Optimization of Water Distribution Networks for Combined Hydropower Energy Recovery and Leakage Reduction

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Abstract: Water supply is energy intensive, resulting in large amounts of greenhouse gas emissions and increased electricity bills for water service providers (WSPs). In recent years, the incorporation of microhydropower (MHP) turbines within water supply networks (WSN) has been shown to be a viable option for pressure reduction and improved water supply sustainability. An option for optimal pressure management of a WSN is presented through the installation of MHP turbines. The optimization objective was to find optimal locations in a WSN to install turbines for maximized power generation. For comparison, a nonlinear programming approach, a mixed integer nonlinear programming (MINLP) approach, and an evolutionary optimization approach, using a genetic algorithm, were employed. The performance and suitability of each method was initially demonstrated on a theoretical five-node WSN. MINLP was found to be the most suitable technique. Further analyses were undertaken of a benchmark 25-node network. It was recommended that WSPs adopt this hydropower optimization approach in the decision-making process to reduce carbon footprint, increase revenue, and reduce the operational costs of water supply. **DOI: 10.1061/(ASCE)WR.1943-5452.0000566.**

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Introduction

Modern water supply networks are under duress as a result of increasing population, urbanization, aging infrastructure, and changing climate factors, affecting both water usage patterns and water resource availability. Optimal design of water supply networks (WSNs) is, therefore, increasingly important to use water as efficiently as possible and to minimize operating costs (Carravetta et al. 2014). The process of water supply and treatment is highly energy intensive, resulting in large amounts of greenhouse gas emissions and increased electricity bills for water service providers (McNabola et al. 2014a). In addition, with global population at an all-time high, the demand for water has never been greater, further increasing the total energy consumption of the water industry. Both governments and water service providers (WSPs) worldwide recognize that there is a need to reduce their energy consumption and develop more sustainable WSNs.

Water leakage is a problem in many aging urban water networks. It is estimated that on average worldwide, 45–88 million m^3 of water is lost every day as a result of leakage from WSNs (Olsson 2012). One option to reduce the amount of leakage and to prevent pipe bursts in a WSN is through pressure management. The control of pressure is therefore of critical importance both operationally and economically for WSPs. The use of pressure reducing valves (PRVs) is common for pressure management and hence, leakage reduction.

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Another key design factor for WSPs today is to reduce carbon emissions and the associated dependency on fossil fuels, with a view to becoming energy secure. Alternative energy options available to WSPs include energy recovery during anaerobic digestion, codigestion and sludge combustion, and also the installation of microhydropower (MHP) turbines, wind turbines, and solar panels on water industry infrastructure. In recent years, the incorporation of MHP turbines within water supply networks for electricity generation has been shown as a viable option for pressure management and improving sustainability and carbon footprint (Carravetta et al. 2014; Gallagher et al. 2015; Fecarotta et al. 2015; Sitzenfrei and Rauch 2015). These MHP turbines can generate electricity without interfering with the level of service provided to downstream consumers (McNabola et al. 2014a, b).

Hydropower turbines have been used within WSNs for many years. Early research in this area was undertaken on the use of pumps as turbines (PATs) for MHP generation (Williams et al. 1998; Williams 1996). Further research has reported that the use of a PAT instead of a turbine provides a cost-efficient alternative for energy production within WSNs (Ramos and Borga 1999; Ramos et al. 2010; Carravetta et al. 2012, 2013, 2014; Fecarotta et al. 2015). A recent study of approximately 100 potential locations for MHP generation in water supply infrastructure in Ireland and the U.K. found that as much as 200 kW could be generated at some sites (Corcoran et al. 2013). Investigations have also demonstrated that MHP can be applied at wastewater treatment works to recover energy (Power et al. 2014).

The conditions within a WSN under which it is technically and economically viable to recover energy using MHP turbines is well understood and have been extensively examined in previous research (Williams et al. 1998; Ramos and Borga 1999; Fontana et al. 2012; Corcoran et al. 2013, 2014; McNabola et al. 2014a, b; Fecarotta et al. 2015). Factors have been examined such as the required flow rate and pressure, turbine type and cost, installation costs, turbine efficiency and flow variations, economic incentives, and the price of electricity generated. Research has also primarily focused on the technical and economic feasibility of replacing existing infrastructure, such as PRVs with MHP technology. Indeed investigators have shown the MHP technology can be used to control pressure in networks in place of PRVs (Carravetta et al. 2013, 2014; Fecarotta et al. 2015). Given that the conditions required for economic and technical viability are known for such activities, this paper focuses on the development of an algorithm to determine the optimal location(s) and number of turbines to be placed in a given network to maximise the energy recovered while also controlling pressure. Therefore, the result of this research will enable the design of new networks to optimise the MHP energy recovery process as part of pressure management instead of retrofitting it to the existing infrastructure.

