Integrated Model for Optimizing Strategic Overhaul Planning of Distributed Pump Stations

R. Pascual¹; P. A. Rey²; M. Hodkiewicz³; and C. Cruz⁴

Abstract: An important part of the lifecycle costs for pump stations are the support costs associated with energy and preventive maintenance of the pumps. Both cost terms are interrelated because a trade-off exists between maintaining pumps frequently (with increased pump efficiency, reduced energy costs and increasing maintenance costs, and pump unavailability) and extending the intervals between the overhauls (increased loss of efficiency, increased energy costs, and decreased maintenance costs). The planner needs to forecast pump overhaul demands to determine budget levels because economic resources are limited. This process is assisted by using mathematical programming methods to prioritize funding for equipment requiring renewal in consideration of limited resources in a strategic time horizon (several years). This work proposes an efficient model to define an overhaul maintenance program for a pump network with a large number of pumps (a few hundred in the case study). The model minimizes the discounted total (energy + overhaul) cost by selecting and scheduling pumps for overhaul subject to budget constraints. The formulation uses 0–1 integer programming. DOI: 10.1061/(ASCE)CP.1943-5487.0000085.

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CE Database subject headings: Maintenance; Overhaul; Shop maintenance; Degrading operational efficiency; Finite time horizon; Aging water networks.

Author keywords: Maintenance; Aging (material); Water distribution systems; Pumping stations; Life cycles.

Introduction

Several agencies worldwide have evaluated the amounts involved in maintenance of water distribution networks. ASCE estimated in 2005 a shortfall of US$11 × 10⁹/year to replace aging facilities and comply with regulations (ASCE 2005). Federal funding for rehabilitation was approximately US$0.85 × 10⁹ in 2005 (below 10% of the total requirement) (Alvisi and Franchini 2006). A major increase of resources for rehabilitation and objective decision making on that subject are necessary (Levin et al. 2002).

Energy costs of pumping often dominate direct costs in water utilities. They have been estimated to up to 65% of a water utilities’ annual operating budget (Moradi-Jalal et al. 2004; Boulos et al. 2001; Ormsbee and Lansey 1994). For some utilities, 90% of the total budget is for energy required for pumping (Kim and Mays 1994). Because energy costs often dominate the cost structure, it makes sense to focus the optimization efforts in this cost item. Energy-saving measures can be taken in many ways from continuous monitoring and proper maintenance scheduling to the use of network computer control. Designing and operating pumps to work at optimal efficiency, reducing the required output head, exploiting the energy price variation along the day, and online control systems are also useful measures.

Pump-driven water-distribution systems usually include a suction-side storage tank, piping and valves, pumps, motors and associated electrical power supply, and instrumentation. The pump efficiency is greatly affected by the design and condition of the pump, the design and condition of the system, the selection of an appropriate pump for the system, and how the pumping system is operated. For example, in the process industry, frame-mounted pumps are able to achieve efficiencies in the region close to 80%, but are usually operated in the partial-load regime and obtaining efficiencies less than 30%. For pumps operated in the best-efficiency region of the pump curve, low efficiency can still result owing to wear of internal casing seals and internal surface deterioration.

Wear and other failure modes are handled by the maintenance function that develops a strategy for each pump. They constitute the reason because pump maintenance costs are a significant secondary component (behind energy costs) of an operation budget (Ormsbee and Lansey 1994). Maintenance strategies can be classified as corrective (run to failure), age centered (time), condition centered, and proactive (redesign to avoid occurrence). In the case of pump stations of water utilities, age centered preventive maintenance is often complemented with condition-based maintenance. Vibration and oil samples are analyzed to determine bearing condition and detect a range of potential failure modes.

Maintenance planning can be managed at tactical and strategic levels. Strategic planning is considered in this work. Pump life cycles range from years to several decades. For example, in water-distribution industries, it is usual to have designs that last approximately 30 years considering that main components and surfaces may be overhauled (or replaced) many times.

