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Optimized Control for Water Utilities

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Abstract

The rising demand for water and the need for more electricity to transport it, from remote sources to consumers, are pushing humanity to find ways to save water as well as energy. Thus, this paper presents a novel technique to optimize the control operations in water utilities, where the water distribution system is modeled as a Markov Decision Process to produce a control policy to minimize the energy expenses. We report experiments in a water utility that provided reduction of 39.3\% in energy expenses. Moreover, it was possible to increase soundness of the system operation in order to avoid water outages.

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1. Introduction

In water utilities the expenditures with energy constitute a significant percentage in their budget. According to Goldstein and Smith (2002) about 3\% of US energy consumption (56 billion kWh/year) were used for drinking water and 2/3 of that are used to deliver potable water from water treatment plants to the final consumers. The optimal operation in terms of energy to transporting the water may lead significant savings in electricity expenses, reducing water leakages, and preventing wear and tear (Haestad et al., 2003).

Since the 1970's, there have been many approaches to deal with minimizing electricity consumption and maximizing energy performance (Goldman et al., 1999). Classical approaches, such as linear (Pasha and Lansey, 2009), non-linear (Skworcow et al., 2009, Yang and Brsting, 2010) or mixed programming (Wang and Brdys, 2006) are not recommended for complex distribution networks with many variables or constraints (Haimes, 1977). Heuristic optimization techniques, like genetic algorithm (Wang et al., 2009, Bene et al., 2010, Savic et al., 2011) or ant colony (López-Ibáñez et al., 2008, Maier et al., 2003), are trendy but, has difficulties in setting the algorithm parameters to obtain good results or the computation get stuck in local minima.

In this scenario, dynamic programming models, such as Markov Decision Processes (MDPs), can deal with those problems and also provide the following advantages compared to other techniques (White, 1993): real world – operates

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in uncertain and dynamic domains; planning – generates control policies to sequential decision processes; and global minimum – guarantee to achieve a lower future payoff.

Thus, this article describes a novel framework, based on MDPs, for energy consumption optimization in water distribution systems. The framework is characterized by information about tank levels, power consumption of pumps, energy price schema, water demand of the final consumers and a detailed description of the network. As result, this technique provides the following features:

- electrical consumption reduction and consequently energy expenses reduction;
- pump efficiency increment so as to maximize the relation between energy and water flow;
- facilitating system operation in complex distribution networks;
- elimination of water outages due to mismanagement in the system operation;
- pump maintenance costs reduction owing to operation of the pumps under better operating conditions;
- prevention of water distribution operations with elevated pressures, hence minimizing the risk of pipe rupture;
- minimization of control valve usage to pressure adjustment, avoiding losses of kinetic energy by passage restriction; and
- provision of foundation to existing control rules and proposes improvement when is necessary.

This new technique have been demonstrated to be effective for reducing the energy expenses and for keeping the pressure in a controlled range as well as increasing the reliability of the entire distribution system.

This paper is organized as follows: Section 2 presents a short introduction to finite-horizon Markov Decision Processes; Section 3 explains how to model water distribution systems as an MDP; In Sections 4 and 5 are described our experiments and results in a real water distribution system; and Section 6 summarizes our conclusions.

2. Markov Decision Processes

Markov Decision Processes are models for sequential decision making in fully observable environments when outcomes are uncertain (Puterman, 1994). This sequential decision process is characterized as follows:

- the environment evolves probabilistically, occupying a finite set of states;
- for each state there is a finite set of possible actions that may be taken by the agent; and
- at discrete times the agent takes an action and a certain cost or reward is incurred.

Thus, a finite-horizon MDP can be formally defined as a tuple \( \langle S, A, D, T, R \rangle \) where \( S \) is a finite set of possible states, \( A \) is a finite set of actions an agent can take, \( D \) is a finite sequence of decision epochs, \( T \) is a state transition function and \( R \) is a reward function.

The states are the characterization of everything which is important for the agent choose an action in the problem that is modeled (Sutton and Barto, 1998). The set of states is defined as the finite set:

\[
S = \{ \sigma_1, \sigma_2, \ldots, \sigma_{N_S} \},
\]

where \( |S| = N_S \) is the number of states.