Optimization of Water Supply Networks

In recent years, increased research efforts have gone into the development and application of optimization techniques for optimally designed networks. Traditional mathematical optimization methods such as linear programming have been used to optimize the installation of pressure controls for leakage reduction (Vairavamoorthy and Lumbers 1998; Germanapoulous 1995; Jowitt and Xu 1990; Sterling and Bargiela 1984).

According to Savic and Banyard (2011), in recent decades, the optimization of WSNs has moved on from the use of traditional mathematical optimization processes to the use of heuristics derived from nature, such as genetic algorithms (GAs), amongst others. These optimization techniques allow for multiobjective optimizations; however, they do not guarantee a global optimum. A GA is an optimization algorithm that uses a search process inspired by natural evolution theory. A GA begins with a randomly generated initial population and applies three operators — the selection, crossover, and mutation operators—to find the optimal solution. Within the water resources field, GAs have been used to optimize pipe diameters for water supply networks (Gupta et al. 1999; Dandy et al. 1996). GAs have also been used for leak detection and to optimize pumping performance (Wang et al. 2009; Barán et al. 2005). A multiobjective GA approach was applied by Nicolini and Zovatto (2009), to optimize the number, location, and setting of PRVs in water networks.

More recent research has seen the application of mixed integer nonlinear programming (MINLP) techniques to the optimal design of water supply networks (Eck and Mevissen 2012; Bragalli et al. 2012; Gleixner et al. 2012). Bragalli et al. (2012) employed the open-source MINLP solver, Bonmin, to optimize the design objective of the selection of optimal pipe diameters at minimum cost. Bragalli et al. (2012) tested two modifications to Bonmin to better handle the nonconvexities of the design objective. One of these modifications has been added to the latest version of the Bonmin solver. Gleixner et al. (2012) applied MINLP to find an optimal pump schedule for minimized operating costs in a WSN. The Darcy Weisbach approximation for headloss was applied. The nonconvex objective function was solved to global optimality using the open source MINLP solver SCIP. Eck and Mevissen (2012) employed MINLP to find optimal locations and settings of PRVs in WSNs. The model was applied to the benchmark 25-node network, reporting optimal PRV locations to be at links 1, 5, and 11, differing from the optimal locations reported in prior research.

The application of optimization techniques to the installation of MHP turbines in WSNs has not been extensively researched. Vieira and Ramos (2008) discussed the optimization of pumped hydro between water supply reservoirs through linear programming (LP) and nonlinear programming (NLP). Further research by Vieira and Ramos (2009) included an investigation of the improvement of the energy efficiency of a WSN through the incorporation of a hydropower turbine, a wind turbine, and optimal pump scheduling. Giugni et al. (2009) reported results of the application of a GA to find optimal locations for PRVs within a WSN in Naples, Italy. The replacement of these PRVs with PATs was then suggested and an economic analysis undertaken. Further to this analysis, Fontana et al. (2012) reported the results of the application of multiobjective GAs for the selection of optimal locations to install PRVs and optimal PRV settings to minimize leakage in a WSN. This optimization approach was tested on a WSN in Naples, Italy. The option of installing a PAT in place of these PRVs was also discussed. To optimize a WSN for energy production, the objective function should be modified. In recent research by Giugni et al. (2014), a modified objective function for maximized energy generation was presented, again applying a GA for solution of the optimization problem. This optimization model was applied to the benchmark 25-node network.

The literature has highlighted that it is possible to recover energy within water supply networks through the installation of MHP turbines. The literature has also shown that both mathematical and heuristic optimization methods can be employed for optimal WSN design. However, the application of optimization methods to the incorporation of MHP turbines has not been extensively researched. This paper will investigate the use of both traditional mathematical methods, including NLP and MINLP, and a heuristic optimization approach, using a GA, for the optimal design of a WSN for MHP generation.

Methods

A hydraulic model of a five-node theoretical water supply network (Fig. 1) was designed and simulated hydraulically using the EPANET 2.0 hydraulic solver. This WSN was then optimized using NLP, MINLP, and a GA. A simplified hypothetical five-node network was used to initially demonstrate the application of these optimization techniques to the concept of MHP energy recovery in WSNs. The optimization algorithm developed was then applied to the larger benchmark 25-node network as reported on in previous research.

As outlined by Sitzenfrei and Rauch (2015), the primary aim of a WSN is to provide water in sufficient quantity and quality, and this aim must not be affected by the production of energy under any circumstances. As such, the optimization algorithm developed in this paper has a primary function of pressure control in WSNs using MHP, with the production of the maximum amount of energy within the network as the secondary function. No actions were taken to increase the production of energy, such as closure of valves or lowering of minimum pressure, which would contravene the primary aim of a WSN.

Water Supply Network Model

The theoretical five-node network model consisted of a reservoir and four junctions (nodes) connected by five pipes (links). Fig. 1 shows a schematic of this gravity fed network. Tables 1 and 2 detail the network input data, such as pipe lengths, diameters, and water demand at each node. The reservoir had an assumed constant head of 100 m. These network input data were also the input data for the optimization models examined.

