Concurrent Pump Scheduling and Storage Level Optimization Using Meta-Models and Evolutionary Algorithms

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Abstract

In spite of the growing computational power offered by the commodity hardware, fast pump scheduling of complex water distribution systems is still a challenge. In this paper, the Artificial Neural Network (ANN) meta-modeling technique has been employed with a Genetic Algorithm (GA) for simultaneously optimizing the pump operation and the tank levels at the ends of the cycle. The generalized GA+ANN algorithm has been tested on a real system in the UK. Comparing to the existing operation, the daily cost is reduced by about 10\%−15\%, while the number of pump switches are kept below 4 switches-per-day. In addition, tank levels are optimized ensure a periodic behavior, which results in a predictable and stable performance over repeated cycles.

Keywords. Pump Scheduling; Meta-Modeling; Graphics Processing Unit; Artificial Neural Network; Genetic Algorithm.

1. Introduction

Drinking water and waste water utilities account for about 3\%−4\% of the total energy use in the United States, and are responsible for more than 45 million tons of greenhouse gas emission annually, as reported by the US Environmental Protection Agency (EPA). According to the same report, these systems account for 30\%−40\% of total energy consumption of municipal governments, and the energy-related operating costs are expected to increase as much as 20\% in the next fifteen years due to population growth and tightening drinking water regulations (EPA (2012)). These facts pronounce the increasing need for the water industry to improve water management strategies.

The problem of operation optimization is most frequently addressed by pump scheduling, i.e., predicting a set of either implicit control rules or explicit time-based specifications on when to turn pumps on and off, such that the supply or disposal service requirements are met with minimal energy cost. Pump scheduling has been extensively researched over the past few decades, using a variety of optimization techniques, the most popular of which has been Genetic Algorithms (GAs), including the studies by Mackle et al. (1995); Beckwith and Wong (1995); Engelbrecht and Haarhoff (1996); Nitivattananon et al. (1996); De Schaetzen et al. (1998); Wu et al. (2001); Kelner and Léonard (2003) and Van Zyl et al. (2004). The earliest studies were mostly conducted based on a single objective function (i.e., operation energy or cost). Multi-objective evolutionary optimization algorithms have also been used by Savic et al. (1997); Sotelo et al. (2002); Barán et al. (2005); López-Ilzáñez et al. (2005), and Wang et al. (2009). In either case, pump scheduling with the
The direct application of hydraulic solvers is computationally intensive when applied to models of large utilities. To overcome this difficulty, parallel computing technology has been utilized by von Lück et al. (2004); Wu and Zhu (2009) and Wu and Behandish (2012a,b) to speed up the optimization. The speed-up factors scale well by increasing the number of physical computing cores; however, expensive multiprocessor systems are required, especially for real-time applications demanding continuous updates of the pump control policies.

In addition to the pump schedule, there are other hydraulic parameters that are indirectly related to the energy consumption. One such set of parameters are the operation ranges of storage tank levels, which can introduce an independent set of additional decision variables alongside pump control settings. In real systems, a tank is not necessarily designed to result in optimal energy consumption when its entire capacity is utilized, nor is necessarily placed at optimal locations. As a result, some tanks might have more impacts on energy saving than the others if they are filled when electricity is inexpensive and drained during the peak-demand periods.

Different techniques have been used for hydraulic system modeling, ranging from empirical models to simplified hydraulic models and state-of-the-art hydraulic simulation packages, as reviewed by Rao and Alvarruiz (2007). An alternative effective solution to reduce the computation time is offered by machine learning. Artificial Neural Networks (ANNs) have been extensively utilized for predicting the hydraulic state of water distribution and disposal systems in the recent years by Broad et al. (2005) and Tabach et al. (2007), and for the specific problem of real-time pump operation control by Jamieson et al. (2007); Rao and Alvarruiz (2007), and Rao and Salomons (2007). These techniques were applied to real systems in Salomons et al. (2007); Martinez et al. (2007); Shamir and Salomons (2008) and Behandish and Wu (2012). Furthermore, the ANN training process lends itself well to high-throughput parallel processing on the Graphics Processing Unit (GPU), as demonstrated by Wu and Eftekharian (2011) and Behandish and Wu (2012). The multi-ANN meta-modeling was later improved and generalized by Behandish and Wu (2013) to encompass a wider spectrum of systems with diverse state variable combinations to be predicted with significantly improved accuracy and robustness.

