Energy recovery and leakage-reduction optimization of water distribution systems using hydro turbines

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Abstract

Potential for energy recovery exists at any point within a water distribution system where the mechanical energy of excess water pressure can be converted into electrical energy. Energy conversion decreases the average operating pressure within a system which in turn reduces water losses from leakages in the system due to the proportionality of leakage and pressure. The paper explores the incorporation of a Genetic Algorithm (GA) in a procedure to optimise the location and size of energy recovery turbines (ERT) within a water distribution system based on maximizing recovered energy and reduced water losses evaluated on an economic basis and assigned a differentiated weighted importance. The developed procedure was tested

on a well-known pressure management benchmark network as well as a water network from previous studies. Where previous studies on the benchmark network were only focussing on pressure management, the current procedure produced results on pressure management with the added benefit of an analysis on both energy recovery and leakage reduction. The procedure provides municipal- and water utility managers with a better-informed basis for pressure management and energy recovery decision making.

Keywords

Genetic Algorithm, Energy Recovery, Leakage Reduction, Water Distribution

Introduction

Apart from generating renewable energy and adding a clean sustainable source of income or savings for the asset custodian, energy recovery in water supply and distribution networks have the added benefit of reducing leakages and increasing the resilience of the system.

Energy recovery in this context called conduit hydropower refers to electricity generation within man-made conduits, such as water pipes, by means of hydro turbines. The turbines convert the mechanical energy of the pressurised water within these conduits, into electrical energy. Potential for energy recovery or conduit hydropower generation exists at any point within a pumping or gravity system with excess water pressure (SEA, 2017).

The minimum residual pressure within the South African municipal water services environment is specified by the Council for Scientific and Industrial Research (CSIR, 2005), as 24m (2.4 bar) for house connections under instantaneous peak demand. Any pressures within the system above this minimum acceptable operating pressure at the end user, is potential excess pressure in the system (Bonthuys, et al., 2018a). Installing Energy recovery turbines (ERTs) in existing municipal water supply systems harnesses this excess pressure in the form of hydroelectric potential (Su & Karney, 2014).

Various studies have been conducted on the pressure within municipal, mines and water utilities' water supply/distribution systems, in South Africa (Van Dijk, et al., 2012) (Loots, et al., 2014) (Van Vuuren, et al., 2014). These studies have highlighted the potential for conduit hydropower and the implementation of hydro turbines for both supplementing and reducing the requirements for pressure control valves. Hydro turbines are analogous to pressure control valves with the added benefit of electricity generation. Several water authorities globally have also implemented generating schemes on water supply/distribution systems after realising the potential of conduit hydropower (Van Dijk, et al., 2018; Carravetta et al., 2014; Loots, et al., 2014; Vilanova & Balestieri, 2014; Butera & Balestra, 2015; Van Vuuren, et al., 2014.).

Leakages within a water supply/distribution system are proportional to pressure within the system and the most general equation for simple analysis and prediction of relationships between pressure (P) and leakage (L) is that L varies with P^{N1}, where N1 is depended upon the type and frequency of leaks. Consequently, A decrease in system pressure will reduce the rate of leakage from the system (Gupta, et al., 2017). Extensive research has been conducted on the reduction of leakage in water systems through pressure management (McKenzie & Wegelin, 2009). Conventionally pressure reducing valves (PRVs) are usually used to manage and control pressure within water supply/distribution systems by dissipating energy in the system above the maximum admissible pressure to avoid pipe rupture (Van Dijk, et al., 2018).

Some of the challenges faced with pressure management and PRVs are related to the determination of the number, location and optimal control setting of the valves. Over the last decade many researches have attempted to optimise pressure management and the location of PRVs in water supply/distribution networks (Nicolini & Zovatto, 2009) (Gupta, et al., 2017). Optimisation techniques employed included linear programming (LP), nonlinear program (NLP) algorithms, mixed integrated nonlinear programming (MINLP), mathematical programming with complimentary constraints (MPCC) and genetic algorithms (GA) (Gupta, et al., 2017). Creaco and Pezzinga (2015) followed a hybrid approach, combining a multi-objective GA for the suitable pipe replacements, control valve installations and isolation valve closures, and Linear Programming (LP) for the optimal settings of the control valves installed.

Moreover, over the last decade, high energy consumption in urban water supply and distribution systems has sparked a growing interest in energy recovery where excess pressure requires dissipation (Colombo & Kleiner, 2011). Research started to combine PRVs and hydro turbines or Pumps operating As Turbines (PATs) with the aim of recovering excess pressure from water supply networks and transforming it into electricity, reducing at the same time water losses (Parra & Krause, 2017). Tricarico et al. (2014) developed a multi-objective optimisation methodology to minimise leakage and optimise energy recovery in water distribution systems by incorporating PATs. The interest in energy recovery with the added benefit of leakage reduction is hence rapidly gaining popularity as researchers are striving towards more sustainable societies with more resilient infrastructure networks (Fecarotta et al., 2014; Butera & Balestra, 2015).

Previous research has highlighted the potential for energy recovery and leakage reduction in municipal water distribution systems, using an isolated district metered area (DMA) within the

City of Polokwane in South Africa (Bonthuys, et al., 2018c). This research used an algorithm developed by Samora et al. (2016) for the evaluation of potential. Shortcomings related to the Samora et al. (2016) algorithm is that process is iterative in sequence, and the effect of subsequent energy recovery installations on previous identified installation locations is not defined. The Samora et al. (2016) algorithm also only focusses on energy recovery and does not evaluate solutions based on their effect on leakage reduction. The Samora et al. (2016) algorithm might eliminate a solution which does not comply to a preconceived increment in energy recovered but might have a large impact on the leakage reduction in the system.

The purpose of this paper is to incorporate a genetic algorithm in the model so as to optimise the use of hydro turbines in municipal water distribution systems in terms of recovered energy and water losses reduction evaluated on an economic basis.

Genetic Algorithms for Water Distribution Networks

A Genetic Algorithm (GA) is a search algorithm based on artificial evolution (Gercek, 2006; Van Dijk, et al., 2008). It implements Darwin's theory of evolution in optimisation applications. Through the GA process the solutions to an optimisation problem are represented as variables or "genes" that are combined to form a string referred to as a "chromosome". Through mathematical operators the chromosomes are evolved according to their "fitness" during subsequent generations of the algorithm. The basic operators applicable to the GA process are Generation, Selection, Crossover, Mutation and Elitism (Gercek, 2006).

