pumps in that combination. For the proposed experimental plant, the values are N_p = 2 pumps (wells), N_v = 2 valves and N_t = 2 tanks. The figure 1 shows a schematic of the system. Pump number 1 can only fill tank 1, no matter the state of the valves. Pump 2 can fill tank 1 if the valve 1 is open and the valve 2 is closed, or tank 2 if the valve 2 is open and valve 1 closed. We assume that valves 1 and 2 cannot be opened at the same time, but pumps 1 and 2 can work simultaneously. Considering the limitations described above, the table 1 shows the matrix that defines de N_c = 6 valid combinations of pumps and valves. The X value means that a closed valve (0) or open valve (1) results in the same flows.

Table 1. Valid combinations

Comb	V_1	V_2	P_1	P_2
0	X	X	0	0
1	X	X	1	0
2	1	0	0	1
3	0	1	0	1
4	0	1	1	1
5	1	0	1	1

For every combination, each pump has an outlet flow, and each tank has an inlet flow. This can be expressed through a pump flow matrix, F_P, with as many columns as combinations, and one row per pump, and a tank flow matrix, F_T, with as many columns as combinations, and one row per tank. The size of matrices F_P and F_T are ($N_p \times N_c$) and ($N_t \times N_c$). In the experimental plant, the resulting flow matrices are (in *l/min*):

$$F_P = \begin{bmatrix} 0 & f_{11} & 0 & 0 & f_{11} & f_{11} \\ 0 & 0 & f_{21} & f_{22} & f_{22} & f_{21} \end{bmatrix} \quad (1)$$

$$F_T = \begin{bmatrix} 0 & f_{11} & f_{21} & 0 & f_{11} & f_{11}+f_{21} \\ 0 & 0 & 0 & f_{22} & f_{22} & 0 \end{bmatrix} \quad (2)$$

Applying the same idea, we can form a matrix P with the electric power consumed by each pump in each combination. This matrix has as many columns as combinations, and one row per pump, thus the size of P is ($N_p \times N_c$). In the plant, the power matrix (in kW) is:

$$P = \begin{bmatrix} 0 & P_{11} & 0 & 0 & P_{11} & P_{11} \\ 0 & 0 & P_{21} & P_{22} & P_{22} & P_{21} \end{bmatrix} \quad (3)$$

The flow and power from pump 2 may be different when pumping to tank 1 or tank 2, meaning that the tanks are located in a different height. The different pressure gradients (or heights) are taken into account in the optimization only through the previous flow and power matrices. Flows from one tank to another located at different height are not considered. The controller must define which one of the N_c combinations is applied at each instant of time. The minimization of the overall operation cost is the natural objective. A binary vector, δ, is defined to formulate the objective function and the constraints for the optimization problem. This vector defines the applied combination as a function of time:

$$\delta(t) \epsilon \{\delta_1, \dots, \delta_{N_c}\} \quad (4)$$

Where

$$\delta_i = [0 \dots 0\ 1\ 0 \dots 0]^T \quad (5)$$

One of the elements of $\delta(t)$ is 1 and the rest are 0 (i.e. the sum of the elements is 1). The vector with the tanks inlet flows can be expressed at a given time as the product

$$f_T(t) = F_T \cdot \delta(t)$$

and the vectors of pump flows and electric power are simply

$$f_P(t) = F_P \cdot \delta(t)$$
$$p(t) = P \cdot \delta(t)$$

The overall cost depends on the electric tariff periods. We can define the tariff as a price in €/kWh as a function of time, $T_i(t)$. Different tariffs are assumed for each pump, hence, a row vector is defined as

$$T(t) = [T_1\ T_2] \quad (6)$$

The total cost in a time horizon t_H can be written (in euros) as:

$$J = \frac{1}{60} \int_0^{t_H} T(t) \cdot P \cdot \delta(t) dt \quad (7)$$

The physical equation of the tanks can be written as:

$$\dot{V}_j = f_{T,j}(t) - f_{O,j}(t) \,, \quad (8)$$

Where V_j is the volume, and $f_{T,j}(t)$ and $f_{O,j}(t)$ are the inlet and outlet flow of tank j. We can write the tank equations in matrix form

$$\dot{V} = \begin{bmatrix} \dot{V}_1 \\ \dots \\ \dot{V}_{N_t} \end{bmatrix} = \begin{bmatrix} f_{T,1}(t) \\ \dots \\ f_{T,2}(t) \end{bmatrix} - \begin{bmatrix} f_{O,1}(t) \\ \dots \\ f_{O,2}(t) \end{bmatrix} = f_T(t) - f_O(t) \quad (9)$$