In this article, the generalized multi-ANN meta-modeling technique developed by the authors is utilized in combination with a modified Genetic Algorithm (GA). The modified GA is employed to search for the decision space made of both discrete variables (e.g., pump/valve statuses) and continuous variables (e.g., tank levels). The results on a case study system are provided and compared with those of the earlier studies in terms of energy saving, number of required pump switches, and periodic tank water level variations.
2. Generalized Meta-Modeling

Fig. 1 (a) is a schematic illustration of the Extended Period Simulation (EPS) in a succession of time, with each snapshot being replicated by a set of independent neural networks (Behandish and Wu (2013)). The initial conditions such as the storage tank levels are specified at time $t_0$, while control variables including pump and valve statuses (on or off), pump speed settings (when applicable), etc., are explicitly controlled for each time interval. In addition, time patterns are pre-specified for nodal demands, electricity tariffs, reservoir heads, etc. Each snapshot of the simulation relates the state variables at time $t_i$ to those at $t_{i+1} = t_i + \delta t$, where typically $\delta t = 1$ hour. Before setting up such a network, a sensitivity analysis was carried out to find out which state variables to select as the inputs of each sub-ANN to predict a particular output (Behandish and Wu (2013)). Fig. 2 (a) shows the results of the sensitivity analysis for a Demand Monitoring Zone (DMZ) system in the UK. The corresponding sub-ANN constructions are depicted in Fig. 2 (b), where the inputs with the highest impacts on each output are maintained. Therefore, 12 sub-ANN structures are formed based on these input/output couplings, together with an additional sub-ANN that is used to predict the energy consumption rates from the pump statuses. The sub-ANNs are trained one at a time or in parallel on the GPU with NVIDIA’s Compute Unified Device Architecture (NVIDIA (2012)), using large datasets obtained with the hydraulic model. The reader is referred to Behandish and Wu (2013) for further details on the generalized meta-modeling.

3. Optimization Model

The trained and verified multi-ANN meta-model was integrated with an evolutionary optimization algorithm to evaluate the fitness of a trial solution for the system operation control, and to search for a near-optimal solution. Two distinct sets of decision variables are considered in general:

1. Control variables: The control variables include the statuses and settings of a control element (i.e., pump or valve) at every control interval. The statuses are defined as the fraction of the time interval $\delta t$ during which the pump or valve has been kept open (e.g., 0 for closed, 1 for open) and the settings can represent pump speeds, valve flow/pressure settings, etc., as detailed by Behandish and Wu (2013).

2. Initial Conditions: The initial storage tank levels, which are typically constrained to be recovered at the end of the operation cycle, are also included in the decision variable set. The tank levels at $t = t_0$ are decided by the optimizer, and those at $t > t_0$ are predicted successively by the meta-model.
Using the convention of Behandish and Wu (2013), all state variables are normalized with the following linear equation, to make them dimensionless and with similar orders of magnitude:

\[
s(t) = \frac{s_i(t) - s_{i,min}}{s_{i,max} - s_{i,min}}, \quad i = 1, 2, \ldots, n.
\]

(1)