The "fitness" of a solution or "chromosome" is a measurement of how well the solution meets the "objective function". The objective function is defined in terms of goals such as lowest cost, highest reliability, lowest environmental impact of highest social benefit or a combination of these. After each generation, solutions with the better fitness values will survive whereas solutions with the lowest fitness (weakest chromosomes) will be eliminated. Through this theory of natural selection, the solutions with the better fitness will propagate to the next generation or populations (Gercek, 2006). **Fig. 1.** shows a schematic of the basic process of a GA.

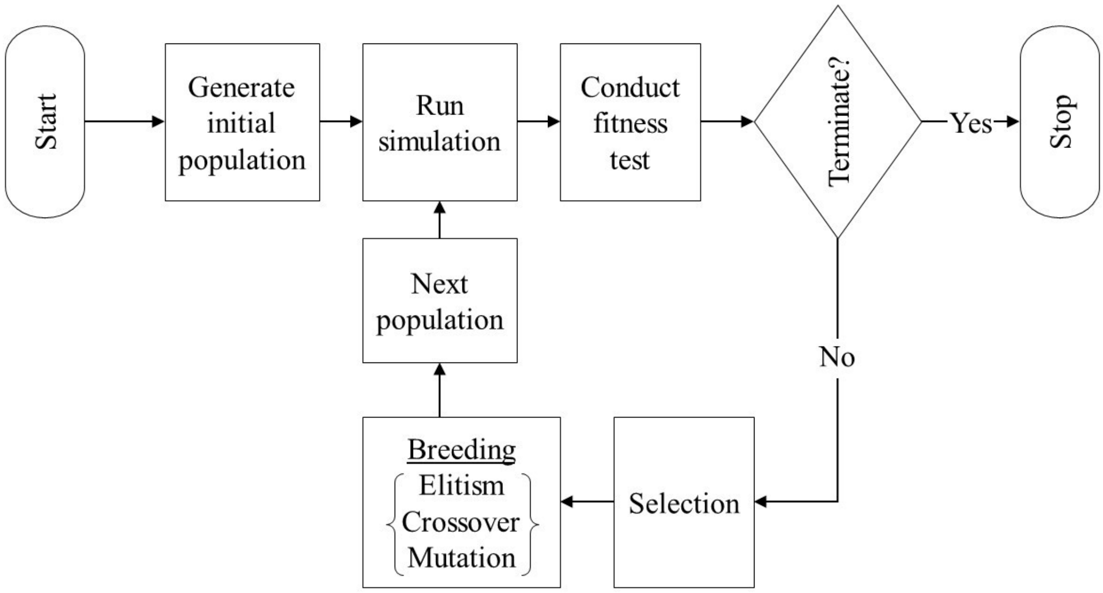


Fig. 1. Basic GA process (adapted from Gercek (2006) and Van Dijk et al. (2008))

Engineering design problems or scenarios often involve simultaneous optimisation of multiple objectives. A single objective function optimisation has the goal of finding the global optimum, whereas with a multi-criterion optimisation or multi-objective problem there is no single optimal solution. The interaction between different objectives results in compromised solutions known as Pareto-optimal solutions. Pareto-optimal solutions cannot be distinguished as one being a better solution to the other without further investigation. The goal of a multi-objective or multi-criterion optimisation is therefore to find as many Pareto-optimal solutions as possible (Prasad & Park, 2004). Based on further higher-level analysis different solutions will be found implementable for different technical, financial and social reasons. The optimisation model is also subjected to certain constraints such as scientific constraints (i.e. nodal mass balance and energy balance), physical infrastructure constraints (i.e. discrete pipe sizes) and design and operational regulations (i.e. residual operating pressures) (Prasad & Park, 2004).

Van Dijk et al. (2008) developed an optimization procedure based on a single objective function (the cost minimisation) and applied a weighted penalty to solutions based on system constraints, in order to optimise the design of water distribution systems. If a solution produces nodes within the system that do not meet the system minimum pressure requirement constraint, the pipes supplying that node are penalised and has an increase calculated cost associated with them. This adversely affects the objective of minimising cost and therefore reduces the solution's chance of "surviving" the evolutionary process of the GA. The cost of the penalty, applied to the nodes, is done on a weighted penalty cost structure to add proportional distribution to the cost. This distribution is based on the importance of certain supply pipes based on the amount of flow through the pipes (Van Dijk, et al., 2008).

GAs have also been applied extensively in the research to optimise pressure management in water distribution systems by optimising the location and operation of pressure reducing valves with the main objective to minimise leakages in a system while maintaining the minimum required operational pressure at every node (Nicolini & Zovatto, 2009). Although the leakages in a system are depended on the pressure within the system, Nicolini and Zovatto (2009) employed a multi-objective GA in optimising the pressure management of a water distribution system by optimising the total number of installed PRVs (objective 1) and minimising the total leakage in the system (objective 2) and considering them as independent. Creaco and Pezzinga (2015) developed a hybrid algorithm using a conventional multi-objective GA and Linear Programming (LP). The multi-objective GA was used for the optimal design of pipe diameters, optimal location of control valves, and identification of the isolation valves that must be closed in the network for pressure management. Subsequently an inner optimization algorithm using LP was used to search for the optimal control valve setting for network operation. The hybrid algorithm proved very efficient in comparison to traditional GA's for the optimization problem considered by Creaco and Pezzinga (2015). Creaco et al. (2016) considered a multistep approach for the optimal design and operation of a water distribution system where engineering judgement is initially employed to obtain first-attempt solutions, followed by optimisation process with three objective functions on installation cost, operational cost and the cost of PRVs to be installed.

When considering leakage reduction as the main objective of pressure management in water distribution systems, Gupta et al. (2017) presented an approach to optimise the location and operating pressure of PRVs for pressure management. Gupta et al. (2017) proposed to optimise the location of PRVs by implementing two rules and to optimise the operating pressure of the PRVs by implementing a GA with two objective functions. The two rules for the optimal PRV location focus first on a reference pressure to restrict candidate valve locations to a set of pipelines and secondly on pipelines connected to subsequent nodes where the pressure difference is higher than a predefined reference pressure. The two objective functions used in the GA for the optimisation of the PRV operating pressure were 1) to minimise the set operating pressure value at the PRV and 2) to minimise the leakage rate within the water distribution system. The optimised set pressure value corresponding to the lowest leakage rate was chosen as the optimal design (Gupta, et al., 2017).

Emanating from the similarities between PRVs and hydro turbines when considering pressure reduction, this paper proposes the use of GAs in optimising the implementation of hydro turbines for pressure management, energy recovery, leakage reduction and revenue generation or cost saving.

Developing an optimisation procedure for Energy Recovery and Leakage Reduction, utilising a GA

The shortage of awareness of the potential for energy recovery within Municipal Water Distribution Systems and the lack of knowledge of the extent and location of such potential, along with the inherent need to optimise pressure management and leakage reduction, catalysed the development of an optimisation procedure for Energy Recovery and Leakage Reduction optimisation in Municipal Water Distribution Systems, which utilises a GA.