Life-cycle cost of pumping systems is usually dominated by the energy consumption during the pump operation, the timing of...
overhaul decisions, and the extent of the overhaul work. This situation is very appealing for the application of mathematical programming methods to optimize the budget allocation. Overhaul decisions are strategic because the period for these systems corresponds to multiple years.

The aim of this research is to propose a model that minimizes total costs of a pump station network (energy + overhaul) subject to budget constraints on an annual and strategic level. This paper will present general background and related research in maintenance scheduling, describe the construction of the model, provide assumptions and a mathematical programming formulation, present computational results, and finally, conclusions and future research directions are outlined last.

**Literature Review**

One way to obtain energy cost reductions is to optimize operation scheduling. Darbyshire and Waterworth (2002) developed a pump operation scheduling procedure combining constrained optimization and factorial analysis. The scheduling algorithm uses linear programming. Among the constraints, they consider the variation of the energy costs at different hours of the day. Moreno et al. (2007) provide a programming model to advise the sequence of pump activation that minimizes the total energy cost of the network. Their methodology requires electrical network analyzers, flowmeters, and pressure transducers to estimate pump parameters. The efficiency of the pumping station (which is measured) is a product of pump efficiency, motor efficiency, cables efficiency, variable-speed drive efficiency, and efficiency related to head losses in pump pipes. They found evidence of pump aging affecting the system efficiency. Baran et al. (2005) use multiobjective evolutionary algorithms (MOEAs) to solve an optimal pump-operation scheduling problem with four objectives to be minimized: electric energy cost, maintenance cost, maximum power peak, and level variation in a reservoir. They assume that the maintenance cost of a given pump is proportional to the number of times it has been switched on (and not to the more natural numbers of hours it has been operating). They do not consider budget constraint. Boulos et al. (2001) consider a nonlinear optimization problem that uses genetic algorithms to minimize total energy costs. The decision variables are control and operation parameters of a water-distribution system. In other cases, modeling of the joint problem of system design and operation strategies is proposed. For example, Planells et al. (2005) optimize the total cost (investment and energy costs) in pumping stations. They do not consider maintenance decision-making.

Often, energy costs are a major concern for policy makers. In some cases, it makes a lot of sense to focus on the rehabilitation of the piping system instead. Kleiner (2001) uses a semi-Markov model to schedule rehabilitation and inspections in large buried pipes. Kleiner et al. (2001) propose a dynamic programming approach to plan pipe rehabilitation in a water-distribution network. The model considers structural and hydraulic capacity deterioration. The model is centered in the water mains and water-main reliability. In this case, a complex network interdependence complicates the solution process. Their methodology does not consider energy costs. The design space increases very fast with the number of pipes in the network rendering the problem very expensive to solve. Lansey et al. (1992) and Kim and Mays (1994) present mixed integer non-linear programming (MINLP) models to select the pipes to be rehabilitated or replaced in an existing water-distribution system. They consider pressure requirements and minimize the total rehabilitation and energy cost. Shinistine et al. (2002) use a minimum cut-set method linked to a steady-state simulation model to perform reliability analysis of water mains of distribution networks. They present two real case studies. Alvisi and Franchini (2006) consider strategic scheduling under budget constraint and minimize rehabilitation costs for a pipe network and maximize its hydraulic performance. They use genetic algorithms. Ansell et al. (2004) propose a stochastic dynamic programming model to handle maintenance, repair, and replacement of water purifiers. Their model compares with the model in this study because both models consider virtual [in their case, Kijima’s model (1989)] and operating age of the equipment. Their model focuses on failures and imperfect preventive interventions and is related to corrective and preventive maintenance strategies. This study focuses on the efficiency decay with age.

Several research investigations are available in the literature for overhaul planning subject to budget constraint. Because the decision problem is similar in other maintenance settings, the review extends beyond the water management arena. Bargeron (1995) proposes an integer programming formulation to plan depot maintenance of a fleet of military systems. His model minimizes the average age of the fleet, in which age is a measure of usage and corresponds to the number of miles since the last overhaul. The hypothesis is that readiness decreases with age. Bargeron (1995) considers depot capacity constraints and a required minimum level of availability. In the field of facility management, Frangopol et al. (2004) review probabilistic models for lifecycle performance of deteriorating facilities.