The first set of decision variables can be represented in two matrices, one for statuses and the other for settings. The former is a \((n_P + n_V) \times m\) matrix \([A_{i,k}]\) made of \(n_P\) pump statuses \(0 \leq A_{P,i}(t_k) \leq 1\) \((1 \leq i \leq n_P)\), and \(n_V\) valve statuses \(0 \leq A_{V,i} \leq 1(t_k)\) \((1 \leq i \leq n_V)\) over \(m\) control intervals starting at \(t_k = t_0 + k\delta t\) \((0 \leq k \leq m - 1)\). Similarly, the latter is a \((n_P' + n_V') \times m\) matrix \([S_{i,k}]\) that represents \(n_P'\) normalized pump settings \(0 \leq S_{P,i}(t_k) \leq 1\) \((1 \leq i \leq n_P')\), and \(n_V'\) normalized valve settings \(0 \leq S_{V,i}(t_k) \leq 1\) \((1 \leq i \leq n_V')\) defined over the same \(m\) control intervals. The second set of decision variables, on the other hand, can be represented by a vector \([P_{j,0}]\) made of \(n_T\) normalized tank levels \(P_{T,j}(t_0)\) at the beginning of the cycle.

As schematically depicted in Fig. 1(b), the Genetic Algorithm (GA) generates the trial solution set \(S_{GA}\) of the aforementioned \(n = (n_P + n_V + n_P' + n_V') \times m + n_T\) variables. The trial solution together with other parameters \(S_{par}\), that may include the demand patterns, the reservoir head patterns, the pre-specified pump and valve settings, etc., all in normalized forms, are passed to the multi-ANN meta-model. For each GA trial, the extended period simulation is replicated by the successive calls to the trained ANNs. The ANN outputs may include the pump energy rates, the tank levels, and possibly other dependent state variables such as the junction pressures and the pipe flow rates. Part of the output is passed to the fitness computing routine, where the object function and penalty function are evaluated.

The objective function is defined as the total pumping energy cost, normalized in the following form:

\[
\bar{C}(S_{GA}; S_{par}) = \frac{1}{m} \sum_{k=0}^{m-1} \bar{C}(t_k) \bar{E}_\text{tot}(t_k),
\]

(2)

where \(\bar{C}(t) = C(t)/C_{\text{max}}\) is the normalized electricity tariff, \(\bar{E}_\text{tot}(t) = \frac{E_{\text{tot}}(t)}{E_{\text{max}}}\) is the normalized energy consumption rate aggregated over all pumps, \(\Delta t = t_{\text{opt}} - t_0\) is the operation time, \(\delta t = \Delta t/m\) is the control interval, and \(t_k = t_0 + k\delta t\) is the discrete time step \((0 \leq k \leq m - 1)\).

The water distribution service requirements are quite diverse among different systems. In this article, three different classes of generalized constraints are defined and implemented as follows:

1. **Time-Based Constraints**: The time-based constraints specify all of the requirements on the selected hydraulic state responses over the control horizon, ranging from the tank levels and the junction pressures to the pipe flow rates, etc. These constraints are typically expressed as \(s_{i,min}(t) \leq s_i(t) \leq s_{i,max}(t)\), where \(s_i(t)\) is any state variable that is dependent on the decision variables, and \(s_{i,min}(t)\) and \(s_{i,max}(t)\) are the prescribed lower-bound and upper-bound. The most common time-based constraints are:

   (a) Lower-bounds on tank levels \(P_{T,j}(t) \geq P_{T,\text{min}}, \quad \text{e.g.,} \quad P_{T,\text{min}} = 30\% \text{ of capacity, maintained for emergency.}\)

   (b) Upper-bounds on tank levels \(P_{T,j}(t) \leq P_{T,\text{max}}, \quad \text{e.g.,} \quad P_{T,\text{max}} = 95\% \text{ of capacity, to avoid water overtopping.}\)

   (c) Requirements on storage at early morning hours \(P_{T,j}(t) \geq P_{T,\text{AM}(t)}, \quad \text{e.g.,} \quad P_{T,\text{AM}(t)} = 80\% \text{ of capacity at early morning } t = 6:00 \text{ to } 8:00 \text{ AM, and } P_{T,\text{AM}(t)} = -\infty \text{ at all other times (i.e., no lower-bound).}\)

   (d) Lower-bounds on node pressures \(P_{j}(t) \geq P_{j,\text{min}}, \quad \text{e.g.,} \quad P_{j,\text{min}} = \text{minimum pressure required at consumer end.}\)