The outflow rate of each tank, $f_O(t)$, is not known in advance, therefore, we must use a prediction $\hat{f}_O(t)$ to estimate the future volume. On the other hand, the inlet flow is a function of $\delta(t)$, hence the evolution of tanks volume (in *l/s*) is defined by equation

$$\dot{V} = \frac{1}{60} \left(F_T \delta(t) - \hat{f}_O(t) \right) \quad (10)$$

The continuous time equations must be discretized to be implemented in a computer. If a constant discretizing period h is used, the vector functions $T(t)$ and $\delta(t)$ must be changed by discrete signals vectors $T[k] = T(t = kh)$ and $\delta[k] = \delta(t = kh)$. We assume that $\delta(t)$ maintains a constant value during interval h, i.e. $\delta(t) = \delta[k]$ for $k\,h <= t < (k+1)h$. Considering he physical units of the variables, the cost index in a time horizon t_H (in euros) can be written as

$$J = \frac{h}{60} \sum_{k=0}^{t_H/h} T[k] \cdot P \cdot \delta[k] \quad (11)$$

We need to discretize also the continuous time equation of the tanks. The resulting equation is

$$V[k+1] = V[k] + \frac{h}{60} \left(F_T \delta[k] - \hat{f}_O[k] \right) \quad (12)$$

with $V[k] = V(t = kh)$ and $\hat{f}_O[k] = \frac{1}{h} \int_{kh}^{(k+1)h} \hat{f}_O(t) dt$.

The main constraints, that are the maximum and minimum values of the tank volumes, can be expressed in matrix form as

$$V_{min} \leq V[k] \leq V_{max} \quad (14)$$

5. OPTIMIZATION PROBLEM

As described in Sanchis (2020), the idea is to run an optimization periodically, with a short period, with a time horizon of at least one equivalent day, but applying only the computed control actions until the next optimization is run, i.e.

a classical predictive control approach. We can define the basic optimization problem as the minimization of the energy cost, with the only constraints of maintaining the volumes of the tanks between their limits. However, as detailed in Sanchis (2020), other conditions must be taken into account for the algorithm to be useful. Some of them will be constraints, while other can be included in the cost function. These are

- We must impose a constraint to guarantee that the tanks finish the day with a volume equal or greater than their initial value (otherwise, the tanks will always finish completely empty).
- We must also impose that the volumes are maximum at a given instant, more precisely at the end of the cheapest tariff period (at 8 a.m.). We can add this objective as a constraint, but if the time when the optimization is run is close to that instant, the optimization could be unfeasible. In that case, instead of a constraint, we can add a term to the cost function, to approach the maximum tank levels as much as possible.
- We add the number of commutations of pumps and valves to the cost index, with a weighting factor. If this is not included, the result may be a huge number of pump starts and stops that are not applicable in practice.
- Another problem that can make the optimization unfeasible is the maximum or minimum volumes violation in the instant when the optimization is run. This can happen due to the uncertainty in the outlet flow, that can result in a final volume higher or lower than expected. The unfeasibility is due to an initial constraint violation. We must do two things to solve this problem. First, the volumes limits must be chosen with a safety margin with respect physical tank limits. And second, we must widen the volume limits constraints at the first instants of the time horizon.
- Two different discretizing periods must be used to reduce the computational complexity: a small one (h) for the first instants that define the control actions that will be applied, and a higher one (Lh) for the rest of the time horizon. Furthermore, the decision variables are initially binary, what results in a high computing cost optimization. To reduce the complexity, the decision variables of the short periods will remain binary, but the ones related to the larger periods (Lh) will be real variables.

Taking all the previous things into account, and defining the following vectors and matrices

$$T[k] = \begin{cases} T(t = kh) & if \quad k \le k_m \\ T(t = k_m h + (k - k_m)Lh) & if \quad k > k_m \end{cases} \tag{16}$$

$$\hat{f}_O[k] = \begin{cases} \frac{1}{h}\int_{kh}^{(k+1)h} \hat{f}_O(t)\,dt & if \quad k \le k_m \\ \frac{1}{Lh}\int_{k_m h+(k-k_m)Lh}^{k_m h+(k+1-k_m)Lh} \hat{f}_O(t)\,dt & if \quad k > k_m \end{cases} \tag{17}$$

$$\Delta = \begin{bmatrix} \delta[1] \\ \vdots \\ \delta[k_M] \end{bmatrix}_{k_M N_c \times 1} \tag{18}$$