Strategic planning of overhaul interventions in complex networks of engineering assets is, of course, not exclusive to pump stations networks. The problem is seen in other contexts. Chan et al. (2001) use genetic algorithms to solve pavement maintenance problems. Guignier and Manadat (1999) present an integrated model to consider joint optimization of maintenance and improvements of the components of a network of infrastructure facilities. They use a Markov decision model. Davis and Van Dine (1988) propose a linear programming model to allocate limited budget resources for pavement maintenance in a strategic time horizon. They use transition probability matrices to model degradation associated with age and other related variables. A primary difficulty of this approach is the estimation of these matrices because they are obtained from Markov models or through regression analysis of data coming from subjective (expert) opinions. Such preprocessing is usually very expensive in data collection and analysis (Frangopol et al. 2004). In the context of this work, transition probability matrices were disregarded because they substantially increase the modeling effort and were considered unnecessary in a first approach. In the electrical distribution industry, Jiang et al. (2002) propose a risk-based maintenance allocation and scheduling methodology for bulk electric power transmission system equipment. Beyond the problem of preventive maintenance, Qiao et al. (2007) develop a method for allocating a security budget to a water supply network to maximize the resilience of the system to physical attack. Risk containment falls within reach of this work, but this methodology can be extended to handle risks such as a terrorist attack and other high risks. Loerch (1999) developed mixed-integer programming formulations to support decision making related to multisystem acquisition and support programs. The models find the optimal quantity of each system to be procured each year of the planning horizon. They concentrate on procurement costs, but the model may be extended to consider lifecycle costs, including increasing maintenance costs. The decision maker’s dilemma resides in choosing how to optimally schedule the acquisition of these systems subject to budget limitations and other requirements. Each system also has an initial cost per unit, which decreases as
more units of the system are produced. Both models may also be used to negotiate a minimum annual budget program to assure minimal lifecycle costs. Barbarosoglu and Phinas (1995) propose an analytical hierarchy process (AHP) and mixed integer programming model to a water and sewerage administration. Their model includes social, political, and economic criteria. As a first step, AHP quantifies project attributes by weights, which are then used in the objective function of the mixed integer programming (MIP) assignment formulation. Similarly, Son and Min (1998) also use integer programming and AHP in a budget allocation problem in the electrical power industry. Their model takes into account financial and regulatory constraints.

Several decision support systems and projects have been developed such as the pipeline asset and risk management system (PARMS; Moglia et al. 2006), water main renewal planner (WARP; Rajani and Kleiner 2001), whole life costing for water-distribution network management (WILCO; Engelhardt et al. 2002), and computer aided rehabilitation of water networks (CARE-W; Le Gauffre et al. 2007). These applications focus in water-mains rehabilitation. The application of these decision support systems and models for water-distribution networks has been very limited. The reasons for this are: (1) the models are quite sophisticated and their parameters are difficult to estimate; (2) a strong interdependence in the network makes it difficult (expensive) to obtain solutions and consider dynamic situations such as unexpected failures and spare availability; (3) the level of detail of the model is coarse and may not capture the dynamics of the problem; (4) solvers often fall into local minima, giving impractical solutions; and (5) lack of user-friendly interfaces. In conclusion, little previous directly-relevant work exists in developing models to minimize the total costs of pump stations (energy consumption plus overhaul costs) subject to budget constraints. Previous work in the area has primarily concentrated on the risks and condition of the piping rather than on the lifecycle costs of the pumps.

