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Critical Elements Analysis of Water Supply Systems to Improve Energy Efficiency in Failure Scenarios

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Abstract

Water supply systems (WSS) are significant energy consumers, which makes it crucial to find methods to increase energy efficiency. A novel approach is presented here to locate and quantify the most vulnerable elements in terms of energetic efficiency. The method is based on a linear programming (LP) optimization model and the elimination of different components in the system to analyze their impact on energy costs. Pump reallocation is then suggested as a novel dynamic design paradigm for temporary changes in the system to cope with extreme scenarios. Exposing the critical components of WSS improves maintenance prioritization and inventory and contributes to the planning of future investments in the system. Pump reallocation provides an innovative approach for response to critical conditions, it is suggesting rethinking the design concepts to incorporate not just long-term solutions but also rapid, temporary steps in response to failures.

Keywords Water supply systems · Optimization · Unavailability · Operation under failure · Linear programming · Vulnerability

1 Introduction

1.1 Problem Statement

Water supply systems (WSS) consume significant amounts of energy. It is estimated that water-related energy consumption accounts for roughly 4% of the total electricity consumed in the U.S (Copeland and Carter 2017) and 7% of the electricity produced worldwide (Wakeel et al. 2016). Upwards of 70–80% of this energy is used for pumping, (Vakilifard et al. 2018). The intensive energy consumption yields challenges such as high electricity costs and sustainable management. Thus, water companies are making efforts to enhance their energy efficiency in different ways. These include system design

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optimization (Wang et al. 2021), pump scheduling (Dini et al. 2022), leakage control (Meseguer et al. 2014), pressure management (Creaco et al. 2019), demand forecasting (Pesantez et al. 2020), pump operation optimization (Mala-Jetmarova et al. 2017), and predictive maintenance (Kiliç et al. 2017; Liu et al. 2022). Although these forms of WSS management are interrelated, most studies have treated them separately. Similarly, most water companies have different departments for design, operation, and maintenance. Splitting the energy efficiency issue into separate problems curtails efforts to optimize energy efficiency. In the current study, a multidisciplinary approach is presented that combines design, operational, and maintenance factors to increase the energy efficiency of WSS. The first section presents a method to determine the most critical elements in WSS for energy efficient operation. Then, a novel design approach is suggested for the reallocation of pumps that can be used for crisis situations involving pump failure, and in routine operations.

1.2 Operation Under Pumps Failure

WSS management includes dealing with interruptions and failures. Interruptions can be due to planned events such as periodic maintenance or caused by unexpected events such as technical failures, extreme weather events, etc. (Turner et al. 2012; Aghapoor Khameneh et al. 2020). Different pumps' failures have different impacts on system performance depending on their location, timing, and duration. The consequences of pump failures range from expensive emergency operations to unexpected water outages (Wang et al. 2012). Clearly, one way of minimizing the impact of pump failures is trying to prevent them by adopting predictive maintenance (PM) strategy (Berge et al. 2014). When pumps fail or other interruptions occur, the most typical solution is to adopt a three-pronged approach consisting of (1) locating the failure, (2) adjusting the operational plan to the new conditions, and (3) recovering availability (Butler et al. 2017). Within this scope, Zhuang et al. (2012) presented a method to quantify the resilience of systems (e.g., time to recover) and how it can be improved by adaptive pump operations. Berardi et al. (2014) quantified the vulnerability of systems as loss of service. Khatavkar and Mays (2019) examined system operations by comparing demand and pressure requirements fulfillment under critical conditions and normal conditions to classify the most critical scenarios. Another approach to estimating system functionality in cases of failure is to eliminate specific components (pipes, pumps, tanks, etc.), and then quantify the impact of each component on the system (He and Yuan 2019; Abdel-Mottaleb and Walski 2021).

All the aforementioned studies quantified the impact of failure through service metrics with a focus on volume not supplied. Even though continuity of supply is the most important metric of WSS, in real-life, small failures and maintenance works are a matter of routine. Under these conditions, the supply is indeed maintained (due to system design with appropriate redundancy), nevertheless, system efficiency is damaged by the partial availability of pumping equipment. This subject of quantification of energetic impact of failure scenarios is addressed here for the first time, aiming to rank systems' pumps according to their energetic vulnerability, quantify the efficiency loss due to pump failure, and try to minimize the efficiency reduction.