The transition from state \( s_t = \sigma \) to next state \( s_{t+1} = \sigma' \), where \( \sigma \) and \( \sigma' \in S \), happens in response to an action. The set of actions \( A \) can be defined as the union of all subset of allowable actions in each state \( \sigma \in S \):

\[
A = \bigcup_{\sigma \in S} A_{\sigma}.
\]

The decision epochs, or time steps, are the instants where the actions need to be taken. In finite-horizon problems, it is defined as the finite sequence of natural number:

\[
D = \{1, 2, \ldots, T_{\text{max}} \},
\]

where \( |D| = T_{\text{max}} \) is the time horizon, in other words, where a finite MDP terminates.
By applying an action $a_t = \alpha$ in the state $s_t = \sigma$ at time step $t \in D$, the agent makes a transition to the new state $s_{t+1} = \sigma'$ based on a discrete probability distribution $\mathcal{T}$ over the set of possible transitions and is defined as:

$$\mathcal{T}(\sigma, \alpha, \sigma', t) = P(s_{t+1} = \sigma'|s_t = \sigma, a_t = \alpha),$$  

(4)

where $\mathcal{T} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \times \mathcal{D} \rightarrow [0,1]$, $\sum_{\sigma' \in \mathcal{S}} \mathcal{T}(\sigma, \alpha, \sigma', t) = 1$ and $0 \leq \mathcal{T}(\sigma, \alpha, \sigma', t) \leq 1$.

Finally, the reward function specifies a value received by the agent for performing the action $a_t = \alpha$ in the state $s_t = \sigma$ accounted at time step $t \in D$ and it is defined as:

$$R(\sigma, \alpha, t) = [r_t | s_t = \sigma, a_t = \alpha],$$  

(5)

where $\mathcal{R} : \mathcal{S} \times \mathcal{A} \times \mathcal{D} \rightarrow \mathbb{R}$. When positive $\mathcal{R}(\sigma, \alpha, t)$ may be regarded as reward, and when negative as cost.

The goal of an MDP is to find a Markovian policy $\pi$ which is the mapping from current states into actions in each time step. When deterministic the Markovian policy is defined as $\pi : \mathcal{S} \times D \rightarrow \mathcal{A}$. Optimizing such policy corresponds to maximize the accumulated reward values received by the agent in the problem horizon. Thus, to connect an optimal criteria to a policy it is defined the value functions or utility.

The value function $V^\pi(\sigma, t)$ in finite-horizon problems is the expected return of rewards when starting in state $\sigma$ and by following the actions contained in policy $\pi$ subsequently and it is expressed as:

$$V^\pi(\sigma, t) = E_\pi \sum_{k=0}^{T_{\text{max}}} r_{t+k} | s_t = \sigma,$$

(6)

where $E_\pi$ is the expected value received by the agent to follows the policy $\pi$.

One fundamental property of value functions is that they satisfy the Bellman’s Principle of Optimality (Bellman, 1957), that allows to break a dynamic optimization problem into simpler subproblems, and can be defined recursively as follows:

$$V^\pi(\sigma, t) = E_\pi [r_t + r_{t+1} + r_{t+2} + \cdots + r_{T_{\text{max}}} | s_t = \sigma],$$

$$= E_\pi [r_t + V^\pi(\sigma', t+1) | s_t = \sigma],$$

$$= \mathcal{R}(\sigma, \pi(\sigma, t), t) + \sum_{\sigma' \in \mathcal{S}} \mathcal{T}(\sigma, \pi(\sigma, t), \sigma', t) \cdot V^\pi(\sigma', t+1).$$

(7)

