Real-time Whole-cost Optimization of Water Production and Distribution

Markus I. Sunela[1], Raido Puust[2]
[1] Fluidit Ltd., Åkerlundinkatu 11 A, 33100 Tampere, Finland
[2] Tallinn University of Technology, Ehitajate tee 5, 12616 Tallinn, Estonia
[1]*markus.sunela@fluidit.fi*

ABSTRACT

Optimizing water production and distribution in near real-time can result in significant savings in energy and chemical costs. This paper presents a novel, generic optimization framework, based on a single-solution meta-heuristic optimization algorithm called modified hybrid discrete dynamically dimensioned search (MHD-DDS). The optimization framework finds optimal settings for all stations in the network and optimal frequencies for all variable-speed driven pumps (VSP) for the 24 hours following the optimization run start. Tampere water supply system was used as a large-scale case-study, and the optimization was able to reduce production and distribution costs by almost 20 % while ensuring better quality of service (QoS) than before.

Keywords: pump scheduling, real-time, case-study

1 INTRODUCTION

Energy is one of the largest expenses for water utilities. Globally water supply uses 2–3 % of the total energy consumption. Pumping water is the main energy consumer, using up to 80 % of the energy used in water supply systems. [1] Energy balance analysis [2], [3] of five Finnish Water utilities [4] show that on average the electrical efficiency $\eta = \frac{E_{required}}{E_{electrical\ in}}$, is about 36 %, so there's clearly room for improvement in the energy efficiency. In the systems examined, the raw water extraction and treatment used 19 % of the total hydraulic energy on average. Hydraulic losses in pumps amount 29 % of the total electrical energy use, and motor and variable-speed drive (VSD) losses 12 %.

Operational water distribution system optimization, or pump scheduling, problems have been under research for decades[5]. Operational optimization tries to find optimal way to control the system, namely pumps, valves and tanks, so that sufficient quality of service is ensured and energy and possibly other expenses are minimized. Often time-dependent settings for all pumps and valves, or tank trigger levels for each pump are sought for. [6]

The pump scheduling problems are complex non-linear problems, tough there has been success using traditional linear-programming methods too. Since 2000's, the research has focused mostly on meta-heuristic methods, as they are easier to implement and efficient on this class of problems. [6]

Much of the research, however, has focused on optimizing single speed pumps and other water production expenses are typically not included. VSDs are nowadays commonplace, and many utilities have sources with different production costs. Likewise, much of the energy is used for raw water extraction and pumping in treatment processes [4], which are rarely included in the optimization.

Typically the effect of frequency scaling on pump's hydraulic efficiency [7], and motor and VSD energy losses are not modeled. [6] EPANET cannot be relied for energy calculations, as it is shown to give wrong efficiency results, when reduced rotational speed is used [8].

In this paper, a general framework for optimizing total cost of water production and distribution in near real-time is presented (see later in Figure 1) using full-scale models. The optimization process finds out optimal time-dependent pressure and flow settings for all stations and optimal frequencies for all pumps in the water supply system as a function of time for the next 24 hours.

The paper presents a novel way to formulate the design variables of the operational optimization problem as Mixed Integer Non-linear Problem (MINLP) to minimize the size of the search space based on pump battery pre-optimization [9] and a new ways to model pressure and flow controlled pumping [10] and complex control strategies [10] in EPANET. Optimization algorithm in use is a modified version of (Hybrid Discrete) Dynamically Dimensioned Search (HD-)DDS [11], [12].