   (e) Upper-bounds on node pressures \(P_{j}(t) \leq P_{j,\text{max}}, \quad \text{e.g.,} \quad P_{j,\text{max}} = \text{maximum pressure required to avoid leakage, or the maximum pressure that the junctions can endure, whichever is smaller.}\)

   (f) Lower-bounds on pipe flow rates \(Q_{j}(t) \geq Q_{j,\text{min}}, \quad \text{e.g.,} \quad Q_{j,\text{min}} = \text{minimum flows required to avoid stagnation and maintain water quality.}\)

   (g) Upper-bounds on pipe flow rates \(Q_{j}(t) \leq Q_{j,\text{max}}, \quad \text{e.g.,} \quad Q_{j,\text{max}} = \text{maximum flows that pipes can endure.}\)
2. Periodicity Constraints: Regardless of the time-variant constraints on the values, some state variables are constrained to return to their initial values at the end of the cycle as an operational requirement, so that the operation would repeat itself periodically under similar conditions at the subsequent cycles. For instance, a tank level at the end of the cycle can be constrained to be in a tolerance range of its initial water level, e.g., \(|P_{T,i}(t_{opt}) - P_{T,i}(t_0)| \leq \Delta P_{T,i}\).

3. Switch Constraints: A pump scheduling scenario is of practical significance only if the number of pump switches per day (i.e., the number of times that each pump is turned on and off) is restricted, e.g., to 4 or 6 switches per day for each pump. This is because numerous pump switches are detrimental to the pump’s life-cycle, resulting in prohibitively large maintenance and replacement costs.

The violation of each inequality constraint written in the standard form of \(g(\cdot) \leq 0\), is quantified with \(\langle g(\cdot) \rangle := \min\{0, g(\cdot)\}\). For a trial solution \(S_{G,A}\), the violation measured over the cycle \(\Delta t = t_{opt} - t_0\) is formulated as:

\[
\tilde{G}(S_{G,A}; S_{par}) = \sum_{i=1}^{n} \frac{c_1}{m} \sum_{k=0}^{m-1} \left[ (\bar{s}_i(t_k) - \bar{s}_{max,i}(t_k)) + \langle \bar{s}_{min,i}(t_k) - \bar{s}_i(t_k) \rangle \right],
\]

\[
+ \sum_{j=1}^{n} c_{2,j} \left( \Delta \bar{s}_{j|0}^{t_{opt}} - \Delta \bar{s}_{max,j} \right) + \sum_{p=1}^{n_P} c_{3,p} \left( \eta_{p|0}^{t_{opt}} - \eta_{max,p} \right).
\]

where \(\Delta \bar{s}_{j|0}^{t_{opt}} := |\bar{s}_j(t_{opt}) - \bar{s}_j(t_0)|\), and \(\eta_{p|0}^{t_{opt}}\) is the actual number of pump switches per cycle, e.g., 24 hours. The first term on the right is the sum of violations of the time-base constraints, integrated for each state variable over the time interval \(\Delta t = t_{opt} - t_0\). The second term measures the violation of the periodicity requirements with the normalized tolerances \(\Delta \bar{s}_{max,j}\), and the last term quantifies the violation of pump switch constraints with the maximum allowable number of switches \(\eta_{max,p}\). The state variables \(\bar{s}_i(t)\) in the first two terms can be the normalized tank levels \(\bar{s}_i(t) := \bar{P}_{T,i}(t) (1 \leq i \leq n_T)\), the normalized junction pressures \(\bar{s}_i := \bar{P}_{J,i}(t) (1 \leq i \leq n_J)\), the normalized pipe flow rates \(\bar{s}_i := \bar{Q}_{I,i}(t) (1 \leq i \leq n_I)\), etc. The weight factors \(c_{1,i}, c_{2,j}\), and \(c_{3,p}\) are set to 1 by default for constrained variables, and to 0 for the unconstrained variables.