An optimal policy, denoted by $\pi^\ast$, is such that $V^\pi(\sigma, t) \geq V^\pi(\sigma, t)$ for all $\sigma \in \mathcal{S}$ and $t \in \mathcal{D}$. Thus, the optimal value function can be evaluated as follows:

$$V^\ast(\sigma, t) = \max_{\alpha \in \mathcal{A}} \left[ \mathcal{R}(\sigma, \alpha, t) + \sum_{\sigma' \in \mathcal{S}} \mathcal{T}(\sigma, \alpha, \sigma', t) \cdot V^\ast(\sigma', t+1) \right].$$

(8)

Finally, the optimal policy $\pi^\ast$ are the optimal actions selected from the optimal value function $V^\ast$ and is summarized by the equation:

$$\pi^\ast(\sigma, t) = \arg \max_{\alpha \in \mathcal{A}} \left[ \mathcal{R}(\sigma, \alpha, t) + \sum_{\sigma' \in \mathcal{S}} \mathcal{T}(\sigma, \alpha, \sigma', t) \cdot V^\ast(\sigma', t+1) \right].$$

(9)

In short, the best action will be the action that has the highest expected value based on possible next states resulting from taking that action (Wiering and van Otterlo, 2012).

Since finite-horizon problems have acyclic spaces, due to time is always increasing, they do not require an iterative algorithm for solving MDPs. There is an optimal backup order that starts from states with maximum horizon and incrementally computes the values of states with lower horizons. The solution can be achieved in a single pass updating the full layer of states before moving to the previous layer (Mausam and Kolobov, 2012).
3. Modeling a Water Distribution Systems as an MDP

The topology of a typical water distribution system is shown in Fig. 1. In those systems there are the following hydraulic components: a reservoir ($R_1$), which provides potable water to a water treatment plant; $N_U$ pumps in parallel ($U_1, U_2, \ldots, U_{N_U}$), which deliver water in the distribution network; $N_H$ storage tanks ($H_1, H_2, \ldots, H_{N_H}$), which keep the pressure equalized in the distribution network and provide complementary supply during the peak hours; $N_L$ pipes ($L_1, L_2, \ldots, L_N$), which transport water in the network; and $N_J$ junctions ($J_1, J_2, \ldots, J_N$), which link all hydraulic components in the network and where the consumers are tapped.

![Fig. 1. Topology of a typical water distribution system.](image)

A water distribution system can be modeled as an MDP to minimize energy costs over a finite-horizon under operational constraints by the tuple $(S, \mathcal{A}, D, T, R)$. Thus, in that model the finite set of states $S$ can be completely defined by level in the $N_H$ storage tanks, that results in:

$$S = (H_1, H_2, \ldots, H_{N_H}).$$  

(10)

Each state variable $H_i$, where $i = 1, \ldots, N_H$, has domain in its respective close interval $[H_i^{\text{min}}, H_i^{\text{max}}]$. In order to deal with continuous variables modeled as an MDP it is necessary to discretize them.

The discretization concerns the process of converting continuous variables to discrete sets. In the literature there are several approaches to do it such as uniform spacing, indicated when the number of states is small, structured representation (Feng and Hansen, 2002), adaptive discretization (Munos and Moore, 2002) as well as symbolic representation (Sanner et al., 2011). The level of discretization may be decided by the available memory and the desired accuracy of the solution (Sutton and Barto, 1998).

The set of actions $\mathcal{A}$ is represented by the variables that can change the states of the system. In water distribution systems, they are represented by the status of the $N_U$ pumps in parallel, as follows:

$$\mathcal{A} = (U_1, U_2, \ldots, U_{N_U}).$$  

(11)

In the case of pumps driven directly, they can be modeled by the discrete sub-set $U_d = \{0, 1\}$, where 0 represents pump off and 1 represents pump on. Additionally, when the pumps are associated with a variable frequency drive (VFD) they can be discretized in their respective closed interval $U_c = [0, 1]$.

The transition function $T$ in a water distribution system cannot be formally defined due to recurrence relation between the variable that compose the system. Moreover, these transitions are associated with some uncertainty. Thus, we can describe the state transition as Normal distributions over the $N_H$ tank levels at next instant:

$$H_i(t + 1) \sim \mathcal{N}(f_i(t), u(f_i(t))),$$  

(12)

where $H_i(t + 1)$ is the tank level at instant $t + 1$, $f_i(t)$ describes the recurrence relation to evaluate the tank level and $u(f_i(t))$ is the uncertainty in the state transition.