The optimization procedure, utilising a GA, was coded in Visual Basic (with the hydraulic modelling performed in EPANET (Rossman, 2000)) and was named Programme for Energy Recovery and the Reduction of Leakage (PERRL). **Fig. 2.** outlines a flowchart that describes the procedure of the PERRL. The procedure will be described in detail in the subsequent sections.

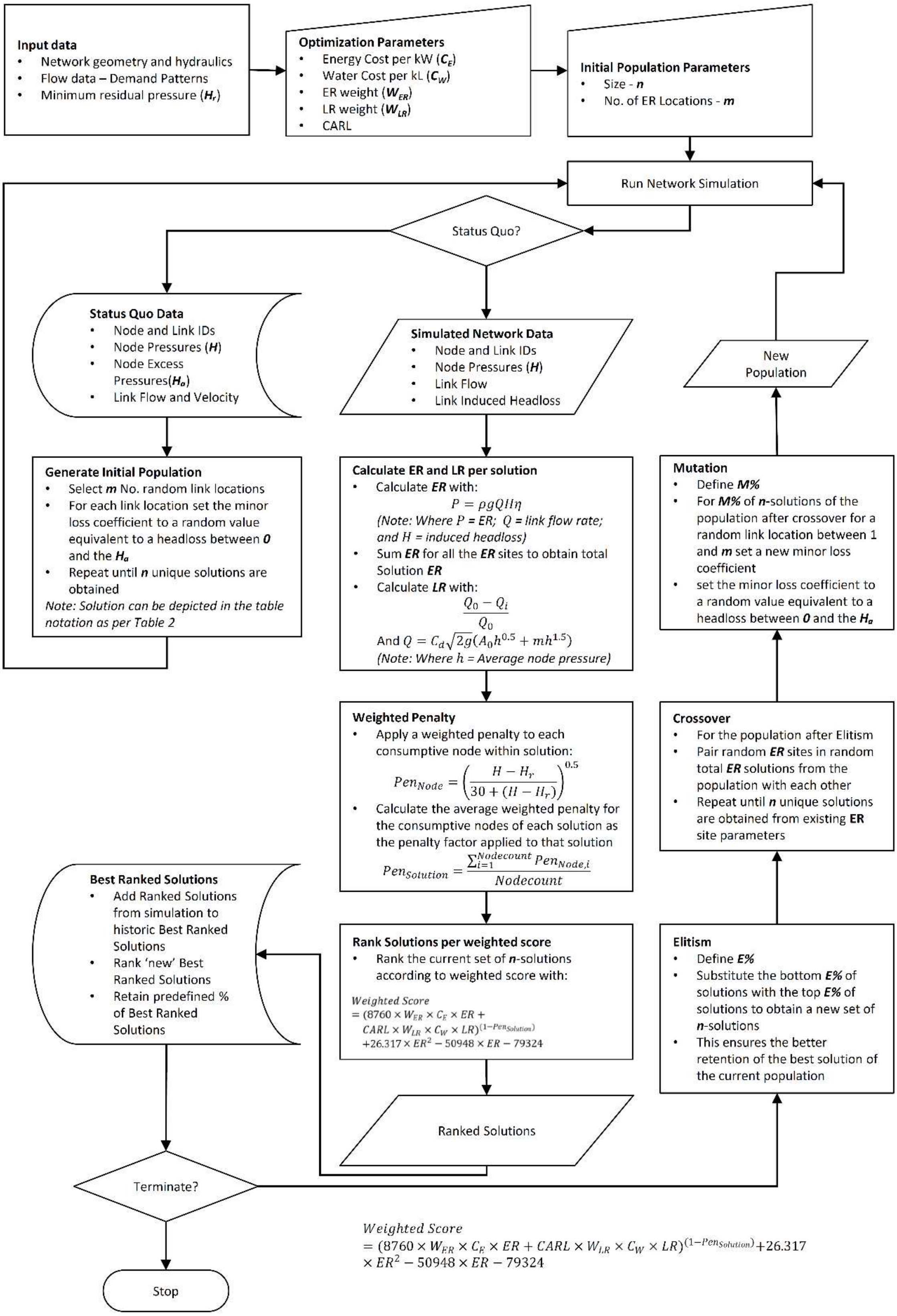


Fig. 2. Simulation flowchart of Programme for Energy Recovery and Reduction of Leak (PERRL)

Although EPANET is a demand-driven model software, any potential energy recovery solution that results in negative pressures or pressure below the minimum residual pressure at consumptive nodes is heavily penalised per the weighted penalty discussed later. This dismisses all negative or low-pressure zones from the population, which cannot be modelled adequately by a demand-driven model such as EPANET.

The GA incorporated in the developed procedure is discussed in the subsequent sections under the headings of both the different requirements, parameters and procedures involved in the optimisation process.

Input Data and Optimization Variables

The input data should be provided to the GA and refers to the geometric and hydraulic characteristics of the water distribution network under investigation to implement in the EPANET hydraulic model. In addition to this data the EPANET model requires flow data, either as steady flow data for a specific timestep or flow following a pre-defined demand pattern. The minimum input data required is summarised in **Table 1.** The input data to the procedure does not change throughout the analysis.

Bonthuys et al. (2018c) shows how asset data contained within statutory required asset management plans (AMP), can be used to populate a hydraulic model. The more detailed and correct the AMP and corresponding asset register are, the more accurate the hydraulic model and the subsequent simulation and optimisation will be.

Table 1. Minimum input data - Network characteristics

Network Element	Geometric	Hydraulic
Junctions	Coordinates Elevation	Base demand Demand pattern
Reservoirs	Coordinates	Head
Pipes	Start node End node Length Diameter	Diameter Roughness
Pumps	Start node End node	Pump curve
Valves	Start node End node Diameter	Valve type Loss coefficient

An important parameter to include in the input data is the minimum residual pressure within the water distribution system. Any pressure over and above the minimum residual pressure is potentially excess pressure which can be converted into energy through energy recovery devices (Bonthuys, et al., 2018c). However, any energy recovery installation resulting in consumptive nodes having an operating pressure below the minimum residual pressure is seen as not viable. The Guidelines for Human Settlement Planning and Design published by the South African Council for Scientific and Industrial Research (CSIR) indicates that the reticulation system in a water distribution network should be designed to have residual pressure in the reticulation main at any point above 24m under instantaneous peak demand and below 90m under zero flow conditions (CSIR, 2005). The residual pressure only applies to consumptive nodes which are defined as nodes having a base demand associated with them. All other nodes are defined as non-consumptive and only has the restriction that pressure at these nodes should be positive.