Model Construction

This study considers the following:

1. Strategic planning under-budget constraint over a finite time horizon (a strategic plan is defined for a given number of years).
2. Interest is focused on allocating resources for the overhaul maintenance, which returns the pump to a “good as new” condition and operational efficiency, or very close to it.
3. Unplanned works (owing to failures or triggered by condition monitoring and inspections) are not considered in this study because they represent nondeterministic budget demands and may be treated in the tactical time horizon.
4. The strategic budget must cover the planned maintenance costs of the pumps. This condition is considered as a constraint for the overhaul policy. The overall objective is to minimize total costs (planned maintenance plus energy consumption).
5. All nonoverhaul actions are considered minimal in relation to pump efficiency ($\eta$).
6. At the beginning of the analysis, the elapsed time from the last overhaul is known for all pumps.
7. The energy consumption of a pump is the hydraulic power divided by the pump efficiency. Because pump efficiency deteriorates with pump age, energy required to produce the desired hydraulic power output increases. This increases the energy cost and hence, the operating and maintenance cost.
8. As the calendar time increments, the age and efficiency changes over time.
9. Decisions are made at the beginning of the calendar time period.
10. If the pump is selected for renewal at the beginning of calendar time $t$, it is assumed to go to the shop for a time unit and does not reenter the model until the beginning of calendar time unit $t + 1$. No temporary replacement is assumed when a unit is out for repair.
11. Each pump belongs to a pump class $k$ that is assigned before the beginning of the model and may depend on factors such as design power rate, type of pump (dry well, submersible), age since purchase, cumulative number of overhauls, and utilization factor. The inclusion of $k$ is a key feature in the model. It allows the model user to group pumps with similar deterioration of efficiency profiles into the same class.
12. Each pump class $k$ has a unique relationship between an age-segment period and the pump efficiency. All pumps in a class have the same age-segment period and efficiency relationship that is expressed as a continuous function. Different classes $k$ allow for different rates of deterioration according to predefined values.
13. The efficiency in a single age-segment period is constant and equal to the efficiency at the beginning of the age-segment period.
14. The cost of overhaul is linear in relation to the pump nominal power.
15. For some classes (only the most critical), a periodic condition monitoring program exists that measures instantaneous pump efficiency. These measurements are assumed to not affect the planned overhaul program (because they are scarce) and are mainly useful to adjust the age-efficiency degradation models used to generate the age class and efficiency continuous functions.
16. Shop capability is not limited because overhaul services can be contracted.
17. The model does not consider a replacement after a selected number of overhauls. This may be included in a later version.
18. Pumps with a predefined maximum age (MaxAge) are forced to be overhauled in the next time period. This parameter is used to restrict the size of the design space.
19. Overhaul decision-making is not limited to periodic overhauls.
20. No economies of scale are made for grouping overhauls.
21. Corrective maintenance is assumed to not affect pump efficiency (only overhauls), and the replacement problem is not considered because this study utilizes a renewal process.

Model for Pump Aging

To model the aging effect on pump energy efficiency, this study uses the general Weibull-like model

$$\eta(t) = e^{-((\frac{t}{\beta})^\gamma)}$$

(1)

which shows different aging patterns as shown in Fig. 1 and is used for the case study explained subsequently. Variable $t$ = elapsed time since the last overhaul or replacement; and $\beta$, $t_0$, and $\gamma$ = Weibull parameters. Eq. (1) is considered a general case of the one proposed by Grishko and Polezhaev (1975), in which they only consider the case $\beta = 1$. They propose a model that estimates an optimal for the interval between overhauls for dredging pumps to minimize the global cost, but do not consider the influence of a budget constraint in a pump network. Other references have dealt with the degradation of operation efficiency as a function of wear. For example, Townsend et al. (2003) propose a reliability model in which the effect of age (measured from the last overhaul) affects the mean production rate of a dragline.
Mathematical Formulation

This section describes the proposed model. The simple problem of programming the maintenance for a single pump is described, and then a model for the whole set of pumps is derived with budget constraints.

Planning Maintenance for a Single Pump As a Shortest Path Problem

To introduce the model, it is desirable to optimize the total costs for one isolated pump to avoid a budget constraint. The planning horizon has $T$ periods. A maximum age of $\text{MaxAge}$ is set to all pumps. That is, if a pump has age $\text{MaxAge}$ in period $t$ it should be overhauled in period $t+1$. This does not impose any additional constraint because $\text{MaxAge}$ is defined sufficiently large to be unattained for the considered pump during $T$ periods.

