Environmental Sciences Proceedings

MDPI

Proceedings

Optimal Regulation of Variable Speed Pumps in Sewer Systems †

Luigi Cimorelli and Oreste Fecarotta *

Department of Civil, Architectural and Environmental Engineering, University of Naples "Federico II", via Claudio 21, 80125 Naples, Italy; luigi.cimorelli@unina.it

* Correspondence: oreste.fecarotta@unina.it

† Presented at the 4th EWaS International Conference: Valuing the Water, Carbon, Ecological Footprints of Human Activities, Online, 24–27 June 2020.

Published: 5 September 2020

Abstract: In this work, the optimal regulation of variable speed pump (VSP) was solved by means of two optimization algorithms: a mixed-integer optimizer based on the BONMIN (Basic Open-Source Nonlinear Mixed Integer Programming) package, and an original hybrid genetic algorithm (GA) called GA–Powell's direction set method (PDSM), which employs a derivative free inner optimizer, that is, the Powell's direction set method (PDSM). The obtained results show how the use of a strategy based on the optimal regulation of VSP allows to obtain huge energy cost savings. The analysis of the results shows that the regulation of the plant does not apparently follow a general rule.

Keywords: energy saving in water systems; optimal sewage pump scheduling; optimal management of hydraulic systems

1. Introduction

The modern trend in the management of hydraulic systems is largely focused on reducing energy consumption. Great economic savings and environmental benefits can be achieved by changing the control techniques of pumping systems. According to recent reports [1,2], the energy used for pumping constitutes 4% of the entire amount of national electricity consumed in the U.S. [3,4] and 7% of the electrical energy worldwide [5,6]. The reduction of pumping energy use within water networks is one of the most promising fields in the context of energy recovery and efficiency [7–9].

Pumping systems within water supply and drainage networks are equipped with multiple pumps, starting with a minimum number of two, one of them kept for replacement purposes. Pumping systems have been commonly designed to work at a fixed speed and constant hydraulic conditions (head and discharge) which are close to the best efficiency point (BEP) of the pump, so to have the best possible performances. Given the presence of multiple pumps in the system, and possible variations in the operating conditions (variable discharges and variable tank level to make an example), scheduling is needed to optimize system performances. A modern trend in the management of pumping systems is based on the use of variable speed drives (VSDs) to change the impeller rotational speed of one or more pumps.

Several examples of scheduling optimization exist in the literature, with different optimization algorithms, different variables and different objective functions; the evolution of research in the field of energy efficiency optimization complies with the development of more and more sophisticated optimization tools and algorithms. A first attempt of reducing operational costs in water networks concerns the use of linear programming [10], integer linear programming [11], non-linear programming [12,13] and dynamic programming [14], with limited possibilities of generalizing the results to any water network different from those tested. More recently, heuristic algorithms, such as genetic algorithms, ant-colony or harmony search [15–18], were applied in the coupling with hydraulic simulators, that were often overcome by using artificial neural networks to reproduce the results of the hydraulic simulations [19].

Optimal control, based on the use of VSD on existing pumps, allows to achieve significant reductions in energy consumption. In a wastewater pumping system, with a classical wet well, the problem of setting the optimal daily ON/OFF distribution, and the pump speed (rpm) as well, is more complex than pumping clean water, as the storage volume is usually lower. In the present work, with reference to a classic wet well equipped with a submersible wastewater pump, two optimization algorithms have been used in order to evaluate the benefit that can be obtained through optimal programming in terms of ON/OFF operation and pump speed regulation. The first model, of the mixed-integer type, is based on the use of the BONMIN package [20]; the second, called genetic algorithm (GA)–Powell's direction set method (PDSM), is an original model proposed by the authors, based on the hybridization of a genetic algorithm (GA) with an optimization algorithm of the derivative free type, that is, the Powell's Direction set method (PDSM) [21]. The results obtained show how the use of a strategy based on the optimal regulation of the ON/OFF operation type plus a regulation of the number of revolutions per minute, allows to obtain great savings in terms of energy cost.