The optimization variables for the procedure are the location and size of an induced headloss at the end node of any specific link within the system. Whilst the input data remains constant throughout the procedure, the optimization variables are modified after every iteration and the solutions obtained with the modified variables are ranked according to a weighted function which incorporates the procedures optimization goals and objective function as discussed in the following paragraph. The initial size and location of the optimization variables are determined through the initial population phase of the PERRL procedure. Subsequently the optimization variables are modified using elitism, cross-over and mutation techniques.

Optimisation Goals

The PERRL optimises the energy recovery and leakage reduction from the system based on three criteria:

- Amount of energy recovered;
- % reduction in leakage from the system;
- Monetary value of energy recovered, and water saved through leakage reduction.

The energy recovery and leakage reduction weights ($\boldsymbol{W_{ER}}$ and $\boldsymbol{W_{LR}}$), as indicated in **Fig. 2**, are incorporated in the GA in order to assign importance to the two different aspects of the analysis when optimising the monetary value of the installation. In the same way the energy cost and water cost are used for the optimisation of the monetary value.

The energy cost per kilowatt (kW) and water cost per kilolitre (kL), at the most basic level, relate to the unit cost of procuring the said resource from the utility. In a more detailed analysis where the installation is done on the utility's own infrastructure for own use, the energy cost can be expanded to include all generating, transmission and distribution cost per unit. The transmission and distribution cost will however only be applicable if the energy recovery installation is off-grid. In the same way, the water cost can be analysed in more detail to include the unit rate or electricity cost of abstraction, treatment and distribution of the potable water.

In order to calculate the % leakage reduction, the current annual real losses (CARL) of the system needs to be added under the optimisation parameters. The CARL can be defined as the annual water volumes lost through all types of leaks, bursts and overflows on mains, service reservoirs and service connections, up to the point of customer metering (Lambert, 2003). The calculation of the leakage reduction from the network simulation and the CARL is discussed in Section 3.6.

Hydraulic Network Simulation

The hydraulic network simulation part of the PERRL procedure is performed in the EPANET hydraulic modelling software developed by the US Environmental Protection Agency, and is available as freeware (Rossman, 2000). Input to the hydraulic modelling is the geometric and hydraulic data as discussed earlier. The optimization variables change throughout the optimisation process as the GAs parameter's ER sites within the different solutions of the population change.

The output of the network simulation is either the status quo data as discussed in Section 3.4 or the simulated network data as per the PERRL procedure described in **Fig. 2.** The most important output of the network simulation is the Node and Link IDs, Node Pressures, Link Flows and the Induced Head loss in the ER device. From the simulated network data, the energy recovery and leakage reduction potential are calculated for the specific solution within the associated population. These calculations are described in Section 3.6.

Status Quo

The status quo of the water distribution network as defined in the PERRL is the results of the network simulation run on the hydraulic model using the geometric and hydraulic input data as discussed in Section 3.1, without any form of energy recovery present in the network. The important data obtained from the status quo analysis are as follows:

- Node and Link IDs;
- Node Pressures (***H***);
- Node Excess Pressures (pressure above the minimum residual pressure) ($\boldsymbol{H_a}$);
- Link Flow (***Q***); and
- Link Velocity (***V***).

From the status quo data, the available excess pressure at all the nodes (consumptive and non-consumptive) are used to calculate the potential energy recovery at each specific node in isolation. There are several well-established methods of energy recovery within water networks. The current proposed method for the South African market is to install a turbine (PAT-Pump as Turbine- or a conventional hydraulic turbine) to minimise capital cost and maintenance and operations (Bonthuys, et al., 2018c). The operation of the turbine is modelled as pressure loss within the supply Link to a specific Node. This pressure loss is characterised by a minor loss coefficient calculated using Equation 1.

$$k = \frac{2gH_a}{V^2} \tag{1}$$

where k = minor loss coefficient, g = gravitational acceleration (m/s^2), H_a = excess pressure head (m), V = flow velocity (m/s)

Initial population

A population in the terms of the PERRL procedure GA consists out of ***n***-number unique solutions. A solution in turn is defined as set of ***m***-number Energy Recovery (ER) locations within specific network Links connected at their end to specific network Nodes.

The process of developing the initial population is as follows:

- Define population size, ***n***.
- Define number of ER locations, ***m***.
- At random choose ***m***-number different Links from within the top 5% of pre-screened network locations (discussed below) and identify the associated end Nodes.
- For each selected Link where energy recovery is simulated set the minor loss coefficient to a random value equivalent to a head loss between zero and the Node Excess Pressures ($\boldsymbol{H_a}$) for the associated end Node as calculated in the Status Quo.
- Repeat the process until ***n***-number unique solutions are obtained as the initial population.

In order to refine the initial population procedure, and to refrain from constantly selecting inadequate energy recovery locations, a pre-screening of locations was introduced. In the pre-screening process all locations are ranked according to excess pressure and flow. The top 5% of locations according to the combination of excess pressure and flow then becomes the pool from which ***m***-number different Links are chosen at random.

The solutions of the initial population can be depicted as in the table notation per **Table 2**. The ER potential of the solutions of the initial population is calculated similarly to that of the subsequent generations of populations. The calculations are described in Section 3.6.

Table 2. GA Solutions framework

Solution No.	ER Site	Link ID	Node ID	Flow	Head lossHead loss	Energy
1	1	L_1	N_1	Q_1	h_{L1}	P_1
	2	L_2	N_2	Q_2	h_{L2}	P_2
	⋮	⋮	⋮	⋮	⋮	⋮
	n	L_n	N_n	Q_n	h_{Ln}	P_n
2	1	L_1	N_1	Q_1	h_{L1}	P_1
	2	L_2	N_2	Q_2	h_{L2}	P_2
	⋮	⋮	⋮	⋮	⋮	⋮
	n	L_n	N_n	Q_n	h_{Ln}	P_n
⋮	1	L_1	N_1	Q_1	h_{L1}	P_1
	2	L_2	N_2	Q_2	h_{L2}	P_2
	⋮	⋮	⋮	⋮	⋮	⋮
	n	L_n	N_n	Q_n	h_{Ln}	P_n
m	1	L_1	N_1	Q_1	h_{L1}	P_1
	2	L_2	N_2	Q_2	h_{L2}	P_2
	⋮	⋮	⋮	⋮	⋮	⋮
	n	L_n	N_n	Q_n	h_{Ln}	P_n

Energy Recovery and Leakage Reduction per simulation

As outlined, a single solution will consist out of a predetermined number of energy recovery sites within a network. Each energy recovery site is located at the end of a specific supply pipe to a specific node within the network. The data stored will, for each individual solution, contain the link IDs of the energy recovery sites. For each link ID the GA stores the node ID (end node), the link flow, the induced head loss and the potential energy recovery. The induced head loss is calculated from the minor head loss coefficient related to the status quo excess pressure as discussed. This induced head loss along with the link flow for the associated network simulation is used to calculate the potential energy recovery according to Equation 2, using a turbine and generator group defined % efficiency. The turbine generator group efficiency is defined as the ratio of the actual electrical energy output to the net input energy supplied by the kinetic and potential energy of the access pressure energy in the system at the point of interest.

$$P = \rho g Q H \eta \tag{2}$$

where P = power output (watt), ρ = density of fluid (kg/m^3), g = gravitational acceleration (m/s^2), Q = flow rate (m^3/s), H = head (m) and η = ERT system efficiency.