The problem was formulated as a minimum cost flow (actually, a shortest path problem) as shown subsequently. Define the following auxiliary state-time network $N = (V,A)$; the nodes of the network (set $N$) are pairs $(a,t)$ for each possible “age” $a$ of the pump (state) and time period $t$; the arcs correspond to feasible “transitions” for $a < \text{MaxAge}$ and $t < T$; arcs exist from node $(a,t)$ to $(a+1,t+1)$ (“use” arcs); and from any age $a$ and $t < T$, arcs exist from node $(a,t)$ to $(0,t+1)$ (“overhaul” arcs). Add to this network an auxiliary sink that has arcs coming from all $(a,T)$ nodes. Consider the following costs: $c(a,t; a+1,t+1) = \text{energy consumption of a pump of age } a$; and $c(a,t; 0,t+1) = \text{cost of overhauling a pump of age } a$.

The problem can now be stated as finding the shortest path from the initial state $(a_0, 1)$ to the sink in the auxiliary network. Fig. 2 shows an example of this case, the initial age of the pump is 2 and is marked with an entering left arrow, the descending arcs represent periods when the pump is operating (Periods 1, 2, 4, 5, and 6) and increasing arc represents overhaul (in this case, just one overhaul in period 3). The last black arc indicates the age of the pump at the end of the planning horizon (in this case, 3 periods).

Notice that without the budget constraint, the problem of optimizing the total cost for a set of many pumps could be separated in optimizing the maintenance for each separated pump. However, it could yield an overhaul policy more expensive than the funds available for a given time period. Hence, it is necessary to formulate an optimization model which optimizes simultaneously the actions to be carried out for all the pumps.

To do this, the planning model for each single pump is combined with the additional budget constraints. The complete model is presented in the next section.

Complete Model for a Set of Pumps

For the general case, consider the preventive maintenance plan for a set of $I$ pumps identified with an index $i$ ($i = 1, ..., I$). These pumps belong to $K$ classes identified with a label $k$ ($k = 1, ..., K$). When needed, $k(i)$ denotes the class pump $i$ belongs to. The initial age of pump $i$ is $a_0(i)$. The planning horizon spans $Y$ years, each year subdivided into $P$ periods of the same duration. Thus, the planning horizon comprises $T = Y \times P$ periods, $t = 1, ..., T$. $T(y)$ denotes the set of periods corresponding to year $y$ and by $\text{MaxAge}$ the maximum age (in periods) a pump can reach. That is to say, a pump with age of $\text{MaxAge}$ periods should be overhauled in the next period.

Assume that $a_0(i) < \text{MaxAge}$ for any pump $i$, that is, if wanted, all pumps can operate during the first period of planning.

Denote by $B$ the total strategic budget available and by $B(y) = B/(1+\delta)$ the maximum budget for year $y$ ($\delta$ is the excess allowed on the average yearly budget). $\text{PowCost}$ is the cost per power unit per time unit (in monetary units), and $\text{HPCostOvRatio}$ is the cost of overhaul per nominal power unit.

For each pump $i$, $\text{HP}(i)$ is its design hydraulic power and $\text{Util}(i)$ the fraction of the period the pump is actually utilized if not overhauled. Additionally, $\text{IEF}(k,a)$ is the inverse efficiency of a pump of class $k$ with age $a$, denoted by $e^{(\gamma-k)/\text{IEF}(k,a)}$ (see Fig. 1).

With this notation, define the cost of an overhaul for pump $i$ as $\text{CO}(i) = \text{HPCostOvRatio} \times \text{HP}(i)$ and the energy consumption cost of pump $i$ with age $a$ as $\text{CE}(i,a) = \text{HP}(i) \times \text{Util}(i) \times \text{PowCost} \times \text{IEF}(k(i),a)$.

