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Optimum location for energy recovery and leakage reduction in water distribution networks

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ABSTRACT

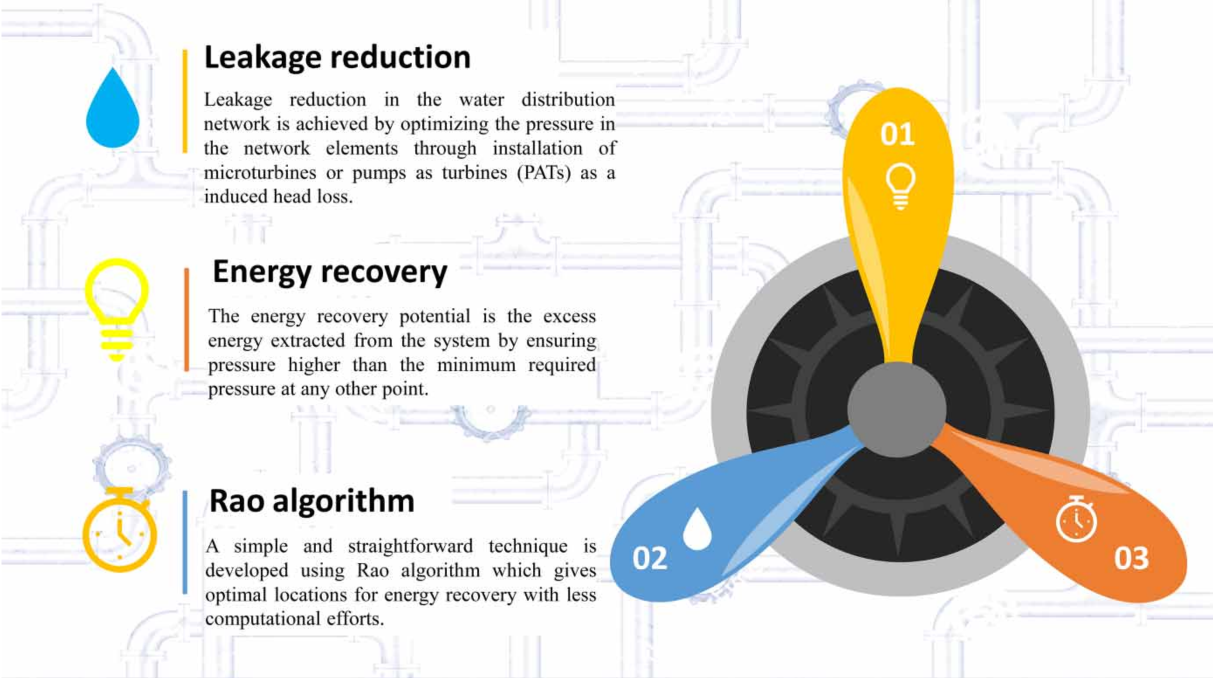
The excess pressure in water distribution networks (WDNs) can be utilized to reduce leakage and produce energy by installing energy recovery devices (ERDs) like microturbines or pumps-as-turbines. The major challenge in adopting ERDs in pipe networks is to locate the optimum location for their placement. An optimization procedure is proposed in this work to find the optimum locations of energy recovery (ER) and leakage reduction (LR). The optimization method is based on the Rao algorithm, written in Python, coupled to an EPANET-implemented hydraulic model. With optimal ER of 543.46, 648.24 and 154.58 kWh/day and LR of 61.1, 13.6 and 6.8%, three benchmark networks – the 5-node, the 25-node and the 46-node network – serve as the basis for validating the proposed approach which converges to the best solution in only 2,000, 4,000 and 10,000 function evaluations. For large networks, solutions with two ideally located devices gave higher ER than three imperfectly located devices. This methodology is verified to give optimal ER locations and can be applied to any pipe network regardless of size and location. This work made it easier to analyse the potential for ER in WDNs and promotes the use of sustainable leakage management methods.

Key words: energy recovery, leakage reduction, optimization, Rao algorithm, water distribution network

HIGHLIGHTS

- This work suggests a sustainable leakage reduction technique providing renewable energy.
- A parameter-less Rao algorithm was used for the optimization of a normalized objective function.
- Method can indirectly reduce the water and carbon footprint of WDN.
- It is observed that optimum pipe locations are crucial in getting optimum results.
- This method can be applied to find potentially recoverable energy of any pipe network.