$$T = \frac{h}{60}[T[1] \cdots T[k_m] \; T[k_m+1]L \cdots T[k_M]L] \tag{19}$$

$$P = \begin{bmatrix} P & 0 & \cdots & 0 \\ 0 & P & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & P \end{bmatrix}_{k_M N_p \times k_M N_c} \tag{20}$$

$$F_k = \Big[\underbrace{F_T \cdots F_T}_{k_m} \quad \underbrace{LF_T \cdots LF_T}_{k-k_m} \quad 0 \cdots 0\Big]_{N_t \times k_M N_c} \tag{21}$$

$$I_k = \Big[\underbrace{0 \cdots 0}_{(k-1)N_c} \quad \underbrace{1 \cdots 1}_{N_c} \quad 0 \cdots 0\Big]_{1 \times k_M N_c} \tag{22}$$

$$\hat{F}_O[k] = \sum_{i=1}^{k_m} \hat{f}_O[i] + L\sum_{i=k_m+1}^{k} \hat{f}_O[i] \tag{23}$$

$$V_{sup}[k] = \begin{bmatrix} V_{sup,1}[k] \\ V_{sup,2}[k] \end{bmatrix} \tag{24}$$

$$V_{sup,j}[k] = \begin{cases} V_{max,j} & if \quad V_j(0) \le V_{max,j}, \forall k \\ V_{max,j} & if \quad V_j(0) > V_{max,j}, \forall k > k_m \\ \frac{V_j(0)(k_m-k)+V_{max,j}k}{k_m} & if \quad V_j(0) > V_{max,j}, \forall k \le k_m \end{cases} \tag{25}$$

$$V_{inf}[k] = \begin{bmatrix} V_{inf,1}[k] \\ V_{inf,2}[k] \end{bmatrix} \tag{26}$$

$$V_{inf,j}[k] = \begin{cases} V_{min,j} & if \quad V_j(0) \ge V_{min,j}, \forall k \\ V_{min,j} & if \quad V_j(0) < V_{min,j}, \forall k > k_m \\ \frac{V_{j(0)(k_m-k)+V_{min,j}k}}{k_m} & if \quad V_j(0) < V_{min,j}, \forall k \le k_m \end{cases} \tag{27}$$

With this, the cost indexes for the optimization are defined as

$$J_0 = TP\Delta \tag{28}$$

$$J_C = \alpha_c sum\left(abs\left(Y_{N_c}[\delta_{ant}; \Delta(1:(k_m-1)N_c)]\right)\right) \tag{29}$$

$$J_v = \alpha_V\left(\hat{F}_O[k_V] - F_{k_V}\Delta + 60\frac{V_{obj}-V(0)}{h}\right) \tag{30}$$

While the common constraints are

$$F_k\Delta \ge 60\frac{V_{inf}[k]-V(0)}{h} + \hat{F}_O[k], \; k = 1, \dots, k_M \tag{31}$$

$$F_k\Delta \le 60\frac{V_{sup}[k]-V(0)}{h} + \hat{F}_O[k], \; k = 1, \dots, k_M \tag{32}$$

$$F_{k_M}\Delta \ge \hat{F}_O[k_M] \tag{33}$$

$$I_k\Delta = 1, \; k = 1, \dots, k_M \tag{34}$$

$$\Delta_i \epsilon \{0,1\} \epsilon \, \mathbb{N}, \; i = 1, \dots, k_m N_c \tag{35}$$

$$\Delta_i \epsilon \{0,1\} \epsilon \, \mathbb{R}, \; i = k_m N_c + 1, \dots, k_M N_c \tag{36}$$

With an additional constraint to impose max. volumes at 8 p.m.

$$C_V := \quad F_{k_V}\Delta \ge \hat{F}_O[k_V] + 60\frac{V_{obj}-V(0)}{h} \tag{37}$$

The possible optimization problems are both Mixed Integer Programming

1) Minimize J_0+J_C subject to common constraints plus C_V.
2) Minimize J_0+J_C+J_V subject to common constraints.

We propose at each sampling time to first use problem 1 to try to assure maximum volumes of the tanks at the required time, but change to problem 2 in case of unfeasibility.