The complete model can be stated as

$$\min \sum_{i=1}^{N} \sum_{t=1}^{T} \left[ \sum_{a=0}^{\text{MaxAge}-1} \text{CE}(i,a)\text{U}_{a,t}(i) + \sum_{a=0}^{\text{MaxAge}} \text{CO}(i)\text{O}_{a,t}(i) \right]$$

subject to

$$\text{U}_{a(i),t+1}(i) + \text{O}_{a(i),t}(i) = 1, \text{ for } i = 1, ..., I$$

$$\sum_{a=0}^{\text{MaxAge}} \text{O}_{a,t}(i) = \text{U}_{a,t+1}(i) + \text{O}_{a,t+1}(i), \text{ for } i = 1, ..., I,$$

$$t = 1, ..., T - 1$$
\[ U_{a,t}(i) = U_{a+1,t+1}(i) + O_{a+1,t+1}(i), \quad \text{for } i = 1, \ldots, I, \]
\[ t = 1, \ldots, T - 1, \quad a = 1, \ldots, \text{MaxAge} - 1 \] (5)

\[ U_{\text{MaxAge},t+1}(i) = O_{\text{MaxAge},t+1}(i), \quad \text{for } t = 1, \ldots, I, \]
\[ t = 1, \ldots, T - 1 \] (6)

\[ \sum_{i=1}^{N} \sum_{t \in T(y)} \sum_{a=0}^{\text{MaxAge}} CO(i)O_{a,t}(i) \leq B(y), \quad \text{for } y = 1, \ldots, y \] (7)

\[ \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{a=0}^{\text{MaxAge}} CO(i)O_{a,t}(i) \leq B \] (8)

\[ O_{a,t}(i), \quad U_{a,t}(i) \in \{0, 1\}, \quad \text{for } i = 1, \ldots, I, \quad t = 1, \ldots, T, \]
\[ a = 1, \ldots, \text{MaxAge} \] (9)

The unknown binary design variables are \( O_{a,t}(i) \) and \( U_{a,t}(i); O = \) overhaul; and \( U = \) usage. Variable \( O_{a,t}(i) \) corresponds to overhauling pump \( i \) (1 if overhauled, but 0 otherwise). Similarly \( U \) corresponds to using pump \( i \) (1 if used, but 0 otherwise).

Constraint Eqs. (3) and (4) ensure the flow conservation for the auxiliary network of pump \( i \); the first ensures that the initial age of pump \( i \) is \( a_0(i) \); the second reflects that a pump overhauled during period \( t \) starts period \( t + 1 \) with age 0. Constraint Eq. (5) represents the aging process: a pump with age \( a \) used during period \( t \) has age \( a + 1 \) in period \( t + 1 \). Eq. (6) forces to overhaul a pump with age equal to MaxAge. Constraint Eqs. (7) and (8) are budget constraints. The left-hand side of Eq. (7) is the overhaul cost for year \( y \), which should respect the available budget \( B(y) \). Constraint Eq. (8) ensures that the whole overhaul cost for the horizon should respect the strategic budget \( B \). Finally, all the variables are binary [Eq. (9)]. In case that \( \sum B(y) = B \), i.e., when the yearly budget has already spent the whole strategic budget, the fifth set of constraints is redundant. These inequalities are included and take into account the more general case of deciding how much of the strategic budget has to be allocated for each year considering a predefined year maximum.

**Case Study**

**Initial Situation and Model Parameters**

The case study considers a water pump network of a midsize city. Overhaul planning is done traditionally by hand and by a group of high ranked engineers at the budget planning unit. The group leader declares that decision-making effectiveness is significantly dependent on the experience and the information available. After the tedious job of information gathering, decisions are quite resource-consuming and the related tasks are performed in periods that may vary from a few weeks up to several months.

To evaluate the effectiveness of the approach, a small case study is designed and solved considering 150 pumps of four classes. The preventive maintenance is planned for 5 years and is divided into periods of three months, i.e., considering a total of 20 periods. MaxAge is set to 40 periods and no pump has initial age greater than 20 periods. Thus, no pump will be forced to be overhauled during the planning horizon. Table 1 describes the value of parameters for the base case, Table 2 gives pump parameters, and Table 3 details the parameters used for the efficiency curves.