Following the analyses of the theoretical five-node network described previously, the more complex benchmark 25-node network (Sterling and Bargiela 1984; Nicolini and Zovatto 2009; Eck and Mevissen 2012; Giugni et al. 2014) was then analyzed. This network layout is presented in Fig. 2. Further network details can be found in Sterling and Bargiela (1984).

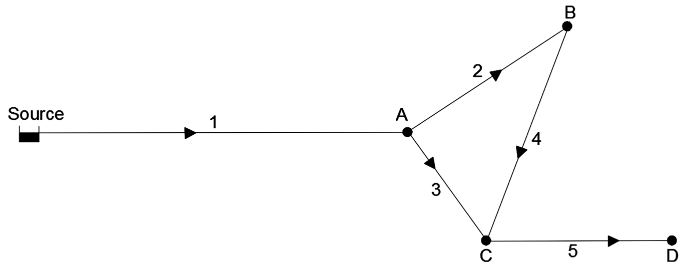

Fig. 1. Theoretical five-node water supply network for analysis

Table 1. Theoretical Five-Node WSN Node Input Data

Node	Elevation (m)	Demand (m^3/h)
A	12	41
B	8	34
C	9	55
D	6	23

Table 2. Theoretical Five-Node WSN Pipe Input Data

Identifier	Node i	Node j	Length (m)	Diameter (mm)
1	Source	A	1,000	200
2	A	B	800	150
3	A	C	1,200	200
4	B	C	1,000	150
5	C	D	2,000	150

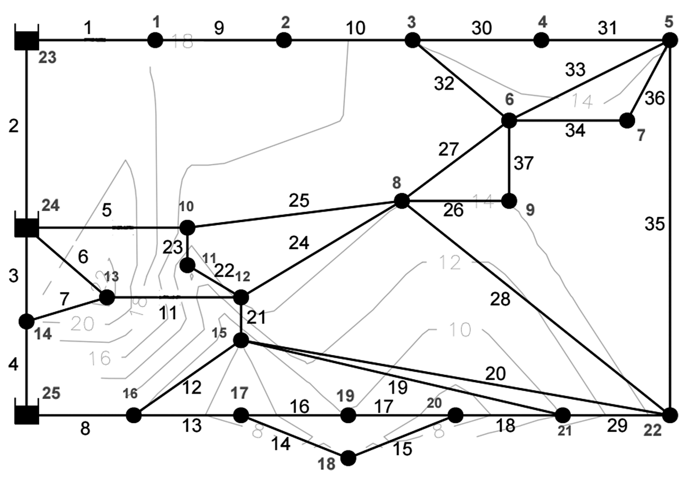

Fig. 2. Benchmark 25 node Network layout

This benchmark 25-node network is fed from three sources, at nodes 23, 24, and 25. To simplify this analysis, the head was assumed constant at each of the source nodes, as has been assumed in previous work (Giugni et al. 2014). In early research, the location to install three PRVs was assumed, then the optimization algorithms were applied to optimise the settings of these valves. The location assumed for installation of these was at pipes 11, 21, and 29 (Sterling and Bargiela 1984; Jowitt and Xu 1990; Araujo et al. 2006). Later research, however, to find optimal locations to install PRVs has found other pipes more efficient at minimizing pressures and leakage. These locations have been found on pipes 1, 11, and 20 [Nicolini and Zovatto (2009)]; pipes 1, 5, and 11 [Eck and Mevissen (2012)]; and pipes 1, 11, and 21 [Giugni et al. (2014)]. Optimal locations for turbine installation were found to be at pipes 1, 5, and 11 by Giugni et al. (2014) using a GA.

Mathematical Optimization Problem Formulation

Objective Function

The primary objective function, as defined for this model, was to maximize the total net power generated when hydropower turbines were installed in a water supply network to reduce network pressures to target pressure levels. Through the introduction of an additional binary variable, the total number of turbines to install could be constrained. The power formula is a function of both water pressure and flow rate:

$$\sum_{t=1}^{T} P_{\text{output}} = \rho g \sum_{t=1}^{T} Q_{i,j} D_{i,j} e_0 \tag{1}$$

where T = number of turbines to install in the network; $Q_{i,j}$ = flow rate across pipe length i, j; $D_{i,j}$ = head drop across the turbine; ρ = water density; g = acceleration due to gravity; and $e0$ = turbine efficiency.

Initially, for the purposes of the development of the optimization algorithm, a constant turbine efficiency of 100% was assumed as carried out in Guigni et al. (2014). Subsequent to this, the effect of variations in turbine efficiency in response to variations in flow and pressure, according to a diurnal demand pattern, was assessed for four different turbine types.