The recurrence relations $f_i(t)$ are functions of water demand, previous tank levels and action taken, all of them at instant $t$. The solution of that equations are provided by the hydraulic simulation software EPANET (EPA, 2000). In this software, the water distribution network is described by reservoir, tanks, pumps, nodes (consumers or connections) and links (pipes), similarly to the diagram shown in Fig. 1. Besides the network description it uses fluid mechanic equations to solve the head losses, flow rates and power consumptions.
Additionally uncertainty also plays an important role in decision processes since it characterizes the dispersion of the values attributed to a measured quantity, and it also reflects the knowledge, or the lack of it, of the real value (Dieck, 1997). The uncertainty evaluation, accurately stated in Guide to the Expression of Uncertainty in Measurement (ISO, 2008), evaluates and combines the variances of each source of error. The combined uncertainty of one variable $Y$, denoted as $u(Y)$, is computed by taking the square-root of the quadratic summation of the variance of an error source times their respective sensibility factor, as described below:

$$u(Y) = \sqrt{\left(\frac{\partial Y}{\partial x_1} \cdot u(x_1)\right)^2 + \cdots + \left(\frac{\partial Y}{\partial x_{N_e}} \cdot u(x_{N_e})\right)^2},$$  \hspace{1cm} (13)$$

where the variable $Y$ is functions of $N_e$ sources of error, such that $Y = f(x_1, \ldots, x_{N_e})$, and $u(x_j)$ is the variance of the $j$-th source of error such that $1 \leq j \leq N_e$.

Thus, in a water distribution system modeled as an MDP the uncertainties in the state transitions $u(f_j(t))$ are function of water demand, and calculating imprecisions, due to hydraulic network description and truncation error in EPANET.

Finally, the reward function $\mathcal{R}$ can be considered as the energy expenses during a billing cycle, normally 30 days. Those expenses are composed by the consumption cost $C_C$ and the demand cost $C_D$ and described as:

$$\mathcal{R} = C_C + C_D.$$  \hspace{1cm} (14)$$

The consumption cost is the energy used (kWh) along the billing cycle times the energy price ($/\text{kWh}$). As the energy consumption is not flat during the day, the energy utility companies can not maintain the energy price constant, thus the day is divided in two period, on-peak and off-peak. The on-peak period reflects the highest consumption of electricity and corresponds to higher price. On the opposite side, the off-peak period is when power demand is usually low and has lower price. The consumption cost $C_C$ can be defined as:

$$C_C = \sum_{OP} \left(\sum_{Pw(t)} \cdot \Delta T \cdot P_{OP} + \sum_{FP} Pw(t) \cdot \Delta T \cdot P_{FP}\right),$$  \hspace{1cm} (15)$$

where $BC$ is the billing cycle period, $OP$ and $FP$ are the on and off-peak periods, $P_{OP}$ and $P_{FP}$ are the energy prices at on and off-peak periods, $Pw(t)$ is the electrical power measured at instant $t$, and $\Delta T$ is the time period between two successive time steps.

On the other hand, the demand cost is the maximum electrical power (kW) achieved during the billing cycle times the demand price ($/\text{kW}$). That cost reflects the utilities’ fixed costs of providing a given level of power availability to the customers and is defined as:

$$C_D = \max_{BC} [Pw(t)] \cdot P_{DM},$$  \hspace{1cm} (16)$$

where $P_{DM}$ is the demand price.

Thus, our proposal consists in model a water distribution system as a finite-horizon MDP and solved it by backup order algorithm. At the end, we will use the optimal policy obtained to control the status of all pumps in the system as function of the time and level of the storage tanks.

4. Experiments

We compared the actual controller and our proposed technique in a real water distribution system, that is simulated in hydraulic simulation software EPANET. This comparison is done to assess potential energy cost reductions, and to verify the proposed modeling and its comprehensiveness.