2. The Problem Formulation

Following the work of [22], for a classic sewage pumping station represented shown in Figure 1, the energy minimization problem can be formulated as follows:

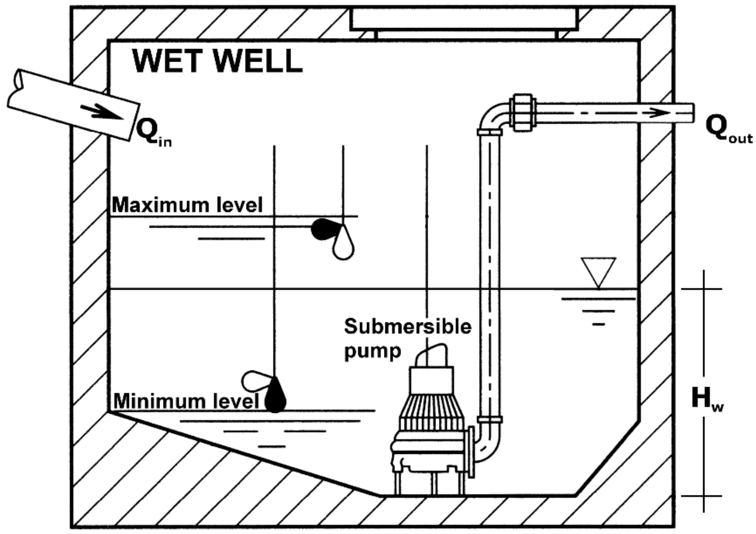

Figure 1. Classic wet well with submersible pump.

$$h_{well}(t) - h_{well}(t - \Delta t) = 0.5\Delta t\left[Q_{in}(t) + Q_{in}(t - \Delta t) - Q_{out}(t) - Q_{out}(t - \Delta t)\right] \quad (1)$$

$$Q_{in}(t) = Q_{BEP}\frac{c_Q(t)}{c_Q^{design}} \quad (2)$$

$$H_m(t) = \left[H_v - h_{well}(t)\right] + \beta Q_{out}(t)^2 \quad (3)$$

Equations (1)–(3) represent, respectively, the discretized continuity equation, the input hydrograph and the manometric head. The meaning of the symbols is the following: $h_{well}(t)$ is the flow depth within the well at time *t*; $Q_{in}(t)$ and $Q_{out}(t)$ are the inlet and outlet flow rate at time *t*; Q_{BEP} it is the flow rate at the point of maximum efficiency of the pump; $c_Q(t)$ is the flow rate coefficient defined as the ratio between the flow rate at time *t* and the average flow rate at time *t* demand coefficient, while c_Q^{design} is the design demand coefficient. $H_m(t)$ is the manometric head at time *t*; H_v is the flow depth within the downstream well; β is the resistivity of the pipe downstream from the pump, whose value is calculated as

$$\beta = \frac{H_v - h_{\max}}{H_{BEP}} \tag{4}$$

The values of $c_Q(t)$ were generated with an autoregressive moving average, ARMA(2,2), model [23] calibrated on a 30 day historical time series of inflow discharges at a wet well equipped with pump in Netherlands with 5 min of sampling frequency, and its parameter are reported in Table 1.

Table 1. Parameters resulting from the ARMA(2,2) regression.

Parameter	**Value**	***p*-Value**
Constant	-8.87×10^{-5}	9.45×10^{-1}
AR(1)	1.40×10^{1}	0.00
AR(2)	-4.07×10^{-1}	3.27×10^{-61}
MA(1)	-6.19×10^{-1}	1.52×10^{-126}
MA(2)	-1.52×10^{-1}	1.35×10^{-37}
Variance	2.17×10^{-1}	0.00

The value of $c_Q^{design} = 2.46$ was used herein, and it corresponds to a 10 years return period in the cumulative distribution of $c_Q(t)$.

With the calibrated ARMA model, it was possible to generate 1000 equally likely synthetic hydrographs, each one with the length of a day and with a time step of 1 min. The series of generated inflows compares well in terms of first and second order statistics with the observed data.

3. The Optimization Models

In this section, the two optimization models are briefly described. The optimizations are performed for each synthetic inflow hydrograph generated by the ARMA(2,2) model described in the previous section, with a time step of 1 minute.