6. OUTPUT FLOW PREDICTION

For the previous optimization problem a prediction of the future output flow is needed. As described in Sanchis (2020), we propose, at each instant, to set the prediction for the instant located 24 hours in the future as a weighted average of the current measurement and the one taken 6 days before. The weights depend on the type of day in the week. The current prediction would be simply updated as

$$\hat{f}_O[k] = f_O[k] \tag{38}$$

where $f_O[k]$ is the output flow measured at the instant $k = \frac{t}{h}$ (with h the sampling period). Defining the weighting factors β_d and β_w, such that $\beta_d + \beta_w = 1$, the prediction for the 24 hours future instant is

$$\hat{f}_O\left[k + 1440 \cdot \frac{60}{h}\right] = \beta_d \hat{f}_O[k] + \beta_w \hat{f}_O\left[k - 6 \cdot 1440 \cdot \frac{60}{h}\right] \tag{39}$$

The weighting factors depend on the type of day in the week. For example, from Monday to Thursday, β_d should be closed to 1, because the next business day should be similar to the current one.

On the other hand, we can improve the prediction of the immediate future instants with the last measurement taken. The next predictions are updated with an exponential weighting (defined by time constant t_f) from the current prediction error

$$\hat{f}_O[k+i|k] = \hat{f}_O[k+i|k-1] + e^{\frac{-ih}{t_f}}\left(f_O[k] - \hat{f}_O[k|k-1]\right), \quad i = 0, \dots, 4t_f \tag{40}$$

where $\hat{f}_O[k|k-1]$ is the prediction at instant k before the measurement $f_O[k]$ is taken.

7. EXPERIMENTAL SETUP

The output flow to consumers is emulated with a Fourier series (41) that is computed by the PLC.

$$f_O = \left(a_0 + a_1\cos(wt) + a_2\cos(2wt) + a_3\cos(3wt) + b_1 sin(wt) + b_2 sin(2wt) + b_3 sin(3wt)\right) \cdot \varepsilon \cdot (1 + rand) \tag{41}$$

Where $w = 2\pi/1440$, $a_0 = 97.64, a_1 = -36.18, a_2 = -4.421, a_3 = 14.34, b_1 = 1.699, b_2 = -17.57, b_3 = 4.85$. The constant ε is selected such that the flow varies from a minimum of 0.5 to a maximum of around 2 *l/min*, as shown in figure 2. The *rand* term has average 0 and amplitude 0.1.

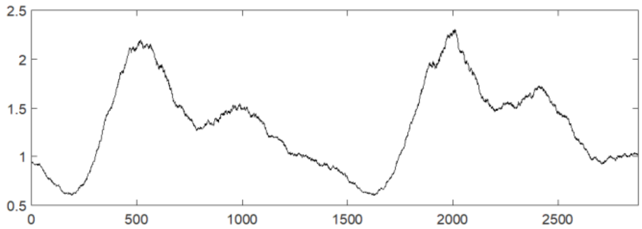

Fig. 2. Output flow to consumers.

For the experiments, the lab plant described in section 2 has been used. The flows supplied by the filling pumps are fixed as $f_{11} = 2$, $f_{21} = 1.7$, $f_{22} = 1.9$. The electric tariffs of the pumps are detailed in table 2.

Table 2. Electric tariffs

Periods	Pump 1	Pump 2
0 < t < 480	0.063	0.066
480 < t < 540	0.079	0.088
540 < t < 600	0.1	0.088
600 < t < 900	0.1	0.099
900 < t < 960	0.079	0.099
960 < t < 1440	0.079	0.088

Finally, for the electric power of the pumps, three different cases are considered, as detailed in table 3.

Table 3. Electric power of pumps

Case	P11	P21	P22
1	45	60	30
2	60	45	30
3	45	45	30

On the other hand, the parameters used for the optimization are: short period *h*=1.3 *s*, long period *L*=30, prediction horizon t_H =1872 *s* (equivalent to 1 day in large scale), number of short periods k_m=30, total number of periods k_M=77, weighting factors $\alpha_c = 0.05$, $\alpha_v = 0.001$.

8. RESULTS

Three different experiments have been carried out with the setup described in the previous section, with the electric power of pumps according to cases 1 to 3 in table 3. The duration of the experiments is 3744 seconds, that is equivalent to a two days in a large scale system. The figures 3, 4 and 5 show the behaviour of the tank volumes, the flow of the pumps, the outlet flow and the state of valves for the three cases. Depending on the power of the pumps, the result of the optimization tends to use more frequently the lowest power one. This can be seen especially in the number of commutations of valves in the case 2, where the pump 2 is used whenever is possible to fill up tank 1.