For an analysis with a chosen initial population of $\boldsymbol{m}$ solutions and $\boldsymbol{n}$ energy recovery sites, the solutions can be depicted as a table following the framework of **Table 2**.

The energy recovery potential is calculated for each solution by adding the individual potential per ER location. The leakage reduction potential cannot be calculated per ER location as it is affected by the combination of the ER for all the locations.

The effect of the total ER per solution is a change in average operating pressure within the system. From the proportional relationship of leakage to pressure in a system (Gupta, et al., 2017) it is known that a reduction in the average operating pressure will reduce the leakage from the system. May (1994) postulated that leakage in a system can be represented by a two part equation that represents both the flow from expanding areas (variable area) or from leakage paths which do not change with a change in pressure (fixed area), i.e. major bursts (Bonthuys, et al., 2018c). May's theory gave way to the development of the widely accepted FAVAD equation for leakage (Equation 3).

$$Q_l = C_d\sqrt{2g}\left(A_0 h^{0.5} + m h^{1.5}\right) \tag{3}$$

where Q_l = leakage rate (m^3/s); C_d = discharge coefficient; g = gravitational acceleration (m/s^2); A_0 = initial leak opening without any pressure in the pipe (m^2); h = pressure head (m); m = slope of the pressure area line (m).

From the proportionality of leakage and pressure and subsequently Equation 3, the leakage reduction in the system for the different solutions within the population is calculated by Equation 4.

$$LR = \frac{Q_{l0} - Q_{li}}{Q_{l0}} \tag{4}$$

where LR = leakage reduction (%); Q_{l0} = leakage rate at Status Quo (m^3/s); Q_{li} = leakage rate after network simulation with current ER parameters (m^3/s).

For the LR calculation the pressure head used in Equation 3 refers to the average operating pressure within the system. If leakage is predominantly by variable area leaks and if initial leak opening term of the FAVAD equation tends to be negligibly small, the leakage reduction potential of a system through ER can be calculated from the percentage reduction in the average operating system pressure of the system through the variable area term of the FAVAD equation (Bonthuys, et al., 2018c) and Equation 3 can be simplified to Equation 5.

$$Q_l = C_d\sqrt{2g}(mh^{1.5}) \tag{5}$$

where Q_l = leakage rate (m^3/s); C_d = discharge coefficient; g = gravitational acceleration (m/s^2); h = average operating pressure (m); m = slope of the pressure area line (m).

The discharge coefficient as well as the slope of the pressure area line may differ from one network to next depending on the size and location of leakages and their reaction to varying network pressures. It is recommended that these coefficients be calibrated with measured data to increase the accuracy and reliability of the optimisation procedure.

The ER potential per solution (calculated as the sum of the individual ER location potentials) and the LR potential per solution, in conjunction with the ER weight and LR weight discussed earlier, are used to calculate a weighted score per solution within the population. This weighted score is in turn used to rank and store the best ER and LR solutions after each iteration.

Weighted penalty and ranked solutions

As discussed in Section 3.1, any energy recovery installation resulting in consumptive nodes having an operating pressure below the minimum residual pressure is seen as not viable. In this respect a penalty function, Equation 6, has been developed that calculates a penalty per consumptive node within each solution from the population. The penalty for all non-consumptive nodes are set to 0. The only constraint with regards to non-consumptive nodes is that the nodes must have a positive operating pressure head. The penalties applicable to the individual nodes are determined as:

$$Pen_{Node} = \left(\frac{H - H_r}{30 + (H - H_r)}\right)^{0.5} \tag{6}$$

Where Pen_{Node} = node penalty; H = node operating pressure (m); H_r = minimum residual pressure (m).

These penalties are averaged to obtain a solution penalty (Equation 7) for each solution within the associated population. Employing well defined penalty factors to penalise incoherent or invalid solutions, rather than identifying and eliminating these invalid solutions, rapidly increased the computational speed of the GA and the overall effectiveness of the optimisation procedure.

$$Pen_{Solution} = \frac{\sum_{i=1}^{Nodecount} Pen_{Node,i}}{Nodecount} \tag{7}$$

Where $Pen_{Solution}$ = solution penalty; Pen_{Node} = node penalty; $Nodecount$ = number of network nodes within the hydraulic model.

The energy recovery and leakage reduction weights are incorporated in the GA procedure in order to assign importance on the two different aspects of the analysis during the optimisation. The weights, along with the energy and water unit costs, cost of the ER installation, the CARL and energy recovery and leakage reduction potentials are used to calculate a weighted score for each of the ***n***-solutions within the population according to the following equation:

$$Weighted\,Score = (8760 \times W_{ER} \times C_E \times ER + CARL \times W_{LR} \times C_W \times LR)^{(1-Pen_{Solution})} + 26.317 \times ER^2 - 50948 \times ER - 79324 \tag{8}$$

where W_{ER} = energy recovery weight; C_E = energy cost (ZAR/kW); ER = energy recovery (kW); $Pen_{Solution}$ = solution penalty; $CARL$ = current annual real losses (kL); W_{LR} = leakage reduction weight; C_W = water cost (ZAR/kL); LR = leakage reduction (%);

The solutions from every population are ranked within the population according to the weighted scores, and the best predefined % of solutions within the population compared to the historic best ranked solutions. Population solutions having a better fit according to the weighted scores in comparison to the historic ranked solutions, are added to the historic best ranked solutions and new historic best ranked solutions are sorted and stored. After this process the GA is either terminated or continues with elitism, crossover and mutation.

Elitism, Crossover and Mutation

Within the PERRL procedure, after each network simulation using a population of energy recovery locations and sizes (phase 1), the solutions are ranked (phase 2) and the best ranked solution is selected (phase 3). If the best ranked solutions do not converge to a single solution after a predefined number of iterations of the GA, the current population evolves to form a new population or next generation and the process is repeated. The three main evolutionary techniques employed by the PERRL procedure is elitism, crossover and mutation.