Decision Variables

The decision variables for this problem are Q_{ij}, Pn, and Di, j, where Qij is the flow in each link between nodes i and j; Pn is the hydraulic head at each node n; and Di, j is the head drop or head loss across an installed turbine along pipe i, j. For all pipes $k = 1, \ldots, K$ and for all nodes $n = 1, \ldots N$ where K is the total number of pipes and N is the total number of nodes in the network.

Constraints

For a WSN with known layout and demands, the optimal WSN design for hydropower turbine inclusion is to position a turbine at a location at which the most power can be generated. Certain constraints must also be met, such as maintaining adequate services water pressures. This optimal design was subject to the following constraints:

1. Continuity of flow

$$\sum Q_{\text{in},n} - \sum Q_{\text{out},n} = \text{Demand}_n \tag{2}$$

For each node n, the flow into and out of each node was represented using Eq. (2). This is in accordance with the continuity equation, such that the sum of the flows into each node must equal the sum of the flows out of that node. There are N equations, to represent the flow into and out of each node $n = 0, 1, \ldots N$.

2. Conservation of energy

The hydraulic head is the total energy per unit weight of the water, and is expressed in terms of height. The head loss, hi, j between nodes i and j is

$$H_{i–}H_j = h_{i,j} \tag{3}$$

where Hi and Hj = total hydraulic head at nodes i and j, respectively.

According to Bernouilli's equation, the hydraulic head is the sum of the pressure head, elevation head, and velocity head, all of which are measured in units of length (m). The velocity head (kinetic energy) in this case can be ignored because it is much smaller than the elevation and pressure head (Bragalli et al. 2012). The hydraulic head is therefore a combination of the pressure head pi and the elevation head ei.

3. Head loss along pipes

For this analysis, the Hazen-Williams approximation for head loss was applied

$$h_{ij} = 10.67 \frac{Q_{i,j}^{1.85}}{C_{i,j}^{1.85} \cdot D_{i,j}^{4.87}} L_{i,j} \quad (4)$$

where C = Hazen-Williams friction coefficient is the water dynamic viscosity; Li, j = pipe length; and Di, j = pipe diameter. This empirical head loss approximation is commonly applied by water supply engineers for optimization modelling because it is less computationally expensive than other approximations, such as the Darcy Weisbach and Colebrook-White approximations.

4. Minimum and maximum pressure head

To ensure adequate service pressure for end users, a minimum pressure of 10 m was required at all nodes. The maximum pressure level was constrained to be less than 40 m.

5. Maximum number of turbines to install

To constrain the number of turbines to install, another decision variable was added. A binary variable at each node $t \in [1, 0]$. The total number of turbines to install was then constrained by

$$\sum_{t=1}^{T} T = \text{Maximum turbines} \quad (5)$$

The addition of this integer decision variable requires the use of an optimization solver capable of handling both continuous and integer variables, such as a MINLP solver.

Optimization Solver Selection

As the objective function to be maximized was nonlinear, initially the problem was solved using the NLP solver Fmincon from the *Matlab Optimization Toolbox* (*MATLAB version 8.2*). Fmincon finds a minimum (or maximum) of a constrained nonlinear multivariable function. This solver will only allow continuous decision variables and so the final fifth constraint on the number of turbines to install could not be applied.

Subsequently, because of the nonlinear nature of the objective function and constraints and the presence of both continuous and integer decision variables, MINLP was assessed. As has been applied in recent research (Eck and Mevissen 2012; Bragalli et al. 2012), the basic open source nonlinear mixed integer programming (BONMIN) solver was employed in this case (Bonami et al. 2008). This is an open source code for solving general MINLP problems. The NLP branch-and-bound algorithm was employed (BONMIN B-BB). This is a simple branch-and-bound algorithm based on solving a continuous nonlinear program at each node of the search tree and branching on variables (Bonami and Lee 2007). The different methods that BONMIN implements are exact algorithms when the objective function and the constraint function are convex but are only heuristics for a nonconvex problem, as in this case.

Finally, for comparison a genetic algorithm was also applied to this optimization problem. The genetic algorithm solver from the *Matlab Optimization Toolbox* suite was applied (*MATLAB version 8.2*).

Results

Five-Node Network

The results of each optimization model for the five-node network are presented in Table 3. For the initial run, using the NLP solver, a turbine was set to be installed at all nodes. The optimal arrangement found link 1 to be the location with the most power generation potential at 14.99 kW, with the other three locations all generating less than 0.00001 kW. Despite the inability of the NLP solver to select a specified number of turbines to install, it could be clearly identified which of the five pipes was the optimal pipe to install a turbine for maximized power generation.

The MINLP model was then constrained such that only one turbine be installed. The optimum link selected by the algorithm was at link 1, which again had a power generation capacity of 14.99 kW. The GA solution, similar to the NLP model, found Link 1 to be the node with the most power generation potential; however, it reported an optimal solution at a lower point at 11.56 kW. The total power generation potential at all nodes as found by the GA was 11.74 kW. Although the output variables of the GA solution were all within the problem bounds and constraints, it did not find the absolute optimal point.