2 METHODS

2.1 Framework overview

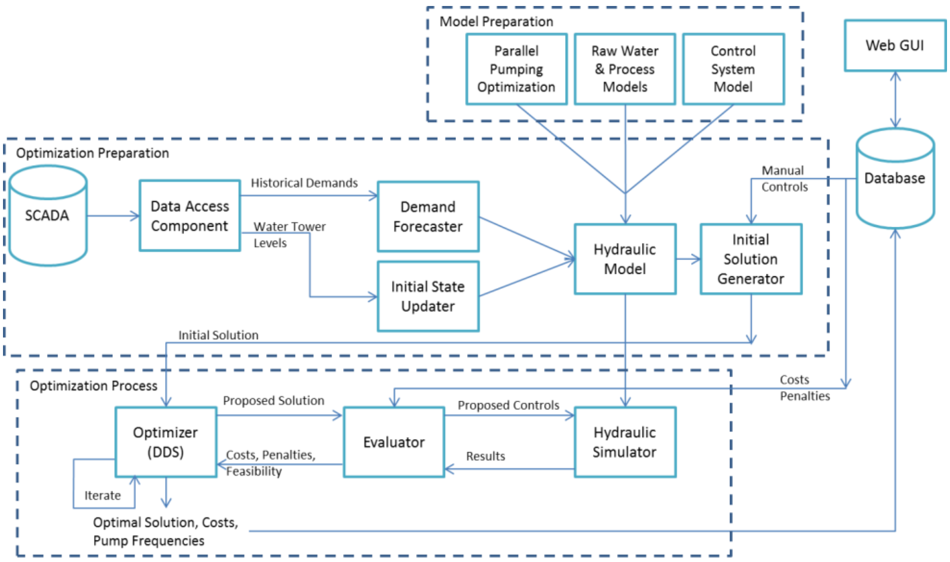

Figure 1. The optimization framework

Figure 1 shows the general overview of the optimization framework developed in this paper. The framework was developed using Java EE 7 technologies and Java 8 programming language, and it uses enhanced version of EPANET as simulator. The framework is used via a web interface or a REST API, which both allow configuring the optimization model and parameters, and include possibility to set timers to automatically perform the optimization at defined intervals. The optimization results are transferred back to SCADA.

The optimization framework consists of nine components and three processes. Model preparation is done once per project, and it refers to building the hydraulic model to include all the relevant components, in desired accuracy, pump battery pre-optimization, and building optimization model. Optimization preparation is performed once per optimization run. The process includes demand forecasting, updating the model initial state and generating an initial solution. Finally, the model is used in the optimization process, which finds the near optimal settings for pumps and valves.

2.2 Model preparation

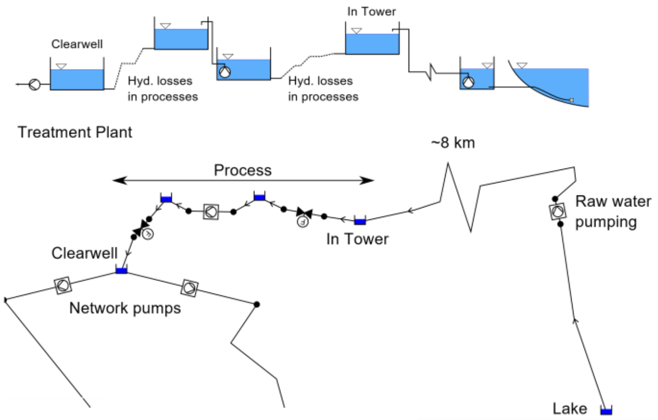

Figure 2. Modeling hydraulics, pumping and control of a surface water source

One of the key features of the proposed framework is to show that it is possible to use full-scale, all-pipe, non-simplified hydraulic model for a large-scale network in a real-time optimization setting. The hydraulic model should include all pipes, consumers, pumps, valves, tanks and reservoirs in the system, including raw water extraction, conveyance and treatment processes. Figure 2 shows an example how a surface water source and treatment process hydraulics are modeled.

VSD pumps that can work in parallel are modeled as pump batteries and pre-optimized[9], so that for every working point, that can be produced by the battery, the optimal combination of pumps and their frequencies are known. All pump energy use calculations account for frequency scaling, motor and possible VSD losses as function of pump working point and frequency.

Control system model [10] is constructed for all treatment plants and raw water networks. Control system model ensures right amount of water, including any water needed in the treatment process itself, is pumped from different wells or other sources, and through the process.