1.3 Pumps Reallocation

The problem of determining elements dimensions and topology of WSS are typically addressed as a design problem (Qiu et al. 2020). One sub-class of the design problem relates to the redesign of an existing network, which involves adding, replacing, and upgrading pipes, tanks, pumps, etc. (Mala-Jetmarova et al. 2018). For example, problems of system strengthening relate to the network capacity to meet increasing demands (Dandy et al. 1996; Minaei et al. 2020). Other redesign problems focus on the rehabilitation of aging systems (Jin et al. 2008; Kanta et al. 2012). Design studies dealing with pumps' specifications were presented by Walters et al. (1999) and Lee et al. (2016), where the goal was the minimization of the overall cost of design and operations, similar to most design optimization studies which tend to concentrate on finding long-term design solutions.

The current study addresses both the described above issues, of locating critical system components and suggesting immediate pump reallocation solution in case of a failure. The novelty of this approach lies not in its optimization methodology but rather it is the system analysis point of view. While many studies have quantified vulnerability in terms of loss of supply, the impact of pumps' failures on energetic efficiency has not been addressed before. Here the vulnerability is measured by additional energy costs caused by failures. Another contribution of the presented paper is the dynamic design strategy of reallocating pumps to overcome failures and extreme events. This approach can reduce the cost of crisis events through immediate short-term steps to restore efficiency as well as supply continuity, service pressure, etc.

The remainder of this paper is organized as follows: the next section presents a detailed description of the methodology with respect to other methods that have been used to optimize WSS operation. The following sections present case study analyzing two failure scenarios: individual pumps' failures, and pumps' pairs failures. The discussion centers on insights for policy makers and water companies.

2 Methodology

The methodology is based on an optimal operation model that finds the optimal pump scheduling for a given pump's availability configuration. Optimal operation models are one of the most extensively researched areas in the field of water resources, as reviewed by Lansey (2007) and Mala-Jetmarova et al. (2017). The problem can be formulated as a mixed-integer-non-linear problem, MINLP, (Gleixner et al. 2012). Nonlinear optimization, however, is NP-Hard, where an efficient solution is not available. That is why many simplifications of the problem have been suggested, such as mixed-integer linear programming (Salomons and Housh 2020), dynamic programming (Zhang and Zhuan 2019), and heuristic modeling (Dini et al. 2022).

Here a linear programming (LP) formulation, to which an efficient solution is available was used. Under this formulation, there are no limitations on the network size, or the operational horizon, and the solution is guaranteed to be the global optimum. In addition, the linearization of the WSS operation problem does not necessarily decrease accuracy dramatically (Zhou et al. 2019; Moazeni and Khazaei 2020).

The formulation is based on Jowitt and Germanopoulos (1992) approach, which is based on the discretization of the hydraulics of the network into a finite number of possible states. To this end, every pumping station is characterized by a set of operational states with their

Table 1 Pumping station hydraulic discretization

Flow (m^3/hr)	Power (KWhatt)	Unit 1	Unit 2	Unit 3
2,970	1,602	1	0	0
2,672	1,342	0	1	0
2,859	1,621	0	0	1
5,422	2,984	1	1	0
⋮	⋮	⋮	⋮	⋮

respective flow and power values. An example of discretization is presented in Table 1. The data for discretization can be extracted from a hydraulic model or real measured data.

The mathematical formulation of the LP divides the simulation duration into discrete time intervals, which in this case were one hour long. The decision variables represent the portion of time steps in which each operational state is operated. The operational state is the combination of ON pumps in each pumping station, each state is characterized by flow and power (Table 1). A decision variable is assigned for every combination of pumping station, state, and time step.

The network topology consists of a set of hydraulic pressure zones such that each zone is associated with a storage tank that determines the zone's pressure. The demands in each zone are given by a single aggregative consumer, and water can flow between neighboring zones through pumping stations or valves. The pumping stations and valves also define the network connectivity, such that each station and valve constitute the inflow or outflow elements (noted *i* and *o* respectively) of the pressure zones according to their flow direction. At any given time, the mass balance at each zone must be maintained such that the sum of inflows, outflows, and demands must be zero.

Let $x_{t,p,c}$ be the portion of the time step (t) in which pumping station (p) is operated with state c. Let $v_{t,s}$ be the water volume at time t in storage tank s, $vl_{t,j}$ is the flow at time t in valve j, and $d_{t,s}$ is the demand from tank s at time t. Since wells can be treated as pumping stations with a single pump, the notation (p) also relates to wells. $SP_{p,c}$, $Q_{p,c}$ denote the specific power (kWhr/m^3) and flow rate (m^3/hr) of the pumping station (p) when activated with state (c) respectively. $Elec_t$ is the electricity tariff at time step t. T is the total simulation duration, P is the number of pumping stations and C is the number of states of a pumping station. Given these notations, the objective function is the sum of the energy costs of all the time steps and pumping stations is given by:

$$Z = \min_{x} \sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{c=1}^{C} x_{t,p,c} \cdot SP_{p,c} Q_{p,c} \cdot Elec_t \tag{1}$$