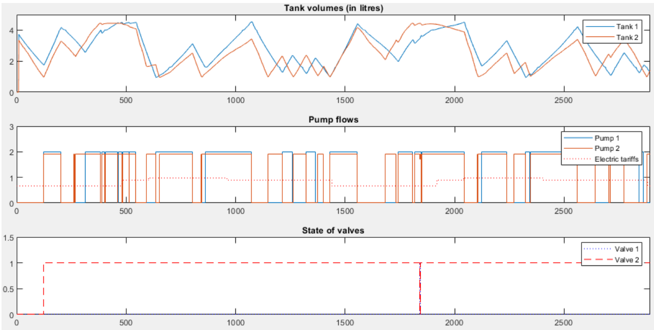

Fig. 3. Results of experiment. Case 1.

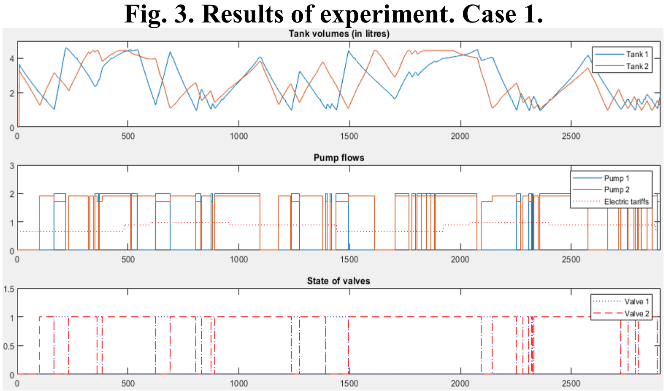

Fig. 4. Results of experiment. Case 2.

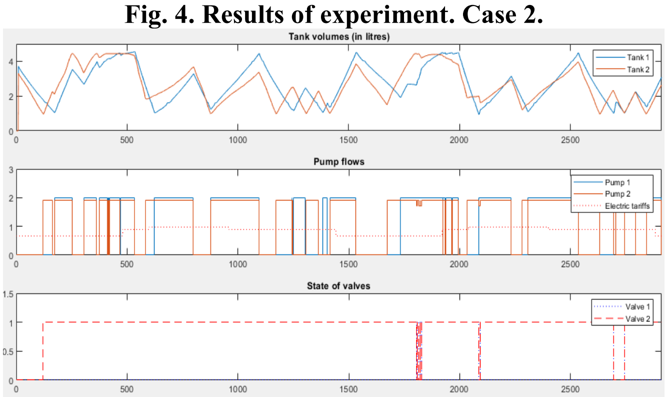

Fig. 5. Results of experiment. Case 3.

The Figure 6 shows the results of the simulation of case 2. Compared to Figure 4, the behaviour is very similar, demonstrating that the experimental plant behaves as expected. The same can be concluded from table 4.

On the other hand, two experiments have been carried out to test the effect of factor α_c. The total cost with $\alpha_c = 0.2$ is only a 0.2% higher than with $\alpha_c = 0.05$, while the commutations are reduced from 36 to 26 per day.

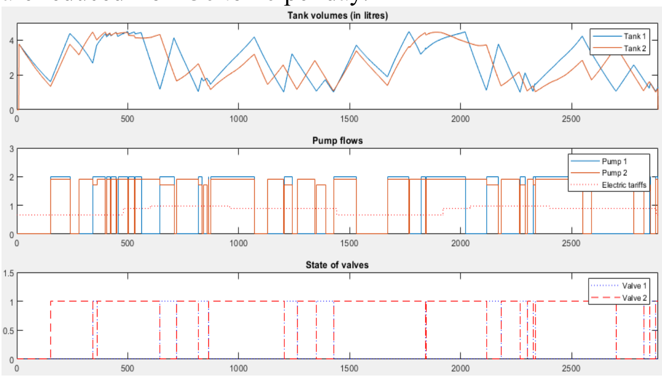

Fig. 6. Results of simulation. Case 2.

Table 4. Experiments vs simulations comparison

Case	%ON P1	%ON P2	J (€)
1 exp.	55.7	66	176.1
1 sim.	55.9	67.2	178.9
2 exp.	44.2	79.6	205.3
2 sim.	45	77.2	204.7
3 exp.	55.8	67.5	179.4
3 sim.	56.1	67	178.5

9. CONCLUSIONS

A lab pumping plant has been developed to emulate a large scale water supply pumping system. It has been scaled both physically and in time. The plant is connected to Matlab via Modbus TCP, and the purpose is to test optimal pumping strategies. The plant has been verified by testing an optimal control strategy, that minimizes the pumping energy cost, leading to results that are comparable to simulations.

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