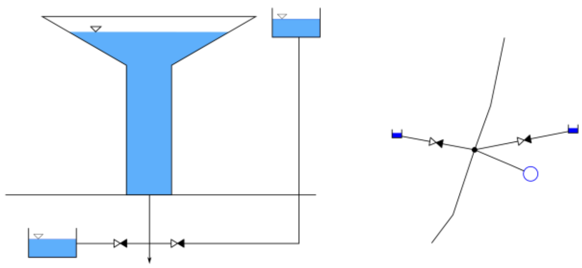

Figure 3. A discharge and feeder reservoirs are connected to the model in each pressure zone to ensure numerical stability in case too much or little water is pumped into the zone

Numerical stability of the model, when flow controlled devices (pump batteries and flow control valves) are used, [13] is ensured by adding a low head feeder reservoir and a high head discharge reservoir into each pressure zone, as shown in Figure 3. Pressure and tank level constraints together with production and pumping costs ensure solutions, where the reservoirs are used, are not favored.

An optimization framework model of the system must also be constructed. The model describes all pressure and demand metering zones in the system, the stations connecting them, whether the stations are one-way or two-way, the station control types (flow, pressure or on/off), tanks and water sources. For each component the penalty parameters, as described later, identifiers in both EPANET model and SCADA system, and energy pricing information and minimum and maximum setting values are specified. The non-energy related unit production costs (€/m³) are specified for all water sources.

2.3 Optimization preparation

Whenever a new optimization run is started, current tank levels and gate valve statuses are fetched from the SCADA system and updated into the model as initial tank levels and pipe status, demand forecast is calculated for each district metering area (DMA) and pressure-zone, and an initial solution is generated for the optimization process.

The demand forecast method used in this work is very simple and could be greatly improved, especially for non-Nordic climates, where weather conditions have strong influence on water demand, by utilizing modern methods, such as Artificial Neural Network (ANN) based methods like Dynamic Artificial Network DAN2 [14].

The demand forecast for an area is constructed by fetching the last 13 weeks' worth demand data for the area, and constructing median, and 10 % and 90 % percentile demand values for each hour of day for each different day of week, taking any national holidays into account. It is then assumed, that the demand for next 24 hours will follow the hour and week day specific median demand curve. The demand curve is multiplied by the fraction of previous 24 hours demand over the median demand for the previous 24 hours and limited between the 10 % and 90 % percentile curves.

The demand for an area is divided to the junctions belonging the area proportionally to the demands currently in the model, and the area's demand pattern shape is updated to match the constructed forecast, and the model is exported in EPANET INP format for simulation.

Previous optimization run's best solution is used as an warm initial solution[15]. If no previous solution exists yet, a heuristic solution is generated by dividing area's the average demand and any flow demanded by neighboring areas proportionally to the maximum flow capacity to the stations feeding the area. For pressure controlled stations a single setting, average between minimum and maximum pressure settings, is used.

2.4 Problem formulation

The aim of the optimization process is to minimize the costs of the water production and supply by choosing appropriate time-dependent flow and pressure settings for all the stations, and ultimately the frequency settings for all pumps in the network, while ensuring sufficient quality of service (QoS): pressures are sufficient, water source yields are not exceeded and water tower levels and capacities stay within the constraints.

Mathematically the optimization can be described as minimization of the objective function $f(\bar{x})$ subject to constraints $g_i(\bar{x})$:

$$\min_{\bar{x} \in X} f(\bar{x})$$

$$\text{subject to } g_i(\bar{x}) \leq 0, i = 1, \ldots, m$$

where $\bar{x}$ is vector containing design variable values chosen from set of possible values X. Objective function includes the costs associated with the operations: water production and pump energy costs.

Constraints define, for example, the acceptable pressure range. The constraints are formulated in the objective function as penalty costs. Thus, the objective function becomes

$$f(\bar{x}) = W(\bar{x}) + E(\bar{x}) + P(\bar{x}) ,$$

where $W(\bar{x})$ is the sum of water production costs, $E(\bar{x})$ is the sum of pumping energy costs and $P(\bar{x})$ is the sum of penalty costs.

The proposed formulation extends the existing research, for example [16], by including raw water extraction, conveyance and treatment pumping and chemical costs in the objective function by including them in the hydraulic model, and by accurately modeling the pump energy usage.