3.1. The BONMIN Package

BONMIN (Basic Open-Source Nonlinear Mixed Integer Programming) is an open-source code for solving general MINLP (Mixed Integer Nonlinear Programming) problems. It is distributed under the EPL (Eclipse Public License), which is a license approved by the OSI (Open Source Initiative).

There are several algorithmic choices that can be selected with BONMIN. In this study, the so-called "B-BB" was selected, which is an NLP (nonlinear programming)-based branch-and-bound algorithm, which uses Cbc to solve MILP (Mixed Integer Linear Programming) problems and Ipopt to solve the NLP (nonlinear programming) problems. The Bonmin algorithm provides exact solutions if both the objective function and the constraints are convex. In the case where f or g or both are non-convex, they are only heuristics.

Additional documentation can be found in [20].

3.2. The Proposed GA–PDSM

The optimization model proposed in this work is based on a classic GA that employs a derivative free optimization algorithm known as the Powell's set direction method (PDSM) as inner optimizer which is used inside the fitness function (FF) computation of the GA. The employed GA is a classical binary GA, and the genetic operators employed are the exponential ranking selection, multipoint crossover, elitism and a simple bitwise mutation [24].

Each candidate solution is represented by a binary chromosome, and the only decision variables left to the GA are the sequence of ON/OFFs with a time step of 1 min and a scheduling horizon of 1 day. Therefore, each decision variable is a binary variable in the range of 1 bit, with 0 and 1 representing the pump turned OFF or ON, respectively.

The optimal speed regulation is performed by the PDSM [21] when the fitness of each candidate solution is evaluated. The decision variable left to the PDSM are the rotational speeds of the pump in the interval (1500–3000) rpm, and their number varies for each candidate solution, because it must be equal to the number of intervals when the pump is ON. The PSDM works on the principle of executing a sequence of line minimization along a set of directions that are linearly independent. Herein, the PDSM was slightly modified to account for the bound constraint of the rotational speed, by equating the rpm to the bound limit when upper or lower bounds are violated.

The FF adopted in this work is the following:

$$FF = F_{PDSM}^{E} + F_{sw}^{p} \tag{5}$$

where F_{PDSM}^{E} is the optimal value of the daily energy consumption returned by the PDSM, and F_{sw}^{p} is the penalty function related to the violation of the maximum number of switching on of the pump in each hour, expressed as

$$F_{sw}^{p} = p_{sw} \max\left\{ \sum_{k=1}^{24} \sum_{j=(k-1)\cdot 60+2}^{k\cdot 60} \left[P_{st}(j) - P_{st}(j-1) \right] - N_{sw}^{\max}, 0 \right\} \tag{6}$$

where $P_{st}(j) \in (0,1)$ is the pump status at the j-th time interval of the day (1 for pump ON, 0 for pump OFF); $N_{sw}^{\max}$ is the maximum number of pump switches in a hour and $p_{sw} = 10^3$ is a penalty coefficient.

The objective function F_{PDSM}^{E} has the following expression:

$$F_{PDSM}^{E} = \sum_{j=1}^{1440} \frac{P(N_j)}{60} + pc \cdot \sum_{j=1}^{1440} \left\{ \max\left[h_{well}(j) - h_{well}^{\max}, 0 \right] + \max\left[h_{well}^{\min} - h_{well}(j), 0 \right] \right\} \tag{7}$$

where, $P(N_j)$ is the power of the pump at the rotational speed N_j at the *j*-th time interval (1 min of length); $h_{well}(j)$ is the flow depth in the wet well at the *j*-th time interval; $h_{well}^{\max}$ and $h_{well}^{\min}$ are the maximum and the minimum flow depth in the wet well, respectively.