For the five-node Network, NLP was found to be an efficient method to find the optimal point to install a turbine, despite not having the capability to model binary variables for the location choice. The solving time was the quickest at 0.56 s, and the result output was very close to the output of the MINLP model. The MINLP also found an optimal solution quickly in 0.92 s. It was decided to proceed with NLP and MINLP for the next case study. The GA option was disregarded because of its longer solving time, combined with its less accurate approximations of flow rates as reported for the five-node WSN. However, GAs may still be suitable in the optimisation of other networks involving a large number of nodes as shown by Savic and Walters (1997).

Table 3. 25-Node Network: Results of Each Optimization Model

	Nonlinear programming (NLP)			Mixed integer nonlinear programming (MINLP)			Genetic algorithms (GA)		
Link	Flow (m^3/h)	Head drop (m)	Power (kW)	Flow (m^3/h)	Head drop (m)	Power (kW)	Flow (m^3/h)	Head drop (m)	Power (kW)
1	153	55.34	14.99	153	55.34	14.99	152.99	42.66	11.56
2	40.69	0	0	40.69	0	0	35.33	0.46	0.029
3	71.3	0	0	71.31	0	0	76.67	0.86	0.12
4	6.69	0	0	6.69	0	0	1.33	2.22	0.005
5	23	0	0	23	0	0	22.99	0.54	0.022
—	—	Total	14.99	—	Total	14.99	—	Total	11.74

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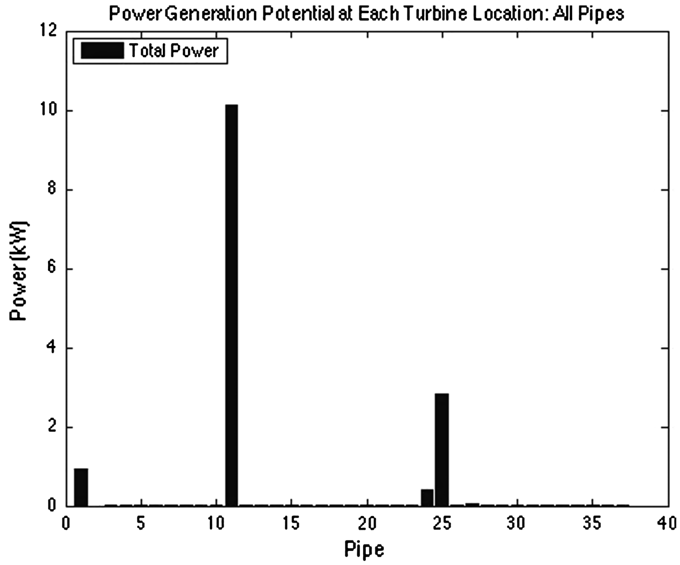

Fig. 3. 25-node WSN: NLP no constraint on total pressure

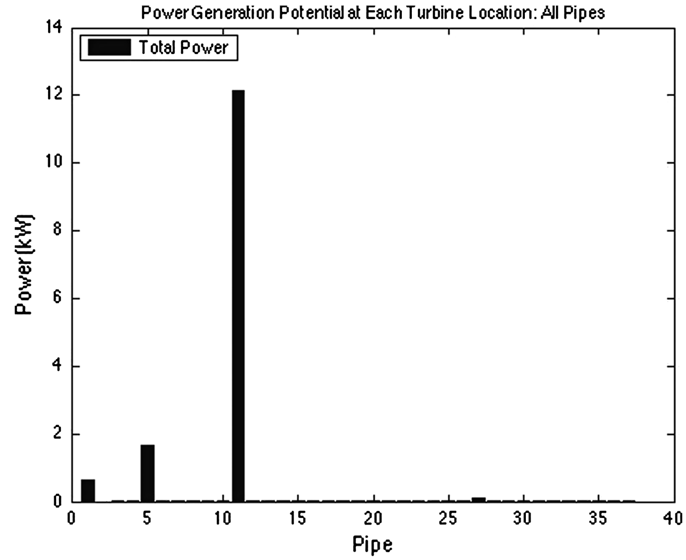

Fig. 4. 25-node WSN: Total pressure drop less than 30 m

The number of continuous variables, binary variable and constraints was 14, 0, and 13 respectively for the NLP and GA approaches. These were 14, 5, and 19 for the MINLP model.

25-Node Network - NLP

The NLP optimization algorithm was applied to the 25-node WSN as described previously. This first analysis assumed a turbine was installed on all links. An optimal solution was found in 44.3 s, with the results shown in Fig. 3. Fig. 3 illustrates that the link with the largest power generation potential was Link 11. Discounting all links with power generation potential of less than 0.1 kW, the solution that would maximize the total power generation in the network would be to install turbines at links 1, 11, 24, and 25. In practice however, an optimal solution with less installed turbines would be preferable once the initial investment costs and return on investment are considered.