The objective function and the violation function formulated in Eqs. \((2)\) and \((4)\) are combined using additive penalty method into the following penalized objective function:

\[
\tilde{F}^*(S_{G,A}; S_{par}) = \tilde{F}(S_{G,A}; S_{par}) + \mathcal{P} \times \tilde{G}(S_{G,A}; S_{par}),
\]

where \(\mathcal{P}\) is the penalty factor, typically selected in the order of \(\mathcal{P} \sim 10^2 - 10^4\) depending on how strictly the constraints are being enforced. The penalized objective function \(\tilde{F}^*(S_{G,A}; S_{par})\) is used as a measure of fitness of the trial decision set \(S_{G,A}\) generated by the GA. The lower the value of this function is, the fitter the trial scenario is, hence more likely it is to survive or pass its properties to the next generations of the evolutionary optimization.

4. Optimization Algorithm

The optimization problem is solved by combining the classic binary operators with those of a modified Genetic Algorithm (GA) \([\text{Mundo and Yan}(2007)]\). The hybrid search algorithm is schematically illustrated in Fig. 4(b). The algorithm iterates over \(n_{\text{gen}}\) generations, and at each generation \(n\) where \(0 \leq g \leq n_{\text{gen}} - 1\), a population of \(n_{\text{pop}}\) individuals (i.e., chromosomes) are maintained. Each individual is represented by a set of normalized decision variables \(S_{G,A,g}\) composed of the control variables (i.e., the matrices of pump/valve statuses and normalized settings) and initial conditions (i.e., the vectors of normalized initial storage levels) as explained in Section 3. The normalized decision variables \(S_{G,A,0}\) of the initial population are randomly assigned with values in \([0, 1]\), corresponding to random values in the physical domain in each state variable’s min/max range. The subsequent generations \(S_{G,A,g}(1 \leq g \leq n_{\text{gen}} - 1)\) are descended from their parents in the previous generation \(S_{G,A,g-1}\), through a series of evolutionary operations. The modified GA utilizes a
combination of evolutionary operators that are designed for binary-coded chromosomes (e.g., for pump/valve statuses that are constrained to a small number of switches) as well as real-valued variables (e.g., tank levels or pump speed settings, if applicable) without a need to use binary-coding for the latter.

At the beginning of each iteration, the fitness of the individuals are computed using the multi-ANN meta-model and sorted in descending order of the penalized objective function $F^*({\mathbf{S}_G};\mathbf{S}_{par})$. The algorithm follows an elitist strategy, hence a constant fraction $f_{elit} \sim 1 - 5\%$ of the population consisting of the fittest individuals are directly sent to the next generation. Another fraction $f_{rand} \sim 5 - 15\%$ of the population is randomized at every generation, to enhance the exploration and avoid local minima. The rest of the population consisting of $1 - (f_{elit} + f_{rand}) \sim 80 - 95\%$ are generated from reproduction (i.e., breeding) operations. The selection of the parents for reproduction can be based on different probability distributions. In this algorithm, the method of normalized geometric ranking selection is used (Mundo and Yan (2007)), in which the probability of an individual to be selected is calculated from its rank in the sorted array based on fitness:

$$P_{\text{rep}}(r) = \frac{P_0(1-P_0)^r}{1-(1-P_0)^{n_{\text{pop}}}}, \quad r = 0, 1, \ldots, n_{\text{pop}} - 1,$$

where $0 < P_0 < 1$ is a constant and is proportional to the probability of selecting the fittest individual, $r$ is the rank of the individual ($r = 0$ for the fittest individual, and $r = n_{\text{pop}} - 1$ for the least fit individual of that generation).

Once the parents are selected, different reproduction operators are employed to produce one offspring at a time:

1. **Linear Combination**: With a probability of $0 \leq P_{\text{com}} \leq 1$, the offspring genes are generated using a linear combination of the parents’ genes:

$$s_{\text{off},i} = \bar{s}_{A,i} + R_{\text{com}}(s_{B,i} - s_{A,i}), \quad R_{\text{com}} \in [-\epsilon, 1 + \epsilon],$$

where the subscripts “off”, $A$, and $B$ refer to the offspring and the two parents, respectively (Mundo and Yan (2007)), as exemplified in Fig. 4 (c) with $R_{\text{com}} = 0.6$. The combination factor $R_{\text{com}}$ is a random number in $[-\epsilon, 1 + \epsilon]$ where $\epsilon \sim 0 - 0.2$ is the overshoot. It is evident that this reproduction scheme applies to the real-valued decision variables only. Therefore, for the pump/valve statuses restricted to binary values, the linear combination is replaced with a simple random selection, i.e., for every gene $\bar{s}_{\text{off},i} := s_{A,i}$, or $\bar{s}_{\text{off},i} := s_{B,i}$, each with 50% probability.