The optimization aims at minimizing the operational cost subject to several constraints. The first constraint is the mass balance at every tank. This constraint forces the model to supply all the required demands and ensures mass conservation over time. The volume pumped by a pumping station in a single time step is given by the multiplication of the duration of the operational state by the respective operational state flow. For example, pumping station (p) at time (t) pumps: $\sum_{c=1}^{C} x_{t,p,c} \cdot Q_{p,c}$. This expression considers the general case where a pumping station can operate in more than one state in each time step (half-hour state A and half-hour state B). The volume delivered through a valve (j) at time (t) is: $vl_{t,j}$. To generalize these expressions for each pressure zone, all the pumping stations and valves that deliver water into a pressure zone are summed as inflows, and similarly with outflows, as negative addends. The term $\left(v_{t-1,s} - v_{t,s}\right)$ represents the change in the tank's volume, $d_{t,s}$ is the overall demand in the pressure zone at time step (t), and s_i and s_o represent the inflow and outflow elements of each storage tank, respectively.

$$\sum_{p\in s_i}^{p}\sum_{c=1}^{C} x_{t,p,c}\cdot Q_{p,c} + \sum_{vl\in s_i}^{vl} vl_{t,j} - \sum_{p\in s_o}^{p}\sum_{c=1}^{C} x_{t,p,c}\cdot Q_{p,c} - \sum_{vl\in s_o}^{vl} vl_{t,j} + \left(v_{t-1,s} - v_{t,s}\right) = d_{t,s} \quad \forall t \in T, \forall s \in S \tag{2}$$

To maintain tanks' volume within the feasible range, the volume at every time step was set to be between predefined values.

$$v_{s,min} \le v_{t,s} \le v_{s,max} \forall t \in T, \forall s \in S \tag{3}$$

A general formulation of the problem requires the definition of initial and final tank volumes. The formulation used in this study only requires the definition of the initial volumes, since the final volumes are defined to be greater than or equal to the initial values by the following constraint:

$$v_{0,s} \le v_{T,s} \forall s \in S \tag{4}$$

The variables $x_{t,p,c}$ indicate the activation portion from a time step with size t of a pumping station (p) operated in state (c). Therefore $x_{t,p,c}$ must be between 0 and 1, and the sum of all activated combinations at any time step must also be between 0 and 1.

$$0 \le x_{t,p,c} \le 1 \forall t \in T, \forall p \in P, \forall c \in C \tag{5}$$

$$0 \le \sum_{c=1}^{C} x_{t,p,c} \le 1 \forall t \in T, \forall p \in P \tag{6}$$

Hydraulic valves regulate the flow between zones. The valves can conduct water in both directions within a maximum flow range, as shown in Eq. (7).

$$-vl_{j,max} \le vl_{t,j} \le vl_{j,max} \forall t \in T, \forall j \in J \tag{7}$$

where $vl_{t,j}$ is the flow of valve j (m^3/hr) at time t and $vl_{j,\,max}$ is the maximum feasible flow that can be delivered through the valve.

2.1 Case Study

The methodology is illustrated on a regional cascaded WSS inspired by a real network. The network consists of two parallel series of pumps and tanks arranged in four hydraulic steps. Most of the water is consumed in the last and highest step. Accordingly, the goal of the pump-tank series is to overcome the significant height difference between the water source and the demand center. The network consists of eight pumping stations denoted by PS_k^N, where N indicates the pump-tank series, (North or South), and k represents the hydraulic step of the series, [A, … D]. Each pumping station has multiple (3–7) pumping units (labeled with serial numbers). The network has seven tanks, marked with similar indices as the stations. The first two stations (PS_A^N and PS_A^S) are assumed to pump water from an unlimited source. Three groups of wells (W_A^S, W_B and W_D) situated at different steps of the