**Base Case**

This section describes the experiment in which the problem is solved by using the parameters shown in Table 1.

The model was implemented by using GAMS v.22.7 and solved with XPRESS solver by using MIP (Brooke et al. 1998). The program was run on a 2.2 GHz AMD Turion 64 CPU PC with 1 GB RAM. Computing properties are shown in Table 4 for the base case.

<table>
<thead>
<tr>
<th>Table 2. Pump Parameters</th>
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<tbody>
<tr>
<td>Class</td>
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<tr>
<td>1</td>
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<table>
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<th>Table 3. Efficiency Curves Parameters</th>
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<td>Class ( k )</td>
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<td>2</td>
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<td>4</td>
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The model was implemented by using GAMS v.22.7 and solved with XPRESS solver by using MIP (Brooke et al. 1998). The program was run on a 2.2 GHz AMD Turion 64 CPU PC with 1 GB RAM. Computing properties are shown in Table 4 for the base case.
Given this problem size and linear nature, the solution process is relatively fast, as expected.

**Optimal Overhaul Program**

For example, Fig. 3 shows the resulting overhaul program for Pump 1, which in general, had no repairs at the end of the last operational cycle of the pump. This lack of overhaul contributes to decreased maintenance costs and therefore, global cost. For this case study, at the end of the time horizon, pumps are left “as old as possible.”

**Budget Usage**

After the last operational cycle of the pump, overhaul is not needed because the cost of repairing is greater than operating. This solution is particular for the selected time horizon. Overhaul is postponed to the next evaluation period. The budget savings in the last operational cycle can be seen in Fig. 4 as a decrease of yearly budget the next evaluation period. The budget savings in the last operational cycle of the pump. This lack of overhaul contributes to decreased maintenance costs and therefore, global cost. For this case study, at the end of the time horizon, pumps are left “as old as possible.”

**Sensitivity Analysis**

Sensitivity analysis is performed by varying the parameters related to strategic budget, budget flexibility, and energy cost increase, respectively. First, different values are assumed for the strategic budget $B$ in the range of €2.5–5 million to analyze the effects of the budget constraint. The second experiment considers several values for δ to analyze the effect of flexibility in allocating the strategic budget along the years ranging from fixed budget for each year from $δ = 0$ to $δ = 1$, which means that it is possible to allocate for one year as much as the double of the equal annual budget case.

Then, it is considered that energy cost rises at a fixed rate $ρ$, whereas the other parameters remain in their base value. The last series of experiments shows how global cost varies with mean time between overhauls (MTBO). The idea of these experiments is to evaluate the impact of rising energy costs because it is a very likely scenario in the long-term. Next, each set of experiments is described in details and the results are reported.

**Effects of Strategic Budget Variations**

For this set of experiments, all the values in Table 1 were fixed and the strategic budget values were in the range €1–5 million.

Fig. 5 shows how total cost decreases as the strategic budget increases until $B$ reaches the value at which the budget constraint becomes inactive. Normalized global cost equals the global cost divided by the minimum possible global cost, and normalized strategic budget equals the overhaul cost of the base problem without considering budget constraints. This last value was calculated and corresponds to €3,321,500.

If the budget is raised from €1–3 million, total cost decreases approximately 6% because of savings in electrical costs. On the other hand, if a sufficient level of budget is given, approximately €3.5 million, cost decrease becomes negligible. When the normalized budget is 1, normalized cost is not exactly 1 because of the yearly budget constraint.

From the side of the decision maker, raising the strategic budget means that it is possible to do more overhauls. Although doing fewer overhauls, electrical costs increase owing to aging pumps. Time between overhauls is shown to be more sensitive to budget variations, with differences in this figure up to 300%.