Traditional pump scheduling problems use tank trigger levels or one binary design variable per hour for each pump, that is 24 binary variables per pump for the whole 24 optimization period. The approach works well, if pumps are on-off controlled and minimum allowed pumping time is one hour. This work uses approach inspired by the in-station scheduling presented in [17], in order to optimize flow or pressure controlled pumping stations with logic control and VSD parallel pumping.

Every optimizable station has five design variables: an integer identifying the time pattern and four real valued settings: morning, day, evening and night settings. The station's setting is transformed into pump specific rotational speed settings by pump battery pre-optimization and control system model. The number of design variables is thus reduced from typical 24 per pump to five per station.

Time pattern is identified by an integer 0…529. The time pattern is a string of 24 characters from set M, D, E and N, representing the morning, day, evening and night settings respectively. All feasible time patterns are enumerated and stored in a database beforehand. Morning values can be used from 05:00 to 12:00, day values from 07:00 to 21:00, evening values from 14:00 to 04:00 and night values from 20:00 to 10:00. Each setting must be present in every pattern, and the minimum length for the different settings are 2 hours for morning, 5 hours for day, 2 hours for evening, and 4 hours for night. The minimum lengths ensure the setting is not changed too frequently.

The constraints used in this work are minimum total volume in a zone, minimum total tank capacity in a zone (i.e. for how many hours the current volume suffices for the zone demand), minimum and maximum tank levels, minimum and maximum pressure and maximum daily yield for water sources.

2.5 Optimization algorithm

The optimization algorithm in used, is a slightly modified version of (Hybrid Discrete) Dynamically Dimensioned Search (HD-)DDS [11], [12] called Modified HD-DDS (MHD-DDS). DDS is a greedy, single-solution, meta-heuristic search, with limited maximum number of function evaluations. In the beginning of the optimization, DDS exhibits strong global search characteristics, but as the maximum number of evaluations approaches, the search becomes more and more local. MHD-DDS combines both original DDS and HD-DDS into one MINLP capable algorithm, and changes the schematics so, that the algorithm is not completely greedy, but solutions with cost exceeding the current best with maximum 10 % are temporarily accepted and improved upon. If they cannot beat the previous best in 50 iterations, then the previous best solution is restored. In the case-study this change improved the final cost by 20.5 %, when 1800 iterations were used.

Ten different optimizations are always run at parallel for each optimization run, and the best result of the ten is chosen as the best solution. Running ten optimizations ensures that there’s 94.4 % probability for the solution to be among the best 25 % possible.

2.6 Evaluator

The evaluator is based on enhanced version of EPANET simulator. The simulator is wrapped in Java Native Interface (JNI) module, which enables calling the simulator from Java programming language.

EPANET is enhanced to include the pump battery component [10] allowing the use of both flow and pressure controlled variable-speed parallel pumping in the same model along with the fixed-speed pumps, modeled as ordinary pumps. Python programming language based control system modeling framework [10] is used for modeling water treatment process behavior based on the amount of water pumped into the network.

EPANET energy calculations are fixed [8] and are enhanced to include the motor and VSD loss components [9]. Pump battery energy use is globally pre-optimized [9] and includes all the energy use components in pumps, motors and VSDs.

EPANET was made thread-safe, for allowing the use of simulator in a server setting and running multiple parallel simulations, by converting all 192 global variables in use to Thread-Local Storage (TLS) using C11 standard (ISO/IEC9899:2011) `thread_local` storage-class modifier. The modifications allow parallel simulations without changing the API and with minimal code changes.

Optimizations and memory-leak fixes for EPANET listed in [18] were applied, among many advanced optimizations available in GNU C compiler (GCC) version 6.2. According to [18], using GCC's O3 optimization level provides about 30 % speedup. The compilation was optimized for the target machine by enabling `core-avx-i` machine architecture and extended instruction sets found in modern processors. GCC flags `--fast-math` and `--fno-math-errno` further speed up floating point operations. Linking time optimization also provides increase in execution speed. These compiler optimizations provide about 50 % reduction in simulation time over the default EPANET.

Further reduction of simulation time is achieved by preempting the simulation, whenever it is apparent that the current solution is worse than the best solution. [19] Preempting is possible because the optimization algorithm in use, MHD-DDS, doesn’t need the final objective function values to work, as opposed to, for example, Genetic Algorithm (GA) and Ant Colony Optimization (ACO). Preemption saves, in the case-study, about 50 % of the time step evaluations on average.