The hydraulic model from this real system is described schematically in Fig. 2. This system provides water to a population of about 12,000 people, with average daily water consumption of 113 gallons per person, and is composed of one reservoir of potable water ($R_1$), one storage tank ($H_1$), two pumps ($U_1$ and $U_2$), and approximately 32,000 feet of pipes, varying from 20 to 30 inches in diameter.

The storage tank $H_1$ keeps the pressure equalized in the system and helps to supply, jointly with the pumps, the water demand. It has maximum level of 22.5 feet and its accumulation capacity is approximately 1.5 million gallons,
about 90% of the daily water demand on a summer’s day. However, due to constant wild fires in the served region, the utility company restricts the operational minimum level to 15 feet that reduces the tank capacity in 2/3, about 37% of the daily water demand on a summer’s day.

On the other hand, the two pumps are identical, connected in parallel, and driven directly, i.e., they assume just two status: on or off. These two pumps deliver water from the reservoir to the water network. Their characteristic curves are shown in Fig. 3, where the solid line describes the relationship between pump head and flow, also called head characteristic curve, and the dashed line describes the isometric curves of efficiency.

In this paper we assume the possibility to install a VFD to drive the pumps. This equipment allows a smoother starter, controllability of head and flow delivered, maintenance reduction in the pumps, and energy savings.

Data about the pipes in this water distribution system are described in Table 1, where there are information about diameter, length, roughness, initial and final elevation.

<table>
<thead>
<tr>
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<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_1$</td>
<td>30</td>
<td>80</td>
<td>0.15</td>
<td>5.168</td>
<td>5.168</td>
</tr>
<tr>
<td>$L_2$</td>
<td>24</td>
<td>9.872</td>
<td>0.15</td>
<td>5.168</td>
<td>5.064</td>
</tr>
<tr>
<td>$L_3$</td>
<td>27</td>
<td>15.050</td>
<td>0.15</td>
<td>5.064</td>
<td>5.074</td>
</tr>
<tr>
<td>$L_4$</td>
<td>20</td>
<td>5.681</td>
<td>0.15</td>
<td>5.074</td>
<td>5.291</td>
</tr>
<tr>
<td>$L_5$</td>
<td>20</td>
<td>1.250</td>
<td>0.15</td>
<td>5.291</td>
<td>5.140</td>
</tr>
</tbody>
</table>

The consumers are tapped in $J_3$, $J_4$ and $J_5$, according to Fig. 2, and during the summer season present water consumption, also known as water demand, according to Fig. 4. In this curve, it is possible to see two peaks during a 24-hour period, one around 7:00 (morning peak) and another around 20:00 (night peak). Moreover, Fig. 4 also show the uncertainty associated with the demand curve, obtained from historical data and evaluated as the standard
The average demand is around 938 gal/min, with a maximum of 1,299 gal/min, a minimum of 634 gal/min, and uncertainty varying from 3.1% to 5.6.

The experiments have been simulated during one billing cycle, adopted as 30 days, with time step of 6 minutes and level starting at 15 ft in the first day. The energy prices assumed were: \( P_{OP} = 0.03749 \text{[$/kWh]}, \) from 9:00 to 20:59, \( P_{FP} = 0.02831 \text{[$/kWh]}, \) from 21:00 to 8:59, and \( P_{DM} = 18.8916 \text{[$/kW]} \).

About the actual controller, it is based on level and works as follow: when the storage tank achieves 15 ft, one pump is turned on until the level achieves 20 ft; then, this pump is turned off until the level achieve again 15 ft; and after that, the process is repeated but alternating the driven pumps.

On the other hand, the optimized controller is modeled as an MDP, according to Section 3, and with the following characteristics: the storage tank is discretized uniformly in 75 levels, that result increments of 0.1 ft in the range from 15 ft to 22.5 ft; the pumps are considered to be driven by a VFD in uniform increments of 1%, that results in 100 possible actions per pump; the state transition and the electrical power used by the pumps \( P_w(t) \) are obtained by the hydraulic simulation software EPANET, assuming the Darcy-Weisbach calculation method to compute head losses in the pipes (Bhave, 1991); and we assume uncertainty of 3% in network description and 0.1% due to truncation error from EPANET.