4. The Employed Pump

In order to model the pump, characteristic curves at the various speed of the pump where derived by the interpolation of experimental data obtained at the Hydro-Energy Laboratory of CeSMA of the University of Naples Federico II as follows:

$$\frac{H_N}{N^2} = \alpha_H \left(\frac{Q}{N} \right)^2 + \beta_H \left(\frac{Q}{N} \right) + \gamma_H \tag{8}$$

$$\frac{P_{N_{\max}}}{N_{\max}^3} = \alpha_p \left(\frac{Q}{N}\right)^3 + \beta_p \left(\frac{Q}{N}\right)^2 + \gamma_p \left(\frac{Q}{N}\right) + \delta_p \tag{9}$$

$$e(N) = \alpha_e N^3 + \beta_e N^2 + \gamma_e N + \delta_e \tag{10}$$

$$P(N) = \frac{P_{N_{\max}}}{N_{\max}^3} \frac{N^3}{e(N)} \tag{11}$$

where N and N_{max} are the pump rotational speed and maximum rotational speed; Q is the pump discharge; H_N is the manometric head at the speed N; $P(N)$ is the power at the speed N and $P_{N_{\max}}$ is the corresponding power at N_{max}; α_H, β_H, γ_H, α_p, β_p, γ_p, δ_p, α_e, β_e, γ_e e δ_e are the interpolation coefficients.

5. Results

The optimization algorithms described in Section 2 were applied to the 1000 inflow hydrographs generated by the ARMA(2,2) model. The optimal values relative to the first five patterns and three values of the parameter β are reported in Table 2:

Table 2. Optimal values of the daily energy obtained with genetic algorithm (GA)–Powell's direction set method (PDSM), BONMIN (Basic Open-Source Nonlinear Mixed Integer Programming) and classic ON/OFF optimization.

	Inflow Pattern	E (kWh/day) GA-PDSM	E (kWh/day) BONMIN	E (kWh/day) CLASSIC ON/OFF
0.25	1	574.54	574.06	1342.1
0.25	2	538.21	536.51	1296.6
0.25	3	482.69	482.93	1204.7
0.25	4	592.57	590.71	1370.9
0.25	5	554.84	553.45	1331.1
0.5	1	874.88	874.07	1336.6
0.5	2	840.1	838.52	1294.4
0.5	3	772.69	774.42	1199.8
0.5	4	893.38	889.88	1368.7
0.5	5	861.36	859.39	1329.8
0.75	1	1170.15	1182.6	1330.7
0.75	2	1135.94	1154.5	1289.4
0.75	3	1058.80	1082.1	1195.5
0.75	4	1193.44	1214.2	1362.4
0.75	5	1167.36	1180.4	1323.8

The results are compared with the classic ON/OFFs optimization, showing how the optimal speed regulation allows to achieve significant reduction in daily energy consumption over the constant speed pump regulation. With $\beta = 0.25$, the highest savings is achieved (58% on average), with a peak of 60% for the third pattern. By increasing the value β to 0.5, the energy savings drop to an average value of 35%, with a peak of 36% for the third pattern. The BONMIN algorithm and the proposed GA-PDSM provided very close results in terms of energy consumption. Indeed, the maximum difference was much less than 1%. In particular, the BONMIN algorithm was revealed to be much slower, with a slight improvement in the objective function in most of the cases with $\beta = 0.25$ and $\beta = 0.5$, while with $\beta = 0.75$, the objective function values provided by the GA–PDSM were slightly better.

Through the inspection of the 3000 solutions obtained (1000 inflow patterns for β equal to 0.25, 0.5 and 0.75), it was not possible to derive an optimal control rule.

In Figure 2, the pump head is plotted (black dots) as a function of Q_{out} for all the patterns when β = 0.25. The characteristic curves at the various speed and Equation (3) are plotted as well, along with the required pumping head when the wet well is full (red line) or empty (blue line). In Figure 3 the water level within the wet well is plotted versus Q_{out} for the same patterns of Figure 2. From the inspection of Figure 3, it is clear that it is not possible to derive an optimal control rule for such a problem.