GRAPHICAL ABSTRACT



NOTATIONS AND ABBREVIATIONS

ER	Energy recovery
ERD	Energy recovery device
LR	Leakage reduction
PAT	Pump operating as turbine
PCV	Pressure-control valve
PRV	Pressure-reducing valve
WDN	Water distribution network
WNTR	Water network tool for resilience
C_{hw}	Hazen Williams roughness coefficient
C_k	Leakage coefficient for pipe k
$\mathrm{ER}_{\max}$	Total excess energy of the network
g	Acceleration due to gravity (m/s^2)
H_{ex}	Excess pressure head at any point (m)
H_i	Available pressure head at node i
H_j	Available pressure head at node j
$H_{j,\min}$	Minimum required pressure head at node j
H_k	Pressure head at pipe k (m)
k_{m}	Minor head loss coefficient
L_k	Length of pipe k (m)
$\mathrm{LR}_{\max}$	Maximum leakage reduction ratio
N	Node number
Q_j	Discharge at node j (m^3/s or L/s)
Q_{L0}	Initial leakage discharge (m^3/s)
Q_{L1}	Final leakage discharge (m^3/s)
Q_{lk}	Leakage discharge at pipe k (m^3/s)
R	Random number between 0 and 1
t	Time duration (h)
V	Velocity of flow (m/s)
w	Weightage
Z	Objective function

α Leakage exponent
ρ Density of water (kg/m^3)

INTRODUCTION

Water has been and will continue to be a significant part of human civilization; thus, water distribution networks (WDNs) are essential for modern civilization (Eissa *et al.* 2022). Water scarcity, which is among the major water problems, is predicted to rise in future (Tsakiris 2015). Leakage in WDNs is a global concern since a significant amount of treated and transferred water is lost due to leakage. Globally, 25–30% of drinking water is lost due to leakages in WDNs (Berardi & Giustolisi 2021). The leakage volume in well-maintained networks varies from 3 to 7% of the water supply and can be more than 50% in poorly maintained networks. As per the report of the Asian Development Bank (Frauendorfer & Liemberger 2010), Asian nations lose about 29 trillion litres of treated water due to leakage, costing 9 billion dollars. Saving one-tenth of this leakage volume can provide water to at least 30 million people.

Hydropower plays an important role at the global level in the energy production sector. However, the construction of large hydropower plants is linked to extremely high costs in terms of the economy, the environment and society and has irreversible environmental impacts (Kuriqi *et al.* 2020; Suwal *et al.* 2020). As a result, micro hydropower plants, which are perceived as sources of sustainable energy, are seeing a worldwide boom. Micro hydropower plants typically refer to facilities with power outputs under 100 kW (Kuriqi & Jurasz 2022). Their main advantage is the negligible environmental impact and low installation cost. Installation of small hydropower generation devices like PATs or microturbines in water distribution systems enables electricity to be produced without impacting the environment with low generation cost (Malka *et al.* 2022) with the added benefit of leakage reduction (LR).

Water loss occurs in all WDNs. The variation in the volume of loss depends on the pipe network characteristics and local factors. Water loss is the sum of real losses and apparent losses. Apparent losses are the unauthorized consumption and inaccuracies in customer metering. Real losses are leakages from pipes, joints, valves, service reservoir floors and walls and reservoir overflows (Farley & Trow 2003). Real losses can be significant and may go undiagnosed for months to years. The volume lost will depend mainly on the pressure in the network.

Along with the wastage of water, the leaking pipeline networks have an environmental impact as it wastes energy, chemicals and labour spent on pumping, purifying and delivering water from sources to consumers' taps (Walsh *et al.* 2017). Leakage in WDNs is also known to reduce network hydraulic capacity and accelerate the number of pipe fractures, subjecting users to an increased risk of inadequate water supply, disruptions and damages associated with failure occurrences (Berardi & Giustolisi 2021).