In the context of single-objective GAs, elitism means that the best solution in the current population always survives to the next generation. Applying this principle to a multi-objective GA results in all non-dominate solutions discovered by the GA being considered as elite solutions. A non-dominated solution is a solution that is no worse than the next solution in all objectives, or strictly better than the next solution in at least one of the multiple objectives. A straightforward implementation of elitism in a multi-objective GA is to copy the elite solutions in population P_t to population P_{t+1}, then fill the rest of P_{t+1} by selecting from the remaining solutions in P_t (Konak, et al., 2006).

Alternatively, the multiple objectives can be scalarised into a single objective by adding each objective pre-multiplied by a user-supplied weight as discussed in Section 3.2.

For the PERRL procedure, an elitism % is predefined as ***E***. The bottom ***E***% ranked solutions of the current population is substituted by the top ***E***% ranked solutions of the current population to obtain a new set of solutions with the same population size to progress to the crossover stage of the GA.

In GA, crossover is used to combine the information or parameters of two parent solutions in a population to stochastically generate new offspring in the next generation or population of solutions. In the proposed procedure, random ER sites in random ER solutions from the population are paired with each other until a predefined number of new unique solutions are obtained as a population.

Where crossover produces a new population by recombining the information from two solutions in a prior population, mutation prevents convergence of the population by changing a predefined small number of randomly selected parameters to continuously introduce variation into the population (Magalhaes-Mendes, 2013).

Within the PERRL procedure, the mutation process reconfigures the minor loss coefficient of random solutions within the population after elitism and crossover. For a population with ***n***-solutions and a ***m***-number of ***ER*** locations, the minor loss coefficient of a random ***m*** location of a predefined ***M***% of the ***n***-solutions is re-configured to a random value equivalent to a head loss of between 0 and the excess node pressure.

After the elitism, crossover and mutation processes the network simulation is run, and the process continues until no significant improvement in weighted solution is reached after a certain number of iterations or until the process is terminated after a predefined number of iterations.

Benchmark water distribution network

The PERRL procedure was used to model a benchmark network in order to evaluate how the algorithm within the PERRL procedure compares to results from studies by previous researchers applied to the same benchmark network. The Jowitt and Xu (1990) water distribution network (**Fig. 3.**) has been used widely by various researchers to analyse and address the problem related to the optimal location of pressure reducing valves for minimizing leakages.

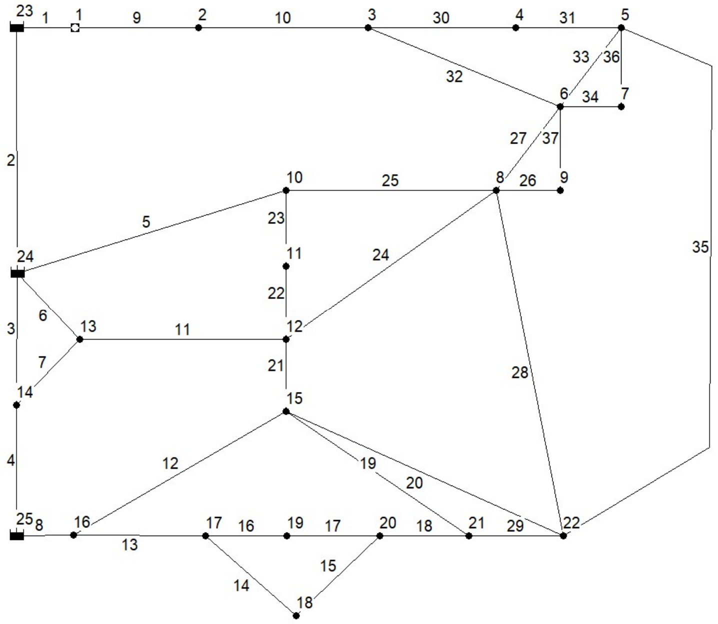


Fig. 3. Benchmark water distribution network (adapted from Jowitt and Xu, 1990)

This benchmark network is composed of 3 reservoirs, 25 junctions (nodes) and 37 pipes having a total pipe length of 44.26 km, ranging in diameter between 152 and 475 mm and having Hazen-Williams roughness coefficients between 6 and 140 (Jowitt and Xu, 1990). The junctions or nodes of the network consist of both consumptive and non-consumptive nodes, with the consumptive nodes having a total base demand of 150 l/s. All the characteristics required to adequately model the network and run the PERRL procedure is contained within the paper by Jowitt and Xu (1990). A variation between the PERRL procedure for the benchmark network evaluation and the initial PERRL procedure is that the emitter coefficient for leakage within the system was set to 1.18 to be able to compare the leakage reduction results of PERRL with the historic research results. The minimum residual pressure requirement for the comparison was set to 30 m.

Previous research was only conducted on the optimum location and size of PRVs for pressure management and leakage reduction. In light of this, the PERRL procedure was only used to evaluate the location of ERTs and the corresponding leakage reduction. A comparison of results obtained from various previous research and this study on the benchmark network is shown in **Table 3** and indicates that the PERRL procedure compares well with other generally recognised pressure management optimisation techniques. The comparison was done solely on a scenario installing 3 PRVs or ERTs. The PRV/ERT locations in **Table 3** refers to the pipe number as per **Fig. 3**.

Table 3. Benchmark network results comparison

Reference	PRV/ERT location (pipe)	Leakage reduction (%)
Jowitt and Xu (1990)	11, 21, 29	20%
Araujo, Ramos and Coelho (2006)	11, 21, 29	15%
Nicolini and Zovatto (2009)	1, 11, 20	15%
Creaco and Pezzinga (2015)	1, 8, 11	33%
Gupta et al. (2017)	1, 8, 11	18%
PERRL	11, 21, 28	24%

Case Study

The PERRL was applied to the Polokwane Central DMA within the City of Polokwane (CoP) Local Municipality in Limpopo, South Africa. The CoP municipality covers a surface area of over 5000 square kilometres and serves around 280 000 residential and non-residential customer units. The CoP water asset portfolio comprises approximately 6 000 km of pipelines configured into 14 regional water schemes managed in seven operational clusters, of which a section was isolated as the Polokwane Central DMA for hydraulic modelling in prior research (Bonthuys, et al., 2018c).

The Variable Area term of the FAVAD equation used for the modelling of the leakages from the Polokwane Central DMA was calibrated by Bonthuys et al. (2018c) using the CARL of the systems as measured by the asset custodians and the assumption that the system is predominantly governed by variable area leaks. The slope of the pressure area line, or the Variable Area term coefficient, m, was calculated as 6.684×10^{-5} and used in the PERRL procedure to optimise the location and size of ERTs (Bonthuys et al., 2018c).