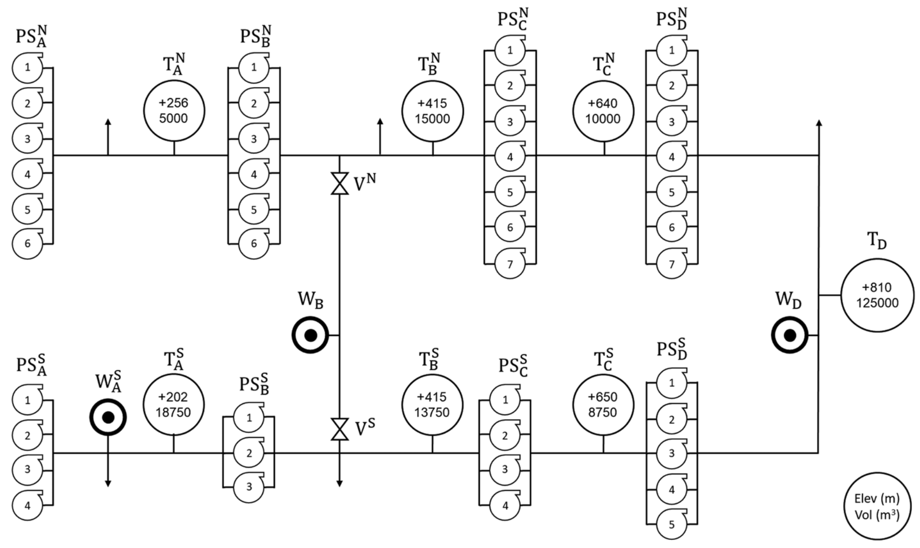

Fig. 1 Case study network layout

cascade, thus adding up to 20 wells for the entire system. The network layout is presented in Fig. 1.

The configuration of the case study network requires an expansion of the mathematical formulation. The pipeline between the two pump-tank series is associated with tanks (T_B^N and T_B^S) with a similar water level on both its edges. The flow between the two series and from the wells in group W_B are regulated by two valves V^S and V^N. Since both edges of the pipeline are associated with a similar hydraulic head, water cannot flow from one side to the other unless the pumping stations at step B are operated. The flow through each valve must be less or equal to the flow of the pumping stations up to the valve, see Eqs. (8) and (9). The valve flows (notated with $vl_{t,j}$) can have negative values, where the positive direction is from south to north.

$$vl_t^S \leq \sum_{c=1}^{C} x_{t,PS_B^S,c} \cdot Q_{t,PS_B^S,c} \forall t \in T \tag{8}$$

$$-vl_t^N \leq \sum_{c=1}^{C} x_{t,PS_B^N,c} \cdot Q_{t,PS_B^N,c} \forall t \in T \tag{9}$$

The electricity tariff structure includes three different tariffs: low, mid, and high with different rates according to the electricity supply voltage. The tariff varies throughout hours of the day and days of the week. Detailed tariffs are in the supplementary data. Due to a lengthy low tariff during the weekend, and the demand pattern that has a weekly cycle, the operation horizon must consider at least one week forward. Another feature of the network is the large number of controlled elements, which constitute the decision variables of the problem. Combining the long operation horizon of 168 h with many decision variables results in a very large optimization problem which provides a further justification for using the LP formulation.

2.2 Operation Under Pumps Failure

Once an optimization model is defined, it is used to examine different pump availability scenarios. To model disabled pumps, new constraints are added to the problem which bounds the operation time of the disabled pumps to be zero. Following the constrained optimization theory, if the disabled pump was not in use before the new constraint, the new constraint is not binding, and the objective value is not expected to change. Otherwise, the new constraint will bind the problem to a worse solution. If one pump's contribution is larger, the disabling of this pump will constrain the optimization problem more tightly, resulting in a worse objective value. This principle serves to identify the most vulnerable pumps since it shows the additional costs that result from different failures. The failure scenarios include the unavailability of individual pumps and each possible pair of pumps. The scenarios are compared based on the total operational costs. In scenarios where only a single pump is disabled, the comparison is simple since each pump is associated with its respective failure cost. To estimate pump's criticality in multi-pump failure scenarios, a criticality index, *CI*, was developed. The index estimates the contribution of a single pump to the overall efficiency by calculating the average cost of all the scenarios in which the pump was disabled.

$$CI(PS.\#) = \frac{1}{|U|} \sum_{i \in U} Z_i \tag{10}$$

where U is a set of all scenarios in which the pump PS.# was disabled, Z_i is the cost of scenario i, and |U| is the size of the set U. The criticality index points to the pumps that are involved in the most expensive and hence least efficient scenarios. For convenience and readability, the index is normalized between 0 and 1.

2.3 Pumps Reallocation

The failure scenarios exposed topological bottlenecks that constitute weak operational spots. A complementary stage is to find ways to reallocate pumps to restore energy efficiency. To do so, two pump replacement scenarios were simulated. The first involved replacing an old pump with a new one. The second looked at a pump failure and the emergency solution of taking a pump from another station to replace the damaged one to temporarily deal with the lack of flow capacity caused by the failure.