Whenever a solution candidate is evaluated, the solution vector is sent to the evaluator. If evaluator is not yet initialized, the EPANET INP file is constructed and opened in the simulator. Writing any hydraulic results, including the intermediate results, is disabled. Further evaluations are performed on the same by calling `ENinitH` to initialize new hydraulic simulation run, and calling `ENrunH` and `ENnextH` functions to advance the simulation. Avoiding reopening model file and writing results for each evaluation can save up to 19.1 % of the total simulation time [20].

`ENsetlinkvalue` function is used for changing the pump battery, pump and valve settings according to the candidate solution, while the control system model drives raw water extraction, conveyance and treatment processes. During objective and constraints evaluation, the hydraulic state of the system is analyzed using `ENgetnode/linkvalue` functions. The examined parameters include junction pressures, tank levels and volumes, pump flows, heads and energy consumption.

3 CASE-STUDY

The methodology was tested in a case-study in Tampere Water Utility, Finland. The study area includes the utility's whole network consisting of over 810 km of pipeline serving some 244 000 inhabitants in city of Tampere and neighboring municipality of Pirkkala. There are 14 pressure zones, seven water towers in six different pressure zones, eight water sources, 12 pressure booster stations and 79 pumps in total. The hydraulic model used in the optimization consists of 5443 nodes and 6457 links, includes all pipes and all 21 368 water consumers, and raw water and treatment model. Currently, the non-energy related water production costs vary 0.013-0.075 €/m³ depending on the source. The electricity price tariff is fixed at 0.085 €/kWh.

The number of optimizable stations is 20 and the number of design variables is 100, while using the traditional formulation would require 1896 variables. Using the design variable formulation search-space is reduced from traditional $1{,}48 \cdot 10^{2765}$ to $2{,}55 \cdot 10^{283}$.

The number of iterations, the DDS's r parameter, whether to allow temporary worse results in MHD-DDS and penalty values were tuned using data from Monday 2nd November 2015. Using 4500 iterations, r=0.2 and allowing 10 % worse results for 50 iterations provided the best results, while taking reasonable time on the test server (2 x 6 core Intel Xeon E5-2620 v2 @ 2.10 GHz, 32 GB, and 500 GB SSD), running 64-bit Windows 7 Enterprise, 64-bit Java 1.8.0u66 and GlassFish 4.1.1 application server.

The performance of the optimization system was assessed by calculating the total production and distribution costs and penalties using the framework with measured settings and demands for a two-week period 2nd to 15th November 2015. Average production and energy cost for the period was 4428 €/d and 5519 €/d including the penalties.

Optimization was tested by optimizing for the next 24 hours at 12 hour interval for the whole two-week period. On the average, an optimization run took 2.1 hours, and the optimized daily production and energy cost was 3556 €/d and 4101 €/d including the penalties; almost 19.7 % savings in the production and distribution costs and 25.7 % savings in the total costs including penalties.

4 CONCLUSIONS

A complete, general framework for optimizing production and energy costs of full, large-scale water supply system in near real-time was developed. The framework utilizes modified version of meta-heuristic optimization algorithm (HD-)DDS, improved EPANET simulator, very accurate pump energy use model for VSD pumps, parallel pump battery pre-optimization and novel optimization problem formulation to improve the optimization time.

The framework was applied in a case study, where production and distribution costs were reduced by 19.7 % while optimization run for 24 h period took 2.1 h on average. The results are good, and show that a full-scale, non-surrogate model can be used in a near real-time setting too, and raw water extraction, conveyance and treatment can and should be included in the optimization.

References

[1] M. Brandt, “Energy Efficiency in the Water Industry, a Global Research Project,” *Water Pract. Technol.*, vol. 6, no. 2, pp. 1–2, Jul. 2011.

[2] E. Cabrera, E. Gomez, E. Cabrera Jr., J. Soriano, and V. Espert, “Energy Assessment of Pressurized Water Systems,” *J. Water Resour. Plan. Manag.*, 2014.