The monetary value of energy recovered was calculated per unit rate using an average electrical cost for 2018/2019 (Eskom, 2018). The energy cost per kW for the CoP was therefore calculated as ZAR 0.84 per kW ($ 0.06 per kW). The water cost per kL was defined as all cost savings from the leakage reduction and included the surface water abstraction and treatment electricity consumption cost, the water distribution electricity consumption cost and the CoP average water rate (loss of sales). The International Energy Agency (IEA, 2016) estimates the energy use for water abstraction, treatment and water distribution as 0.07 kWh/m^3, 0.07 kWh/m^3 and 0.25 kWh/m^3 respectively. The average CoP water rate was estimated as ZAR 17.44 per kL ($ 1.23 per kL) using the CoP tariffs (City of Polokwane, 2018) and an average water consumption per capita of 260 litres per capita (Department of Water and Sanitation, 2017). Considering both the energy usage and the average CoP water rate, the water cost per kL amounts to ZAR 17.71 ($ 1.25).

The PERRL procedure was run using the specific time step during the Polokwane DMA demand pattern when the demand is at its highest and the pressure within the system at its lowest. This specific time step occurs between 11h00 and 13h00. Any excess pressure during this time step is assumed to be excess pressure for the entire duration of normal operating hours. For the purpose of the study the weights for energy recovery and leakage reduction were set to 70% and 30%.

Bonthuys et al. (2018b) analysed the water distribution of the Polokwane Central DMA incorporating an algorithm developed by Samora et al. (2016). After 10 iterations of the algorithm the analysis showed an energy recovery potential of 264 kW and a leakage reduction potential of 3%. This energy recovery and leakage reduction potential amounted to a monetary value of ZAR 6.1 million per annum ($ 430k per annum). The CARL for the Polokwane Central DMA was estimated by Bonthuys et al. (2018c) as approximately 3600 ML and was used in the PERRL procedure.

Results and discussion

The following paragraphs discuss the results obtained in using the PERRL procedure in optimizing the location and size of turbines for energy recovery and leakage reduction within the Polokwane Central DMA.

Several different scenarios could be run using PERRL, depending on the requirements and expected outcomes of the analyses. Firstly, an analysis can run for ERT locations within the network incorporating excess pressures at the time step during the daily operation of the network with the highest demand or flow in the system, the day scenario. This time step will have the lowest average operating pressure and is therefore the most conservative approach to energy recovery when looking at a single specific time step. Secondly PERRL can be run during the time step with the lowest demand or flow and therefore the highest average operating pressure. This time step will have the highest potential for leakage reduction, but the possibly lowest potential for energy recovery. These initial analyses are to narrow down the potential locations based on the requirements of the asset custodian, i.e. a focus on energy recovery or a focus on leakage reduction. However, in real situations the focus is normally a combination of both leakage reduction and energy recovery and this aspect is covered through the weighted score within the PERRL process.

The analyses to obtain the optimum location and size of turbines for the Polokwane Central DMA was conducted through the developed PERRL process. Since energy recovery is of more importance to Polokwane, the process was initially run for the day scenario incorporating weights for energy recovery and leakage reduction as 70% and 30%. After the initial analysis an EPS is run on the locations identified by PERRL using turbine efficiencies as defined in the study by Paish (2002).

Within the PERRL process, ten separate independent simulation runs, consisting of 100 iterations each with an initial population of 100 and an energy recovery location number set to 3 were done, i.e. 10 separate simulations each consisting of the evaluation of 10 000 networks each containing 3 energy recovery locations were run. The elitism and mutation percentages were both set at 20%. **Table 4** shows the details of the globally top ranked solutions. Each simulation run typically takes around 30 minutes to complete.

Table 4. Globally top ranked solutions - PERRL

Link	End Node	Flow (LPS)	Induced Headloss (m)	Energy Recovery (kW)
7035	570	70.97	15.93	8
7013	268	20.24	4.31	1
6429	3025	92.03	43.07	27

The top ranked solutions foresee the installation of turbines of 1 kW, 8 kW and 27 kW at the three locations as indicated in **Table 4**. The magnitude of the results of the PERRL analyses differs from the results obtained for energy recovery for the same area in a previous study by Bonthuys et al. (2018b). The difference in these two studies is that in the previous study by Bonthuys et al. (2018b) only the energy recovery component was used to optimise the location of turbines, and no consideration was given to the effect of energy recovery on leakage within the system. The current study also takes into account the effect of installation costs on the weighted score of the solutions.

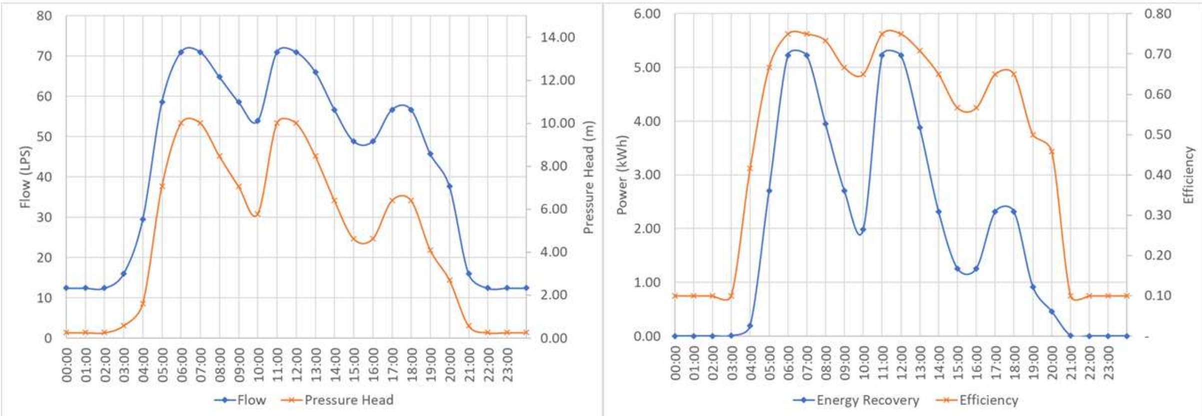
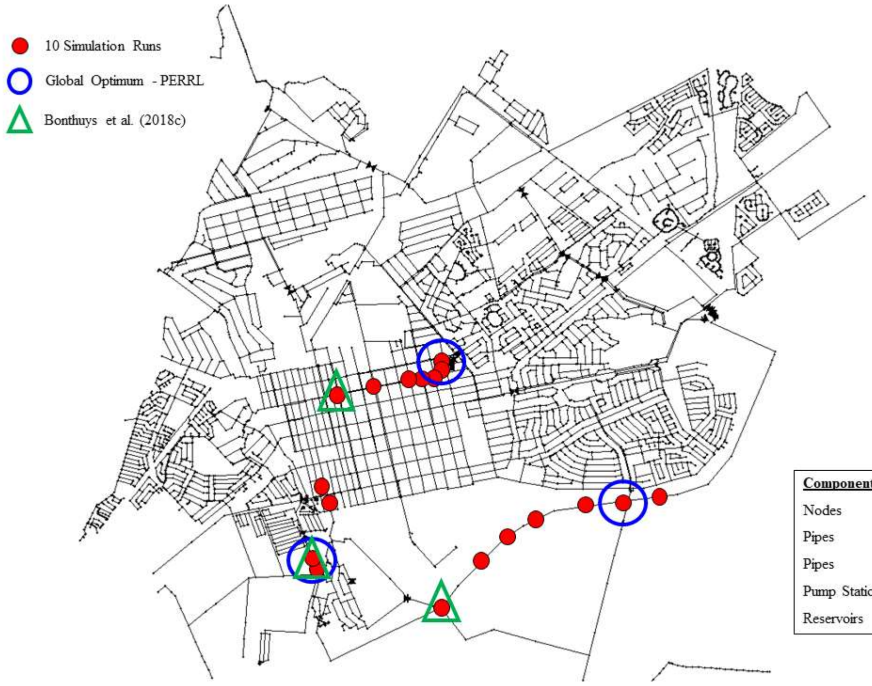