2. **Single Split Cross-over**: With a probability of $0 \leq P_{\text{crs}} \leq 1$, the offspring genes are generated from a single point cross-over operation on the parents. For the pump/valve statuses and settings arranged into matrices, the splitting can occur along the rows or columns, each with a 50% probability. For the initial conditions arranged into a vector, on the other hand, it is a simple splitting along the one-dimensional array, as illustrated in Fig. 4 (d).

3. **Direct Transfer**: With a probability $1 - (P_{\text{com}} + P_{\text{crs}})$, one of the two parents are directly transferred to the next generation, each with 50% probability. This could be replaced with an elitist procedure, in which the fitter parent is more likely to be transferred.

With the above operations, one offspring is created by a pair of parents. The selection of the parents and the reproduction have to be repeated $1 - (f_{elit} + f_{rand})$ times to generate enough number of offsprings for the next generation.

The produced offsprings are subjected to mutation with a small probability $P_{\text{mut}} \sim 1 - 2\%$ to avoid local minima and promote global exploration of the search landscape. For the real-valued decision variables, a uniform random mutation operation is employed, which means a reassignment of one of the normalized decision variables into a random value in $[0, 1]$, corresponding to a random value in the physical min/max range, as illustrated in Fig. 4 (c). For binary-coded decision variables, on the other hand, the mutated gene is changed from 0 to 1 and from 1 to 0, as shown in Fig. 4 (d).

As illustrated in Fig. 4 (b), once the next generation of $n_{\text{pop}} \sim 100 - 300$ new individuals are produced, the procedure is repeated for enough number of generations $n_{\text{gen}} = 5,000$, until a near-optimal set of control variables and initial tank levels is found. In addition to the selection, reproduction, and mutation, every
several generations $n_{res} \sim 100 - 500$, the entire population except the elite fraction are completely reset to random decision variables to simulate several optimization sessions following one another, always keeping the best results obtained so far.

5. Results & Discussion

The generalized GA+ANN technique was applied to a Demand Monitoring Zone (DMZ) in the UK \cite{Wu et al. (2009)}. The hydraulic model for this system is composed of 3,537 junctions, 3,273 pipes, 5 reservoirs, 12 storage tanks, 19 constant-speed pumps, and 420 valves. The optimization was carried out over $\Delta t = 24$ hours with time steps $\delta t = 1$ hour. Two different optimization scenarios are reported here, one with pump scheduling of 9 active pumps (the same pumps utilized in the existing operation), which involves $(9 \times 24) = 216$ decision variables, and the other with simultaneous pump scheduling and storage optimization of all 12 tanks, which gives rise to $216 + 12 = 238$ decision variables. For this particular case study, the three categories of constraints defined in Section 3 are specified, including: (1) for 10 out of 12 tank levels, $P_{T,j} \geq 30\%$ of capacities for emergency, and $P_{T,j} \leq 95\%$ of capacities to avoid overtopping; (2) the periodicities of the same tank levels are enforced as $|P_{T,j}(24) - P_{T,j}(0)| \leq 10$cm, which is less than 2.5% of the smallest tank capacity. (3) For every active pump, a maximum of 4 switches per 24 hours are allowed. No explicit constraints on junction pressures or pipe flow rates are specified. The GA parameters are set as: $P = 1,000, n_{gen} = 5,000, n_{res} = 100, n_{pop} = 300, f_{elit} = 0.01, f_{rand} = 0.10, P_0 = 0.05, P_{com} = 0.40, P_{crs} = 0.50$, and $P_{mut} = 0.01$.