3 Results

3.1 Analysis of Routine Network Operation

The simulation duration was 168 h (one week) starting Sunday at midnight (the work week starts on Sunday) with the tanks filled to 90%. First, a single run with all pumps was conducted. Figure 2 presents the results for the volume at tank T_D throughout the simulation. As expected, the tank was filled during the low tariff period (green background), at a lower rate during the mid-tariff periods (yellow background), and emptied during the high tariff periods (red background). The weekend's sequence of low tariff hours was utilized for moderate filling, which enables lower power consumption. The result of this basic run

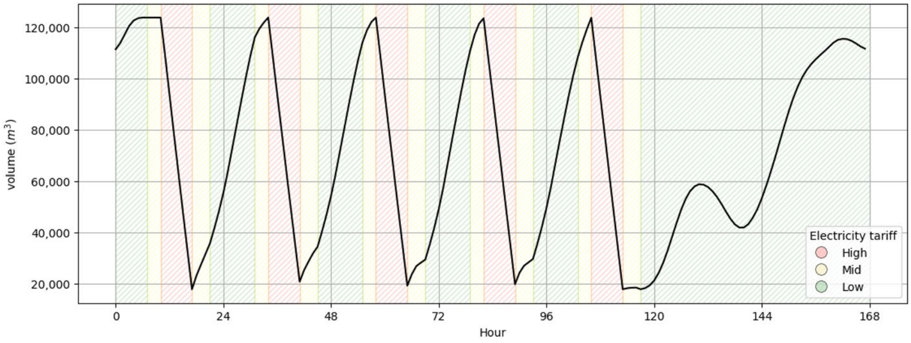

Fig. 2 Tank D volume with all pump units available

thus constituted a benchmark for the failure scenarios. The benchmark energy cost was \$551,961.

Figure 3 illustrates the hydraulic discretization described in the methodology section. It shows all the possible operating states for each pump station. The horizontal axis represents the stations' flow rates (m^3/hour). The vertical axis represents the specific power (kW/m^3). The color code represents the total activation time during the benchmark simulation. The subplots inside Fig. 3 are ordered according to the network layout such that water is pumped from left to right starting from stations PS_A^N and PS_A^S. The bottom subplots show that the first two stations in the south series (PS_A^S and PS_B^S) have more than double of flow capacity than the last two stations (PS_C^S and PS_D^S). While PS_A^S and PS_B^S operate in the range of 6,000–20,000 (m^3/hour), where PS_C^S and PS_D^S maximum flows are less than 10,000 (m^3/hour). This disparity means that some of the water from the south series is delivered to the north series by utilizing the connecting pipeline in step B.

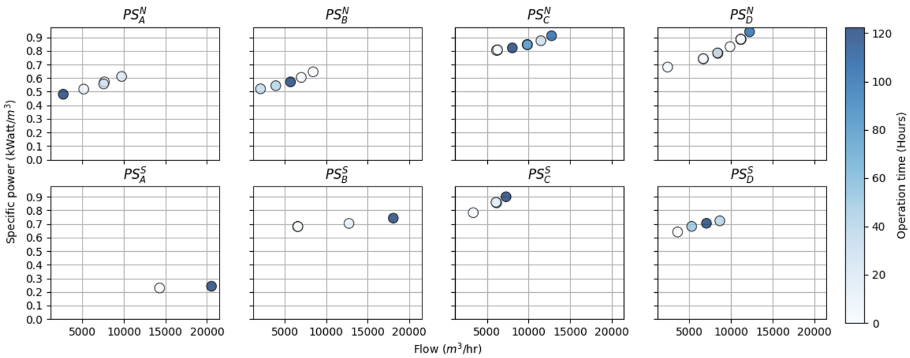

Fig. 3 Stations' operation states and activation time

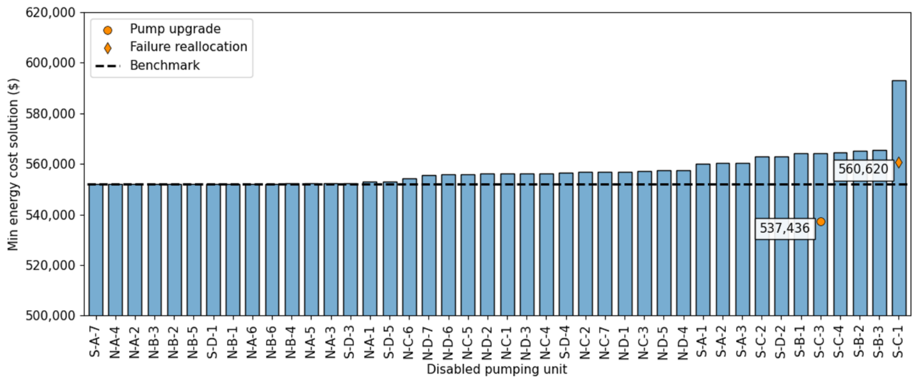

Fig. 4 Operational costs in the case of a single disabled pump unit

3.2 Results for the Operation Under Pumps Failure

The results for the failure scenario simulations are shown in Fig. 4 (single pump disabled) and Fig. 5 (pump pairs disabled). Disabling lasted for the duration of the entire simulation.