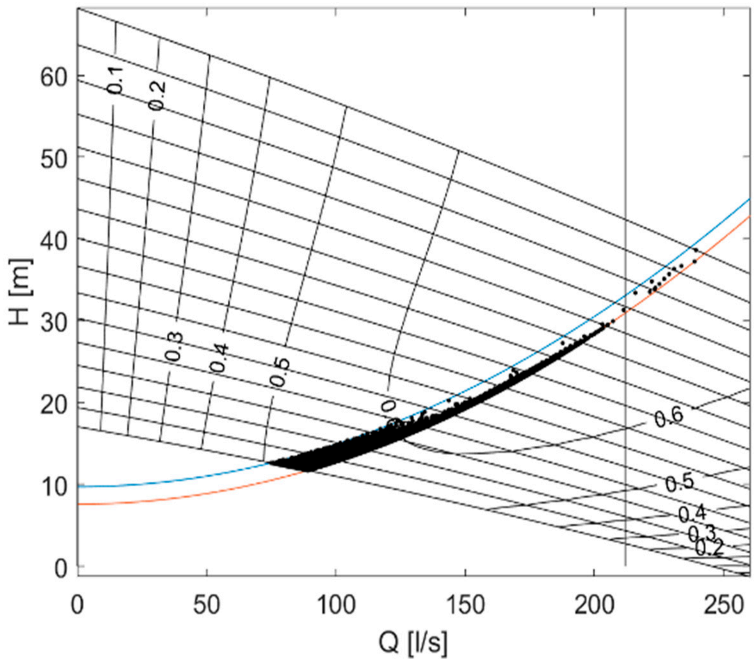

Figure 2. Pumping head plotted as a function of Qout for all the patterns when β = 0.25.

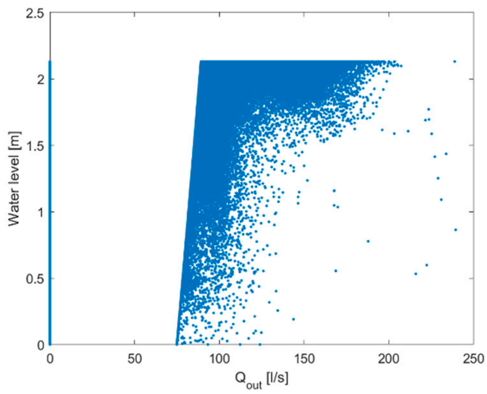

Figure 3. Water level in the wet well plotted as a function of Q_{out} for all the patterns when β = 0.25.

6. Conclusions

In this work, an original hybrid genetic algorithm, called GA–PDSM, is proposed for the optimal regulation of a pumping station within sewer systems in terms of pumps ON/OFFs and speed regulation as well. The presented method employs the Powell's direction set method as an internal optimizer of the genetic algorithm in order to find the optimal pump speed. The results obtained compared well with the well established mixed-integer optimizer BONMIN. Furthermore, it is shown that the optimal regulation of variable speed pumps allows to achieve a great energy savings when compared to the classical ON/OFFs regulation of constant speed pumps. However, it was not possible to derive an optimal control rule from the optimal solutions obtained. Therefore, the obtained solutions will be used as the basis for future work, involving the machine learning method to find a real-time optimal control method.

Author Contributions: All authors equally contributed to this research. All authors have read and agree to the published version of the manuscript.