The GA+ANN solutions are compared with the existing operation and the pump scheduling study by Wu et al. (2009) on the same system. The existing operation uses simple controls that define when the pumps are turned on and off based on tank levels; for instance, the pump “PILWTH” is turned on if the tank “BUTa2” level falls below 5.30 meters, and turned off if the level starts to exceed 5.73 meters. The thresholds are based on experience and do not necessarily ensure cost-effective operation. The study by Wu et al. (2009), on the other hand, used rule-based controls, but additional rules were specified with greater thresholds on the minimum storage at night when the electricity is inexpensive; e.g., at clock-times between 10:00 PM and 8:00 AM, the pump “PILWTH” is turned on if tank “BUTa2” level falls below 5.73 meters, and turned off otherwise. Both simple and rule-based controls secure the controlled tank levels between the limits, but they rely on the known relationships of pumps with tanks, and do not guarantee any bound on the number of pump switches that is required for this purpose. The cost can be significantly reduced by optimizing the rules in the latter method, but as shown in Table 1 this comes at the expense of numerous pump switches enforced by the control rules. For instance, the utilization of pump “PILWTH” is decreased by about 60% with the optimized rules, saving around £190 per day. However, as Fig. 3 shows, the reduced pump utilization is made possible with numerous pump switches at high frequencies to satisfy the rules, which not desirable in practice.

Table 1 compares the pump utilization characteristics of the 4 different operations, obtained with EPANET using a time step of 5 minutes for every one of the 4 scenarios. It is observed that the rule-based control strategy saves about 30% of the daily cost, but the number of pump switches is prohibitively large (see Fig. 3). The near-optimal GA+ANN solution, on the other hand, can results in 10 – 15% cost saving with a maximum of 4 pump switches per day. Furthermore, both of the existing simple and rule-based controls result in large differences between the initial and the final tank levels, making it difficult to anticipate the operating cost and performance of subsequent cycles. The GA+ANN solution, on the other hand, guarantees repeatability of the operation by bringing the tank levels back to the initial conditions at the end of each cycle. It is also worthwhile noting that the existing simple and rule-based controls are on 7 out of 12 tanks, hence emptied or overtopped levels are observed for the other 5 tanks; while GA+ANN studies constrain 10 tanks to be periodic.

Fig. 4 (a) shows the difference between the initial and the final tank levels for the two GA+ANN scenarios where the shaded area represents the feasible space $|P_{T,j}(24) - P_{T,j}(0)| \leq 10$cm. The energy and cost of both scenarios are plotted in panel (b) and compared with those of the current operation. The solution of pump scheduling and storage optimization is obtained with $\hat{F} = 0.4199$ and $\hat{G} = 0.0000$ (no violation), resulting in saving of around £130 per day. However, the result of sole pump scheduling is obtained with $\hat{F} = 0.4687$.
Table 1: Comparison of pump utilization, energy cost, number of pump switches (#PS), and tank level periodicities for 4 operation scenarios.

| Case Studies | Simple Controls (Existing Operation) | Rule-Based Controls (Based on Wu et al. 2009) | Near-Optimal GA+ANN (Pump Scheduling Only) | Near-Optimal GA+ANN (Pump Sch. + Storage Opt.) |
|--------------|--------------------------------------|----------------------------------------------|---------------------------------------------|------------------------------------------------|
| Pump ID      | Util.                  | Cost         | #PS | Util.                  | Cost         | #PS | Util.                  | Cost         | #PS |
| X2420052     | 100%                   | £226.3       | 0   | 100%                   | £179.1       | 0   | 83.3%                   | £183.5       | 4   |
| X2420014     | 100%                   | £350.4       | 0   | 41.7%                  | £222.54      | 3   | 58.3%                   | £239.44      | 2   |
| X2410061     | 36.0%                  | £222.54      | 3   | 41.1%                  | £222.54      | 3   | 75.0%                   | £27.53       | 2   |
| X241008C     | 13.6%                  | £204.14      | 2   | 26.8%                  | £158.69      | 4   | 25.0%                   | £5.67        | 2   |
| X2450024     | 52.7%                  | £246.79      | 3   | 23.0%                  | £15.21       | 56  | 37.5%                   | £44.80       | 4   |
| PILWTH       | 91.6%                  | £276.6       | 2   | 36.0%                  | £84.91       | 116 | 79.2%                   | £123.63      | 4   |
| NEWMKT       | 0.00%                  | £200.00      | 0   | 41.1%                  | £179.6       | 3   | 12.5%                   | £29.48       | 2   |
| Total        | N/A                    | £953.0       |     | N/A                    | £684.8       |     | N/A                    | £960.7       |     |