5. Results

The simulation results from the controller based on level are shown in Fig. 5. In this figure are presented two curves during the first 24-hours of simulation: level in the storage tank (red curve) and flow discharged by the pumps (black curve).

Fig. 5 also shows a triangular curve to the level in the storage tank. This behavior corresponds to the control cycle, where a positive derivative indicates pump on and a negative derivative indicates pump off. With respect to flow discharge by the pumps it is almost twice the maximum demand, an indicative of oversizing.

On the other hand, the control policy provided by the MDP model from the water distribution system described in Section 4 is shown in Fig. 6. In this figure the ordinate axis refers to the states, in other words, the 75 levels of the storage tank, and the abscissa axis refers to the decision epochs, adopted 24-hour and extrapolated to one billing cycle (same control policy every day during the billing cycle). Moreover, it is possible to see just five optimal actions to driven the pumps using a VFD is this state space: OFF (white region), 80% (light-gray region), 81% (medium-gray region), 82% (dark-gray region) and 83% (black region).

In Fig. 6 it is possible to note the shape of the control policy is corresponded to the demand curve, however, with earlier peaks aiming predict the demand to fill in the storage tank. Further, after certain levels and periods in the day it is possible to operates the distribution network only with the stored water in the tank.
Fig. 5. Experiments results in the first day using a level based controller.

Fig. 6. Control policy provided by the MDP model.

Fig. 7. Experiments results in the first day using a control policy from an MDP.
The results in the first day from the control policy provided by the MDP model are shown in Fig. 7. As Fig. 5 there are also two curves: level in the storage tank (red curve) and flow discharged by the pumps (black curve). The level curve presents crescent characteristic until 18:00 due to a VFD operating between 81% and 82%, after that, the pump is turned off.

The numerical results obtained from these two controllers (level based and MDP) were compiled in Table 2. This table shows four different parameters of comparison: off-peak and on-peak energy, demand and total costs. All of them are related to expenses during a billing cycle and their values are expressed in $/month.

Table 2. Numerical results of the experiments during a billing cycle.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Energy Level expenses</th>
<th>MDP</th>
<th>Percentage difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Off-peak</td>
<td>282.43</td>
<td>261.90</td>
<td>−7.3%</td>
</tr>
<tr>
<td>On-peak</td>
<td>415.56</td>
<td>343.33</td>
<td>−17.4%</td>
</tr>
<tr>
<td>Demand</td>
<td>1,397.90</td>
<td>667.82</td>
<td>−52.2%</td>
</tr>
<tr>
<td>Total</td>
<td>2,095.89</td>
<td>1,273.05</td>
<td>−39.3%</td>
</tr>
</tbody>
</table>

According to the Table 2, the MDP approach produces lower energy expenses in all parameters of comparison. The biggest villain to the level based controller is the demand expense that cost more than twice comparing with control policy from MDP model. Moreover, on-peak and off-peak energy expenses are lower in MDP because it tries to avoid higher levels to store water in the tank.

6. Conclusion

In this paper, we have described a new methodology for optimizing the energy expenses in water distribution systems modeling as Markov Decision Processes. As shown, our methodology have been demonstrated to be effective in reducing the energy expenses in a small municipal water utility. Moreover, this approach respects the restrictions imposed by the distribution network, especially avoiding water outages and pipe ruptures.

The expense reductions obtained are result of the following observations: the pump power is proportional to the cube of shaft speed provided by the VFD (affinity law); on-peak energy expense is avoided when you fill in the tank based on a predict demand; and try to keep tank level as low as possible within certain security margins.

An indirect gain of our proposal is the easy implementation of the resultant control policy in a non-intelligent device (e.g. in a Programmable Logic Controller) as a look-up table, since states are directly mapped in actions.

Ongoing work involves extending our framework to deal with uncertainty in the observation due to noisy readings in the sensors (model the problem as a POMDP), and methods to better represent continuous variables in discrete space states.

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