A new constraint was then added to further constrain the total amount of pressure to be removed from the network. This constraint was added to reduce the solution space and improve solving time. The additional constraint limited the total pressure drop removed from all pipes to be less than a certain value. With the maximum total pressure drop constrained to be less than 30 m in total, an optimal solution was found in 24.51 s, with the output file illustrated in Fig. 4. This found the most power generation to be at links 1, 5, and 11, disregarding all links with power generation potential of less than 0.1 kW.

The pressure drop was then constrained to be less than 25 m. An optimal solution was found in 24.97 s. This reported the optimal links for power generation to be links 5 and 11. From all these analyses, it was clear that Pipe 11 was the location with the most power generation potential, whilst also meeting the pressure requirements of the network. Other locations with additional power generation capacity were found at pipes 1, 5, 24, and 25.

25-Node Network - MINLP

An MINLP formulation of this optimization problem was then implemented in *MATLAB* and solved using the BONMIN solver. The ability to include integer decision variables allows the MINLP formulation to select the optimal locations to install turbines. For the installation of one turbine, pipe 11 was again found to be the optimal location, providing a generation capacity of 6.57 kW. The total number of turbines to install was fixed at three. An optimal solution was found in 61.06 s. The optimal locations for three turbines to be installed were found to be at links 1, 5, and 11. The total power generation capacity of this combination was found to be 16.43 kW at average network water demand and assuming a turbine efficiency of 100%. The excess pressure that could be used to drive hydropower turbines was found to be 12.93, 12.8, and 12.68 m at pipes 1, 5, and 11 respectively. The majority of the power generation capacity was found to be at link 11, at 11.59 kW, with a further 2.7 kW available at link 5, and 2.14 kW available at link 1. Through the installation of these three hydropower turbines, the overall average network pressure was reduced to 28.8 m.

Optimal Turbine Operation

An analysis of the optimal operation of one turbine installed at link 11 was then undertaken. This model was solved in 4.9 s. It was found that at pipe 11, there was 14.06 m of excess pressure head which could be used to drive a turbine. This would result in the total average network pressure reducing to 30.04 m. A comparison was then made with the results of the MINLP optimization model and an equivalent EPANET 2.0 hydraulic analysis. The presence of a turbine was modelled using a PRV in EPANET. The PRV output pressure was fixed at the same output pressure as reported by the MINLP optimization algorithm. Both the flows and pressures reported by the MINLP optimization solution were very consistent with the results of the EPANET hydraulic analysis. The largest relative error recorded between the flow rates was 1.964% and occurred at Link 22, representing a 0.01 l/s difference in flow. The largest relative errors between the flow rates were all found for the pipes with the lowest flow rates of less than 2 l/s. For all pipes with flow rates greater than 2 l/s (81% of the pipes), the relative errors were all less than 0.1%. The resulting pressures from the MINLP model were also very consistent with the comparable EPANET hydraulics results, with the largest reported relative error of 0.022% at node 2 and node 17, representing a difference of 0.01 m.

Further analysis was undertaken of the operation of an installed turbine at pipe 11 over a diurnal water demand profile. The demand pattern as reported on for this 25-node network was applied, as

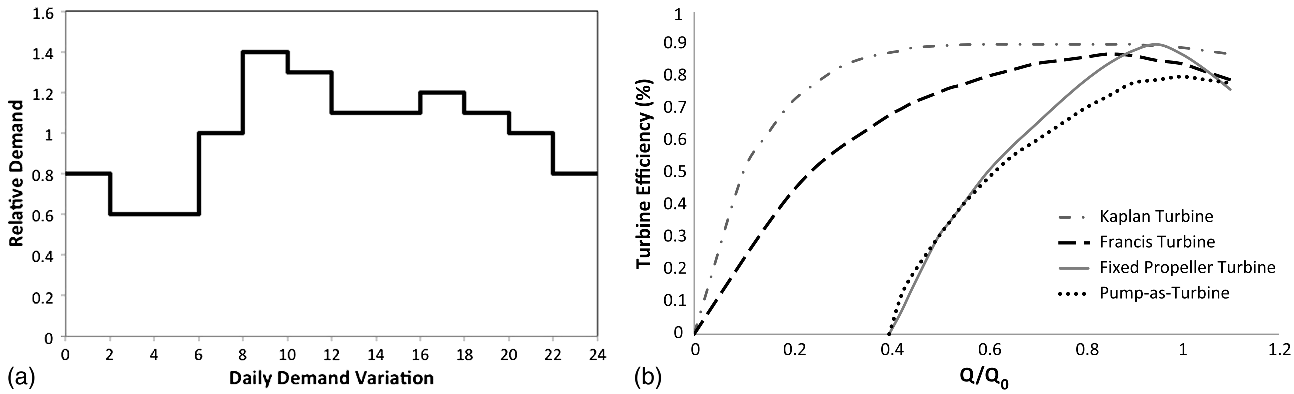

Fig. 5. (a) Diurnal demand pattern; (b) turbine efficiency curves

shown in Fig. 5. A turbine was fixed to be installed at Pipe 11. Optimal operation of this turbine, i.e., the pressure output required at the turbine for each hour was solved using the optimization algorithm. The optimal turbine to install was investigated based on different turbine efficiency profiles as shown in Fig. 5. An efficiency curve for a PAT was also included as an option. PATs have been reported as a more cost-effective solution in comparison to traditional microhydropower turbines on the market (Fecarotta et al. 2015).