[3] M. I. Sunela and R. Puust, “Real time water supply system hydraulic and quality modeling – a case study,” vol. 0, 2015.

[4] S. Saviranta, “Energy Audit of Finnish Water Distribution Networks,” Tampere University of Technology, 2015.

[5] P. W. Jowitt and G. Germanopoulos, “Optimal Pump Scheduling in Water- Supply Networks,” *J. Water Resour. Plan. Manag.*, vol. 118, no. 4, pp. 406–422, Jul. 1992.

[6] B. Coelho and A. Andrade-Campos, “Efficiency achievement in water supply systems—A review,” *Renew. Sustain. Energy Rev.*, vol. 30, pp. 59–84, Feb. 2014.

[7] A. R. Simpson and A. Marchi, “Evaluating the Approximation of the Affinity Laws and Improving the Efficiency Estimate for Variable Speed Pumps,” *J. Hydraul. Eng.*, vol. 139, no. 12, pp. 1314–1317, 2013.

[8] A. Marchi and A. R. Simpson, “Correction of the EPANET Inaccuracy in Computing the Efficiency of Variable Speed Pumps,” *J. Water Resour. Plan. Manag.*, vol. 139, no. 4, pp. 456–459, Jul. 2013.

[9] M. I. Sunela and R. Puust, “A visual tool to calculate optimal control strategy for non-identical pumps working in parallel, taking motor and VSD efficiencies into account,” *Water Sci. Tech Water Supply*, vol. 15, no. 5, pp. 1115–1122, 2015.

[10] M. I. Sunela and R. Puust, “Modeling water supply system control system algorithms,” *Procedia Eng.*, vol. 119, pp. 734–743, 2015.

[11] B. A. Tolson, M. Asadzadeh, H. R. Maier, and A. Zecchin, “Hybrid discrete dynamically dimensioned search (HD-DDS) algorithm for water distribution system design optimization,” *Water Resour. Res.*, vol. 45, no. 12, pp. 1–15, 2009.

[12] B. A. Tolson and C. A. Shoemaker, “Dynamically dimensioned search algorithm for computationally efficient watershed model calibration,” *Water Resour. Res.*, vol. 43, no. 1, pp. 1–16, 2007.

[13] J. Deuerlein, A. R. Simpson, and E. Gross, “The Never Ending Story of Modeling Control-Devices in Hydraulic Systems Analysis,” *Water Distrib. Syst. Anal. 2008*, pp. 1–12, Mar. 2009.

[14] J. D. Velásquez-Henao, C. J. Franco-Cardona, and Y. Olaya-Morales, “A Review of DAN2 (Dynamic Architecture for Artificial Neural Networks) Model in Time Series Forecasting 1,” *Ing. Univ. Bogotá*, vol. 16, no. 1, pp. 135–146, 2012.

[15] M. F. K. Pasha and K. Lansey, “Strategies to Develop Warm Solutions for Real-Time Pump Scheduling for Water Distribution Systems,” *Water Resour. Manag.*, vol. 28, no. 12, pp. 3975–3987, Jul. 2014.

[16] Z. Rao, J. Wicks, and S. West, “Encoms - An energy cost minimisation system for real-time, operational control of water distribution networks,” in *Conference on Computing and Control for the Water Industry*, 2005.

[17] S. S. Hashemi, M. Tabesh, and B. Ataeekia, “Ant-colony optimization of pumping schedule to minimize the energy cost using variable-speed pumps in water distribution networks,” *Urban Water J.*, vol. 11, no. 5, pp. 335–347, Jul. 2013.

[18] M. López-ibáñez, “Operational Optimisation of Water Distribution Networks,” Edinburgh Napier University, 2009.

[19] S. Razavi, B. a. Tolson, L. S. Matott, N. R. Thomson, A. MacLean, and F. R. Seglenieks, “Reducing the computational cost of automatic calibration through model preemption,”

Water Resour. Res., vol. 46, no. 11, pp. 1–17, 2010.
[20] Z. Y. Wu and I. Lee, "Lessons for parallelizing linear equation solvers and water distribution analysis," in *Conference on Computing and Control for the Water Industry*, 2011.