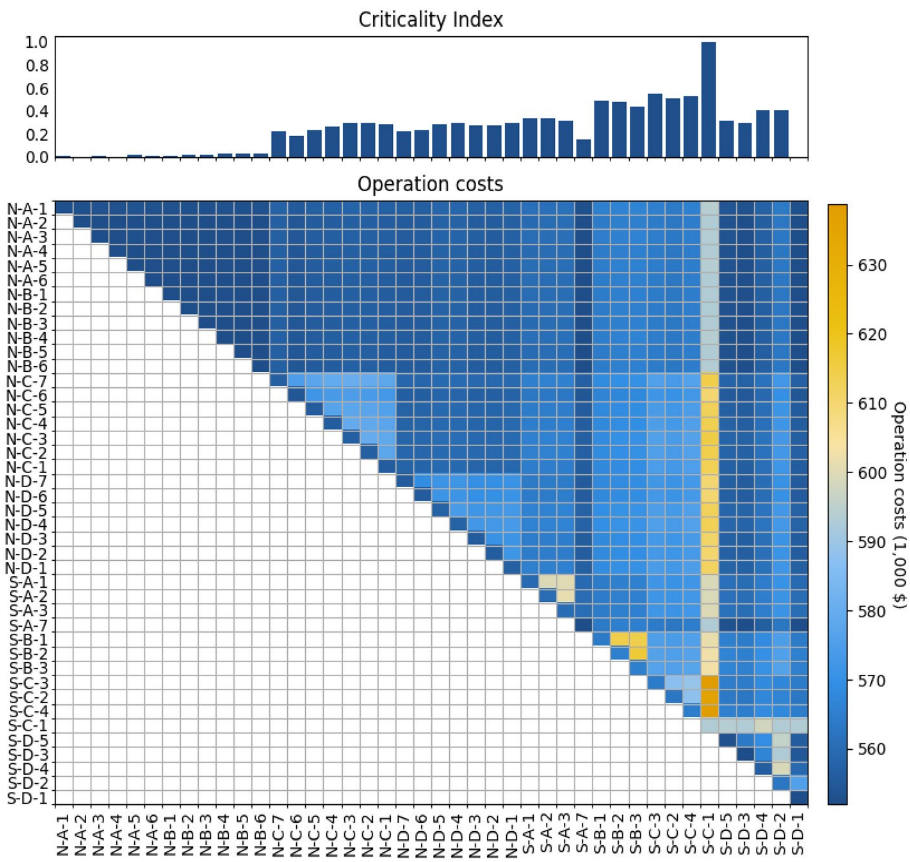

Fig. 5 Optimal solutions with disabled pump pairs and the criticality index

In Fig. 4, the black dashed line shows the benchmark operational costs when all pumps are available. Each bar represents a failure scenario with the respective pump in the horizontal axis disabled. The bars represent the operational costs, and the orange markers show alternative scenarios with pump reallocation (see below). The results clearly show that some pumps do not affect operational cost at all whereas others affect it dramatically. The left side of the chart mostly depicts pumps from stations PS_A^N and PS_B^N, which testifies to the robustness of these stations, as reflected by the stability of the solution regardless of the units that were disabled. The other side of the chart shows the pumps that are the Achilles' heel of the system. For example, of the five pumps that raised operational costs the most, three are at the same station. One noticeable case is pump 1 in pumping station PS_C^S. A failure in this pump will cause a 7.5% increase in energy costs leading to a total cost of \$593,223 per week. Other vulnerable pumps will increase the costs in the range of 2–2.7% (total of \$563,512-\$566,802) if they fail. Insights of this kind can improve maintenance and inventory plans. Additionally, the system development plans should be adjusted to strengthen the weak spots.

The second scenarios set involved simultaneously disabling pump pairs. The results are presented in Fig. 5. In the heatmap, the system pumps are depicted on both axes. Each square in the heatmap represents a scenario where the corresponding pumps are disabled. The color of the squares indicates the operating cost for that scenario. For example, the grey square where the vertical axis equals S-C-1, and the horizontal axis equals S-D-1 (bottom-right area) indicates an operating cost of about 595,000 \$ which is the equivalent of 7.7% more than the benchmark cost. The diagonal squares, where both indices refer to the same pump, correspond to the scenario where an individual pump is disabled. To analyze the effect of a second disabled pump systematically, and to quantify how critical a pump is to the overall efficiency, the criticality index described above (Eq. (10)) was used. The upper subplot in Fig. 5 presents the criticality index where each bar is the normalized average of all the heatmap squares in the corresponding row and column (rows and columns with the same indices).