Power generation potential was found to be significantly reduced at night-time periods when demand was lowest. Optimal power generation was found for the Kaplan turbine, which operated most efficiently over the variable flow rates. The diurnal power generation for each turbine type is shown in Fig. 6. The PAT and Fixed Propeller turbines were unable to efficiently generate any power during low flow nighttime periods. During these periods, the available pressure head to drive a turbine was reduced, because of the need to maintain minimum service pressure of 25 m. The PAT was shown to perform as well as the Francis turbine for higher flow rates. However, this analysis has not considered the effect of cost on the appropriate choice of turbine, nor have we considered the optimisation of turbine performance using hydraulic regulation (Carravetta et al. 2013). The cost of the PAT is known to be considerably lower than the other turbine types considered here, therefore more detailed economic and performance analysis at the local scale would be required here to determine the appropriate choice.

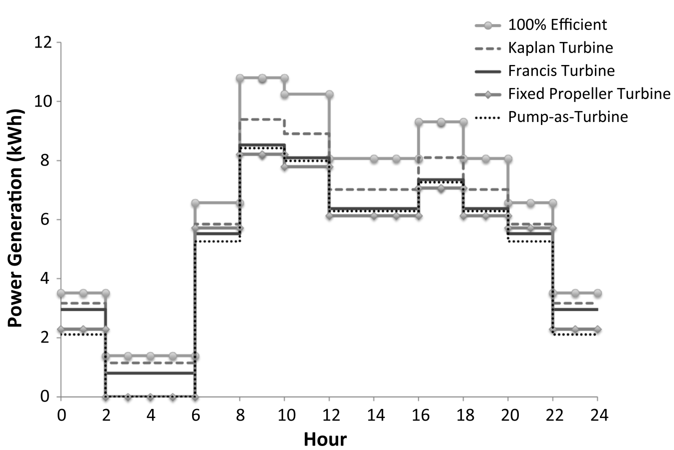

Fig. 6. Turbine selection for turbine installation at Link 11

Nighttime generation may be negligible because of the low flow rate but also lower energy price and lower demands for electricity during this period.

Assuming 100% turbine efficiency, as has been assumed in previous work (Giugni et al. 2014), overestimated the power generated, in particular at higher flow rates, for example between 8 and 10 am.

Discussion

The potential for the application of optimization algorithms to choose optimal points to install hydropower turbines has been explored. The selected objective function was to maximize the total power generation in a given WSN. This objective was dependent on the flow rates and pressures in each pipe. The developed algorithm maximizes this power generation while maintaining required water service pressures. The result is a reduction in network pressures, reducing the intensity of leakage and likelihood of burst pipes, while also generating much needed electricity for WSPs.

The resulting flow rates for each link reported by the NLP model were very consistent with the corresponding EPANET outputs. Relative errors ranged between −0.036 and +0.003%. For small WSNs, such as the five-node network examined here, the NLP algorithm which assumes a turbine is installed at all pipes has been shown to accurately locate the pipe with the most potential for hydropower generation. Following the selection of this point, a further NLP analysis can be run to find optimal settings for a turbine assuming only one turbine is installed at that pipe. However, for more complicated networks with multiple loops, connections and interconnections, it may not be clear from the NLP solution alone as to which link has the most power generation potential.

This hypothesis was then tested on the 25-node benchmark WSN. NLP provided a good approximation of the optimal locations for hydropower energy recovery. A test constraint on the total pressure drop to be removed from the network improved the ability to identify the pipes with the most power generation potential. For the installation of three turbines, there were a number of potential optimal combinations. Through trial and error, these combinations were tested with these results presented in Table 4. The optimal solution was found to be to install turbines on pipes 1, 5, and 11. The peak power generation points identified during the NLP approach were then applied as initial start points for the MINLP solution.

Through comparison with the EPANET hydraulic analysis output, the MINLP approach provided very accurate approximations

Table 4. 25-Node Network: NLP Optimization Results for Installation of Three Turbines

Three turbine combination	Total power generation (kW)	Solution time (s)
Links 5, 11, 24	14.02	8.28
Links 1, 5, 11	16.43	10.87
Links 11, 5, 8	14.96	14.26
Links 11, 24, 25	10.12	7.01

of the flow rates and pressures in the network, with the largest relative error in a link reported as 1.96%.