**Effects of Flexibility on Allocation of the Strategic Budget**

For this set of experiments, all the values in Table 1 were fixed and δ values were in the range $[0, 1]$. When $δ = 0$ the strategic budget is distributed in equal parts for each year, and if $δ = 1$, the model can allocate up to double for each year. The initial budget used in this

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**Table 4. Computing Properties**

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
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<td>Number of constraints</td>
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<tr>
<td>Number of nonzero elements</td>
<td>828,006</td>
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<tr>
<td>Iterations</td>
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<tr>
<td>Cost</td>
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<tr>
<td>LP relaxation</td>
<td>18,444,654.73</td>
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<tr>
<td>Computing time (s)</td>
<td>51</td>
</tr>
</tbody>
</table>

**Fig. 3. Optimal program for pump Number 1**

**Fig. 4. Base case, budget usage by year**

**Fig. 5. Normalized global cost versus normalized strategic budget**
set of experiments corresponds to the aforementioned €3,321,500 and is denoted as $B_0$. Then, different values of $B/B_0$ were used. Owing to integer characteristics of the problem, curves do not seem like continuous functions.

The effect of rising $\delta$ in Fig. 6 is similar to the effect for strategic budget, except that global cost is less sensitive to variations. When $B/B_0 = 1$, the maximum variation is below 0.1%. After $\delta = 0.3$, global cost becomes inactive. The effect of delta variations increases as the budget is reduced. If $B/B_0 = 0.5$, variation between minimum and maximum value is below 0.8%. These values are not enough significant to be considered on a real cost optimization.

Effects of Rising Energy Costs

For this set of experiments, all the values in Table 1 were fixed and the energy cost for period $p$ was PowCost $\times (1 + \rho)^{p-1}$. Discount rate $\rho$ takes values in the range 0–0.05. The maximum value 0.05 corresponds to increasing energy cost of approximately 22% per year. Fig. 7 shows how total cost increases as the energy cost rate is higher.

It was observed that global cost grows slightly faster than linear when compared with growing rate $\rho$. Although electrical costs increase, more overhauls are needed. In this case, time between overhauls decreases in the range 0–0.005 when the budget constraint is reached. After this value, repairs relatively keep their frequency. Minimal variations are attributed to different overhaul assignments.

Effects of MTBO Variations

The sensitivity curve of normalized global cost versus mean time between overhauls (MTBO) is constructed. Every point is a solution of the problem depending on restriction parameters. The right side of the optimum point is constructed and alters the strategic budget. As the budget is raised, more repairs are executed and decreases MTBO. Meanwhile, the left side of the curve is made, decreases the maximum operation age MaxAge, and forces pumps to be repaired.

Fig. 8 shows how normalized global cost reaches the optimum as MTBO is varied. The lowest global cost point represents the condition for which the maximum age MaxAge and budget are high enough to avoid interfering with the most suitable program of operation.

Conclusion

A novel model has been introduced to decide overhaul actions on networks in which aging causes efficiency degradation and consequently, increased energy costs. The exploitation of the model presented in this work may report significant economical and technical strategic benefits to any company that manages fleets of hybrid equipment subject to operational efficiency degradation as a function of age. This case study considered a public water company operating several kinds of pump systems. From a technical point of view, subjectiveness is reduced thanks to the use of objective performance measures such as the total cost. The development of a mathematical model to assist decision-making certainly facilitates the strategic overhaul planning process.

Sensitivity analysis is facilitated because the modeler only has to change model parameters and launch computations, which are very fast owing to the linear nature of the model and the relatively small number of variables and equations. In such a way, decisions may be taken with a clearer view of risk and adaptation for scenario planning.

The model may also be used to develop budgets based on a forward estimate of the pump overhaul schedule aimed at minimizing total costs.

The approach proposed is computationally economic and efficient. It is easy to implement and solve by using standard programming packages. It avoids utilizing the more expensive genetic algorithm approaches seen in the literature.

The problem of jointly deciding pipe rehabilitation and pump overhauls has been avoided because they often appear in different cost or decision centers, and each one is, undoubtedly, complex to solve. Work is needed in this area because both problems compete for the same funding.
References