The second scenario set confirmed the results of the first. Figure 5 shows higher costs in the lower right portion, which represents the south pumps series. As in the first scenario set, pump 1 in pumping station PS_C^S is salient as the most critical pump of the system. The composition of the pumps in PS_C^S combined with the station's location makes pump 1 a critical element for the entire system. As shown in Fig. 3, the flow capacity at this point narrows down and generates a bottleneck. Pump 1 is the largest in PS_C^S, so that disabling this pump will degrade the station's capacity the most. Any decrease in the capacity of the system forces the transmission of water through less efficient paths, thus reducing system efficiency. Figure 5 also shows the effects of disabling two pumps in the same station. The axes of Fig. 5 group pumps from the same stations together so that pumps in the same stations are near each other. Squares immediately above the main diagonal represent two pumps from the same station. Figure 5 shows that these squares have lighter colors, i.e., higher operating costs. For example, in station PS_C^N each pump by itself has a small effect on the costs (dark blue) whereas disabling two pumps results in higher costs (light blue). Typically, pumping stations are designed with some amount of redundancy such that a failure in one unit will not stop supply. Here the supply can be maintained even when two pumps in the same station are disabled, but in some stations, the price of the second pump is significantly higher. Overall, the south series is much more vulnerable to the system's energetic efficiency, which can be seen in Fig. 5. The same conclusions can be derived from the criticality index which identifies pumping station PS_C^S as the most vulnerable station, and pump 1 as the most vulnerable in the system. The remainder of the south series stations are ranked right below PS^S_C. One possible explanation for the difference between the two series is the different configurations of the stations. The south series stations have fewer pumps with larger flows. This makes the south series stations more vulnerable to the loss of a pump. For practical uses, the second disabled pump reveals which pumps must be kept available in the case of a first failure.

3.3 Pumps Reallocation

Based on the analysis of failure scenarios pumps reallocation is suggested. As described above, station PS^S_C is a bottleneck in the south series. Pumping stations PS^S_A and PS^S_B are the most efficient stations in the system, with significantly high flows and low specific power (Fig. 3). Therefore, the best operational strategy would be to utilize stations PS^S_A and PS^S_B as much as possible but given the lesser capacity of station PS^S_C some of the water is shifted to the connecting pipeline between the two series which results in a longer flow path and a drop in efficiency. The best solution will be to upgrade the flow capacity at the bottleneck, i.e., station PS^S_C. The station has four parallel pumps, three of which are identical and one (unit 1) is significantly larger. The curve of unit 1 has larger flow rates and smaller heads than the other three pumps. Eliminating this pump would decrease the station flow capacity significantly and affect the entire system. The curves of all the pumps in station PS^S_C are shown in Fig. 6. The figure shows the four existing pumps, noted as units 1–4, and another curve of an alternative pump. As mentioned