Through the application of this optimization algorithm to the benchmark 25-node network, a direct comparison between the results of this optimization formulation with other research results for PRV location models could be made. The results of this analysis agrees with some previous results. For the optimal location of one PRV, pipe 11 was found to have the greatest hydropower potential, as has been found by Nicolini and Zovatto (2009) for optimal PRV location, and by Giugni et al. (2014) for both optimal PRV and hydropower turbine location. For the optimal installation of two turbines, a different optimal solution to Nicolini and Zovatto (2009) was found at pipes 5 and 11. This optimal solution again agrees with the results of Giugni et al. (2014) for optimal installation of hydropower turbines. For the optimal installation of three turbines, the optimal arrangement reported using MINLP was to install turbines on links 1, 5, and 11. This differed from the results of many previous research publications for optimal location of PRVs. However, it was the same combination as was reported by Eck and Mevissen (2012) for optimal PRV location using a MINLP solver. It was also the same optimal combination as reported by Giugni et al. (2014) for installation of three turbines to maximize power generation.

The Giugni et al. (2014) optimal solution was found using a GA. This optimal solution reported a maximum power generation capacity of 15.9 kW at average demand and 100% turbine efficiency. The optimization algorithm developed in this research reported a 3% higher total power generation capacity of 16.43 kW. The MINLP approach applied in this research was found to provide an improved result over that found using the GA approach. Although the 0.53 kW increase in power capacity represents a small increase in total power generation for this small benchmark 25-node Network, for a larger more complex WSN this increased power generation would be expected to be more significant. However, as discussed previously, for larger more complex networks, the use of GAs may have advantages over the MINLP approach.

However, although total power generation potential of three installed turbines was found to be 16.43 kW, the turbine at pipe 11 contributed the most to total power output. The turbine at pipe 11 was found to generate 11.59 kW, whereas the turbine at pipe 5 generated 2.7 kW and at pipe 1 generated 2.14 kW. This was assuming 100% turbine efficiency. Applying different turbine efficiency curves, the total power generated between these three turbines varied from 14.24 kW for a Kaplan turbine to 10.73 kW for a PAT. Given the optimum turbine location, a cost-benefit analysis of these turbine installations would be required to decide on the economic viability of their installation, such as that described in Corcoran et al. (2013). For a hydropower energy project in a WSN to be deemed feasible, investment payback is usually required to be achieved within ten years. The smaller the power generation potential, the longer it would be likely to take to cover the initial financial investment required for the installation. These initial costs may vary widely depending on the turbine type, site specifications, cost of energy, proximity to the electricity grid, access to site and the amount of civil works required. Furthermore, the presence or eligibility for a green incentive or a REFIT tariff could improve the financial case. Although the Kaplan was found to be the best performing turbine in this analysis from a hydraulic perspective, in practice for such small capacity MHP sites, as would be typical of a PRV, the cost of a Kaplan may be prohibitive. PATs have been recently shown to be the viable option in such cases (Fecarotta et al. 2015). Future work is required to incorporate turbine installation costs into this optimisation process.

To discount power generation at nodes with very small potential excess pressure, the lower bound on the turbine pressure drop could be increased. For this analysis, the lower bound on the pressure drop was fixed at zero, which allowed for sites with very low head to be included. These low head sites were included because the combination of a pipe with high flow rates and low head may still result in sufficient power generation potential. However in practice, it may be effective to introduce a higher minimum turbine head value, to discount sites with low head. The developed algorithm would enable this distinction to be made for future analyses.

In addition to reducing average service pressures in the WSN, installed turbines provide a valuable additional source of electricity for the WSPs. The cost of electricity per kW for industrial users in Ireland in 2013 was reported to be 13.31 c per kWh (Eurostat 2014). For the five-node WSN, if a turbine were installed at Link 1 generating 14.99 kW and the electricity generated was used directly by the water supply provider, this would result in an annual electricity saving of €18,205.92. MHP turbine investment costs are typically in the range of €5,000/kW (Corcoran et al. 2013), thus the turbine at Link 1 would cost approximately €75,000 to install and provide a four to five year payback.

Conclusions

The focus of this paper was to investigate the application of optimization techniques for the optimal location of hydropower turbines within water supply networks for pressure reduction. Using both mathematical optimization and evolutionary optimization algorithms, optimal solutions were found. For the smaller five-node WSN, the optimal location to install a turbine using a GA matched that of the NLP and the MINLP models. However, the maximized power generation using the NLP and MINLP models was found to be higher than the maximized potential using the GA in this case. The results of this analysis show that optimization algorithms can be used as a decision aid in the design process for installation of hydropower turbines in water supply networks.

Further research is recommended on the application of this optimization model on a larger water supply network and real-world case studies. Further research is also recommended on the development of a similar optimization formulation but for a different objective, to minimize the total project costs, or to minimize the investment payback period. These objectives are particularly relevant when the estimated power generation potential is small.

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