Cost Savings: N/A £268.2 (28.15%) £52.36 (5.49%) £131.29 (13.78%)

No. Switches: \( n_{\text{max}} < 4 \text{ per day (✓)} \) \( n_{\text{max}} \gg 4 \text{ per day (✓)} \) \( n_{\text{max}} = 4 \text{ per day (✓)} \) \( n_{\text{max}} = 4 \text{ per day (✓)} \)

Periodicities: \( \Delta_{\text{max}} \gg 10.0 \text{ cm (✓)} \) \( \Delta_{\text{max}} \gg 10.0 \text{ cm (✓)} \) \( \Delta_{\text{max}} = 15.3 \text{ cm (✓)} \) \( \Delta_{\text{max}} = 10.3 \text{ cm (✓)} \)

Figure 3: Pump flows over 24 hours for 4 operation scenarios. The results are obtained with EPANET using a simulation time step of 5 minutes.

Figure 4: GA+ANN optimization results: (a) tank level difference between the two ends of cycle; (b) comparison of the energy consumptions; and (c) comparison of the energy costs. The post-processing results are generated with EPANET using a simulation time step of 1 hour.
Figure 5: Storage level variations over 24 hours for 4 operation scenarios. For GA+ANN results, both meta-model prediction and hydraulic model post-processing results are shown. The post-processing results are generated with EPANET using a simulation time step of 1 hour.

and $\bar{G} = 0.1966$, showing some violation of the periodicity constraints depicted in Fig. 4 (a), and less saving of £50 per day. Although this result after 5,000 GA generations does not necessarily mean that no feasible solution exists for the latter case, nevertheless it shows that starting from non-optimal initial conditions of the existing operation introduces difficulties to the GA optimizer to find a feasible solution with significant cost reduction. This demonstrates the importance of a proper choice of the initial combination of tank levels that would be able to recover in 24 hours, and also explains some of the difficulties faced in the previous pump scheduling studies in Wu and Behandish (2012a,b). Fig. 5 compares the tank level variations for the four operation scenarios. For the GA+ANN solutions, both meta-model predictions (used within GA) and hydraulic model post-processing results are illustrated. The meta-model accuracy was validated with the accumulated errors of less than $\pm 5$cm per 24 hours, which is a significant improvement over the $20 - 30$cm errors of earlier development (Behandish and Wu (2012) and Wu and Behandish (2012a,b)). It is observed that when the initial tank levels are confined to the existing operation values, the GA+ANN results do not deviate much from the existing operation over the first few hours. The solution with concurrent pump scheduling and storage optimization, on the other hand, utilizes a larger fraction of tank capacities and recovers all of the constrained tank levels to $\pm 10$cm of initial values. The saving of around 835KWH (£130) per day corresponds to an annual saving of around 300MWH (£480,000), which is significant for a DMZ system of this size.

6. Conclusions

The study has demonstrated that in addition to the pump scheduling policy, the decisions on tank operation range can play a significant role in water distribution operation cost and storage utilization, and to guarantee the repeatability of the operation policy with predictable behavior over subsequent cycles. The GA+ANN algorithm is generalized to represent a wide range of complex systems and their requirements for pump and valve operation control, carried out concurrently with the optimization of tank operation ranges. Finally, the set of near-optimal tank levels obtained in this offline optimization with a typical demand profile can be useful information for the implementation of the real-time pump operation optimization.
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