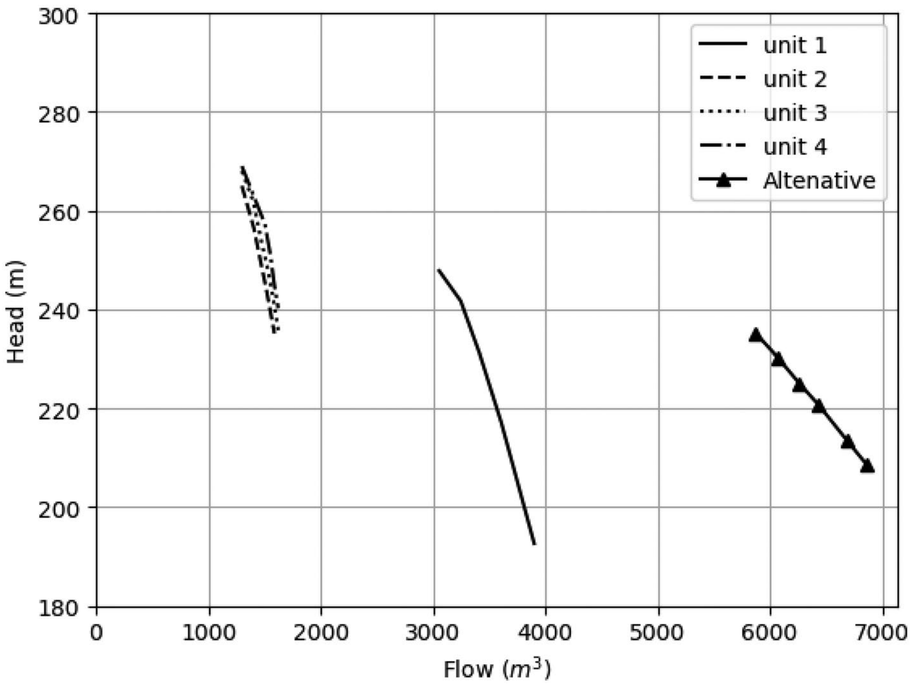

Fig. 6 Pumps' curves at pumping station PS^S_C

earlier, units 2, 3, and 4 are approximately the same size whereas unit 1 can deliver more than twice the flow rate. This difference is what makes unit 1 so critical since without it the station loses 30% of its flow capacity. The alternative unit curve is similar to the curve of pump 2 from station PS_B^S. This unit was used for the pump reallocation scenarios. Given that the limiting factor of the system is the bottleneck in station PS_C^S, it can be seen how the alternative pump can lessen this criticality by increasing the flow capacity of the station.

The alternative pump was used for both pump reallocation scenarios. The first scenario involved replacing one of the small pumps in station PS_C^S with another pump. In this case a pump similar to pump 2 from station PS_B^S was installed in station PS_C^S instead of one of the small pumps. The second scenario involved relocating a pump in the case of failure. Assuming the failure is in the most critical pump (pump 1 in PS_C^S), pump 2 from station PS_B^S replaces the disabled pump in PS_C^S. These two scenarios illustrate the different ways of palliating system vulnerability. In the first, a small pump is replaced by a larger one as a long-term upgrade. In the second case of a failure scenario, a reconfiguration of the system pumps can reduce the additional costs stemming from the failure. The results of both scenarios are presented in Fig. 4 by the orange markers. The round marker on the S-C-3 bar represents the replacement of pump 3 in PS_C^S and clearly shows that the energy costs of the system can be reduced by 2.6% (a total of $537,436) compared to benchmark costs. The diamond marker on S-C-1 bar shows that reallocating a pump from one station to another can reduce the additional cost during a failure. Whereas a failure in pump 1 at station PS_C^S increases the operational costs to 107.5% of the benchmark costs, the reallocation of a single pump can lower the costs back to 101.6%, which means reducing the failure cost by 14.2%. The absolute cost difference is $32,602 and relates to a one-week operation. If extended to a longer failure scenario that might take a few weeks, these steps could save a significant amount of money if carried out in time. Note however that the analyses here did not take the additional unit purchase cost or the costs of moving pumps between pumping stations into account in the total cost analysis, since the focus of this paper is on energy efficiency alone.

4 Conclusions

Traditionally, the design, operation, and maintenance of WSS are treated separately. This is true in theoretical studies as well as for water companies that have separate departments for these different areas. The result is a lack of circulation of information that curtails the maximization of energetic efficiency. Here, a novel approach was presented that analyzed design, operation, and maintenance simultaneously. The approach involved the identification of the most vulnerable pumps for energy efficiency and suggested pump reallocation as a solution in extreme scenarios.

To date, vulnerability has only been studied from the perspective of supply loss. Here, a novel point of view is suggested to measure the vulnerability in terms of energetic efficiency. Most of the time WSS are subjected to small-scale failures and pump maintenance that reduces the system's efficiency. Hence, vulnerability should be explored not just in crises that disrupt the continuity of supply, but also in more commonplace scenarios. The cumulative costs of inefficient operation can result in significant expenses over time. The results illustrate that certain pumps are more critical than others. In terms of optimization theory, the additional constraints of pump availability are not binding for some pumps and have different levels of tightness for others which affects the objective value differently. One prominent case is disabling a single pump which if disabled alone would increase the operational costs by 7% and exacerbates for every pair it is associated with. It was shown that the relocation of a pump from another station can reduce the cost of such a failure. In the case where duration until back to normal can prolong a few weeks, the economic impact of this type of scenario is significant. Thus, water companies can capitalize on the findings in several ways to prioritize maintenance and improve the equipment inventory. From a system design perspective, this approach reveals the weak spots in the network, which can serve to modify future system developments to strengthen these points. The reallocation of available pumping units as a short-term solution in response to an extreme event can minimize the cost of such events. Finally, the findings suggest the need to rethink the design concept that traditionally relates to long-term change alone. A dynamic approach that allows for the reconfiguration of pumps in cases of failures, dramatic seasonal changes, or other reoccurring events that influence the system's operation needs to be taken into account.

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