Funding: This research was part funded by the ERDF Interreg Atlantic Area Programme 2014–2020, through the REDAWN project EAPA 198/2016.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Goldstein, R.; Smith, W. Water & Sustainability: U.S. Electricity Consumption for Water Supply & Treatment—The Next Half Century. *Water Supply* **2002**, *4*, 93.
2. Bunn, S.M.; Reynolds, L. The energy-efficiency benefits of pump-scheduling optimization for potable water supplies. *IBM J. Res. Dev.* **2009**, *53*, 5:1–5:13.
3. Castro-Gama, M.; Pan, Q.; Lanfranchi, E.A.; Jonoski, A.; Solomatine, D.P. Pump Scheduling for a Large Water Distribution Network Milan, Italy. *Procedia Eng.* **2017**, *186*, 436–443.
4. Zhang, Z.; He, X.; Kusiak, A. Data-driven minimization of pump operating and maintenance cost. *Eng. Appl. Artif. Intell*. **2015**, *40*, 37–46.
5. Plappally, A.K.; Lienhard, V.J.H. Energy requirements for water production, treatment, end use, reclamation, and disposal. *Renew. Sustain. Energy Rev.* **2012**, *16*, 4818–4848.
6. Zhang, Z.; Kusiak, A.; Zeng, Y.; Wei, X. Modeling and optimization of a wastewater pumping system with data-mining methods. *Appl. Energy* **2016**, *164*, 303–311.
7. Boulos, P.F.; Wu, Z.; Orr, C.H.; Moore, M.; Hsiung, P.; Thomas, D. Optimal Pump Operation of Water Distribution Systems Using Genetic Algorithms. In Proceedings of the Network & Distributed System Security Symposium, San Diego, CA, USA, 21–24 February 2021; pp. 23–25.
8. Ostojin, S.; Mounce, S.R.S.; Boxall, J.B.J. An artificial intelligence approach for optimizing pumping in sewer systems. *J. Hydroinform.* **2011**, *13*, 295–306.
9. Carravetta, A.; Antipodi, L.; Golia, U.; Fecarotta, O. Energy saving in a water supply network by coupling a pump and a Pump As Turbine (PAT) in a turbopump. *Water* **2017**, *9*, 62.
10. Jowitt, P.W.; Germanopoulos, G. Optimal Pump Scheduling in Water? Supply Networks*. J. Water Resour. Plan. Manag*. **1992**, *118*, 406–422.
11. Little, K.W.; McCrodden, B.J. Minimization of raw water pumping costs using MILP. *J. Water Resour. Plan. Manag*. **1989**, *115*, 511–522.
12. Ormsbee, L.E.; Walski, T.M.; Chase, D.V.; Sharp, W.W. Methodology for Improving Pump Operation Efficiency. *J. Water Resour. Plan. Manag.* **1989**, *115*, 148–164.
13. Tabesh, M. Scheduling and operating costs in water distribution networks. *Proc. Inst. Civ. Eng.* **2013**, *166*, 432.
14. Lansey, K.; Awumah, K. Optimal Pump Operations Considering Pump Switches. *J. Water Resour. Plan. Manag.* **1994**, *120*, 17–35.
15. Van Zyl, J.E.; Savic, D.A.; Walters, G.A. Operational optimization of water distribution systems using a hybrid genetic algorithm. *J. Water Resour. Plan. Manag.* **2004**, *130*, 160–170.
16. Hashemi, S.S.; Tabesh, M.; Ataeekia, B. Ant-colony optimization of pumping schedule to minimize the energy cost using variable-speed pumps in water distribution networks. *Urban Water J.* **2014**, *11*, 335–347.
17. De Paola, F.; Fontana, N.; Giugni, M.; Marini, G.; Pugliese, F. An application of the Harmony-Search Multi-Objective (HSMO) optimization algorithm for the solution of pump scheduling problem. *Procedia Eng.* **2016**, *162*, 494–502.
18. De Paola, F.; Fontana, N.; Giugni, M.; Marini, G.; Pugliese, F. Optimal solving of the pump scheduling problem by using a Harmony Search optimization algorithm. *J. Hydroinform*. **2017**, *19*, 879–889.
19. Shamir, U.; Salomons, E. Optimal Real-Time Operation of Urban Water Distribution Systems Using Reduced Models. *J. Water Resour. Plan. Manag.* **2008**, *134*, 181–185.
20. Belotti, P.; Kirches, C.; Leyffer, S.; Linderoth, J.; Luedtke, J.; Mahajan, A. Mixed-integer nonlinear optimization. *Acta Numer.* **2013**, *22*, 1–13.

21. Powell, M.J.D. An efficient method for finding the minimum of a function of several variables without calculating derivatives. *Comput. J.* **1964**, *7*, 155–162. doi:10.1093/comjnl/7.2.155.
22. Fecarotta, O.; Carravetta, A.; Morani, M.; Padulano, R. Optimal Pump Scheduling for Urban Drainage under Variable Flow Conditions. *Resources* **2018**, *7*, 73.
23. Box, G.E.; Jenkins, G.M.; Reinsel, G.C.; Ljung, G.M. *Time Series Analysis: Forecasting and Control*; John Wiley & Sons: Hoboken, NJ, USA, 2015.
24. Michalewicz, Z. *Genetic Algorithms+ Data Structures = Evolution Programs*; Springer Science & Business Media: Berlin, Germany, 2013.