Fig. 4. EPS results – Link 7035

An extended period simulation (EPS) was run on solutions incorporating efficiency characteristics for the ERT installations as described in the study by Paish (2002). **Fig. 4.** shows an analysis of the EPS conducted on the proposed ERT installed in Link 7035. The EPS was done using a typical efficiency curves from Paish (2002) that the fit the pressure distribution at proposed installation points. Not all water distribution systems are good candidates for pressure management and/or energy production, therefore it is important to install fit for purpose turbines at the proposed locations.



Component	Unit	Quantity
Nodes	No.	6 225
Pipes	No.	7 133
Pipes	km	592
Pump Stations	No.	2
Reservoirs	No.	13

Fig. 5. Optimal ERT locations

Fig. 5. shows the optimum locations of ERTs from the PERRL analyses and the EPS, as well as the ERT locations for the previous study by Bonthuys et al. (2018b). As it can be seen, two of the three locations are identified by both the analyses. The reason of the difference in the third one seems to be related to leakages since both the third locations are situated on the same supply line with the same flow rate but at different locations along the hydraulic gradeline. The previous analysis which focussed solely on energy recovery identified the location with a slightly lower pressure than that of the location identified by the PERRL procedure, which also incorporates the effect of energy recovery on leakage reduction. When considering energy recovery alone, a small difference in head between two potential energy recovery locations does not amount to significant differences when considering a system with an average operating pressure well in excess of the residual pressure requirement. However, when incorporating leakage reduction into the procedure the following plays a major role in identification of potential locations:

- The higher cost of water per kL lost through leakages compared to the cost of energy savings per kW through energy recovery.
- The pressure variable in the background leakage term of the FAVAD leakage equation is an exponential variable and any increase in potential pressure head for energy recovery has an exponential increase on leakage reduction potential.

Depending on the assigned weights for the importance of either energy recovery and leakage reduction, the locations and sizes of installations identified by the PERRL procedure as part of the optimisation of the network, will differ.

Conclusion

From the relationship between pressure within and leakage from water distribution systems, it is well known that an increase in average operating pressure will increase the water losses through leakage in a water distribution system. The inverse is also well established and widely employed as the foundation for pressure management within water networks. Previous studies have researched the installation of Energy Recovery Turbines instead of conventional PRVs for pressure management and have found that, at maximum flow conditions, the leakage reduction as a result of ERTs are comparable to the operation of conventional PRVs with the added benefit of recovering energy from the system (Bonthuys, et al., 2018c).

Previous studies highlighted that even though the potential of energy recovery within water distribution systems are well known, information on the exact location and extend of this potential is lacking (Bonthuys, et al., 2018a) and procedures and practices to identify such potential needs to be developed.

The current study investigated the incorporation of GAs into a procedure for the identification and optimisation of the location and size of ERTs for energy recovery and leakage reduction within water distribution systems. Multiple objectives, relating to quantity of energy recovered, percentage of leakage reduction and monetary implications of both, were defined and a penalty factor developed to evaluate solutions within the different GA populations.

A procedure was developed and termed the Programme for Energy Recovery and the Reduction of Leakage (PERRL). PERRL was tested against the Jowitt and Xu (1990) benchmark model and, although the model was set up and used to developed optimisation procedures and tools for pressure management, PERRL was developed in such a way that it could be scrutinised to analyse energy recovery and leakage reduction (pressure management) separately or simultaneously with different levels of importance assigned to each aspect. The PERRL analyses compared well to the benchmark results from previous studies.

PERRL was used to analyse the Polokwane Central DMA from previous studies by Bonthuys et al., (2018c) where initially the algorithm of Samora et al. (2016) was incorporated in evaluating the potential for energy recovery. The algorithm of Samora et al. (2016) only evaluates the potential for energy recovery and not the subsequent benefits relating to leakage reduction. For this reason, the results of the PERRL procedure differs slightly from the results obtained by Bonthuys et al. (2018c), with regards to the location of ERTs on a single supply line. Due to the fact that energy recovery and leakage reduction are both functions of pressure and flow and as PERRL assigns different levels of importance to both aspects, the location of ERTs will change along a single supply line with multiple demand off-takes to obtain the optimum location according to the energy recovery and leakage outputs as controlled by their pre-defined importance.

Data Availability

Some or all data, models, or code used during the study were provided by a third party. Specific data supplied by a third party relates to the geometrical and hydraulic characteristics of the City of Polokwane Local Municipality water distribution network. Direct requests for these materials may be made to the provider as indicated in the Acknowledgements, or requests can be directed through the author.

Some or all data, models, or code generated or used during the study are proprietary or confidential in nature and may only be provided with restrictions. The following data and code can be provided with restrictions:

- VBA code of the PERRL procedure

This study forms part of a post graduate study and as such the VBA code for the PERRL procedure is subject to the Intellectual Property (IP) Policy of the Tertiary Institution and can only be provided with the necessary restrictions as contained within the policy.

All other data and assumptions used within the study appears in the submitted article.

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Disclaimer

The output of the research conducted in this article is generated from developed hydraulic models of the City of Polokwane's Water Supply Infrastructure. These models incorporate assumptions informed by demand modelling and has not been calibrated to any specific time, date or scenario of measured data from the City of Polokwane's Water Supply Networks. This research does not reflect or constitute the views of the Polokwane LM or any individuals affiliated with the Polokwane LM.

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