The pursuit of advantages in terms of reduced leakage and pipe bursts, as well as increased infrastructure life, has prompted water utilities to execute active management of service pressure in WDNs. In addition, contrasting requirements of minimizing excess network pressure while maintaining the minimum required pressure have created a great demand for pressure management optimization (Araujo *et al.* 2006; Tricarico *et al.* 2018). Many researchers have used pressure-reducing valves (PRVs) (Jowitt & Xu 1990; Araujo *et al.* 2006) and pressure-control valves (PCVs) (Creaco & Pezzinga 2018; Page *et al.* 2018) to control pressure in WDNs to reduce leakages. The drawback of such a technique is the wastage of hydraulic energy as the excess pressure is released into the atmosphere. Utilization of excess hydraulic energy using energy recovery devices (ERDs) such as microturbines and pumps operating as turbines (PATs) is suggested in many studies (Fecarotta *et al.* 2015; Bonthuys *et al.* 2020; Ebrahimi *et al.* 2021). The recovery of excess hydraulic energy in WDNs can be an alternative to the microgeneration of electricity. This technology promotes environmental sustainability in urban areas for self-sufficiency.

The major challenge of the above approach is the time-consuming task of searching for the optimal location of ERDs. Various techniques have been suggested to find the location of ERDs in WDNs. Some studies analysed the nodes with higher energy dissipation for a feasibility study (Samora *et al.* 2016; Fernández García & Mc Nabola 2020). Samora *et al.* (2016) analysed the ER potential based on existing water demand by installing microturbines at multiple locations. Regarding the application of optimization methods, the most commonly used mathematical method is mixed-integer nonlinear programming (Fecarotta & McNabola 2017; Fernández García & Mc Nabola 2020; Morani *et al.* 2021) and the stochastic method is genetic algorithm (Basupi *et al.* 2013; Giugni *et al.* 2014; Tricarico *et al.* 2018). Most previously used techniques are network-specific and/or highly complex to understand and apply. Also, they require tuning algorithm-specific parameters, which increase computational efforts. Thus, there is a requirement for a straightforward technique which can suggest the optimal locations for ER with less computational cost.

Recently, the use of the Rao algorithm has been suggested by some researchers in the optimization of WDNs to minimize cost (Jain & Khare 2021; Palod *et al.* 2021) and maximize reliability (Jain & Khare 2022). In the present work, a straightforward methodology to find the optimum location of ERDs in WDNs with the objective to maximize LR and ER is developed using the Rao algorithm. The goal is to assess the potential of utilizing excess hydraulic energy in WDNs. Besides generating renewable energy and providing a clean, sustainable source of revenue, ER in WDNs has the additional benefit of improving system resilience. Due to already-built basic and expensive components (pipes and storage tanks) and a substantially lower investment cost than a standard micro hydro, the proposed scheme's economic benefits can be guaranteed. Additionally, the requirement for a continuous supply of drinking water ensures effective energy production and a high-capacity factor.

OPTIMIZATION PROCEDURE

WDN problems are considered highly complex and are subject to numerous constraints (Suribabu 2017). Developing a simple and efficient optimization procedure can benefit engineers in solving such problems. A simple method for optimizing WDNs for LR through ER using the Rao algorithm is developed in this work to analyse the potential of ER in WDNs. The primary goal is to find the amount and location of ER potential within WDNs.

Simulation model

A hydraulic simulation model ensures demand satisfaction at each node with minimum required pressure. EPANET 2.2 (Rossman 2000) is used as the hydraulic simulation model linked to a Python code using Water Network Tool for Resilience (WNTR). 'WNTR is a Python package which contains several sub-packages. Each sub-package contains modules that include classes, methods and functions. These classes generate WDN models and run simulations through python code' (Klise *et al.* 2018; Jain & Khare 2021).

The hydraulic model requires geometric and hydraulic characteristics and flow data (as a steady flow for a specific time step or a demand pattern). The input data to the procedure do not change throughout the analysis. The minimum required pressure within the WDN is a crucial input parameter for this study. Pressure above the minimum required level is considered a potential excess pressure and can be transformed into energy using ERDs (Bonthuys *et al.* 2020).

The minimum required pressure is used to measure the feasibility of the selected location for the ERD. Any potential ER solution that results in available pressure below minimum required pressure at any consumptive node is heavily penalized through pressure and discharge-dependent penalty function. Consumptive nodes are nodes with positive base demands. All other nodes are non-consumptive, which only has a restriction for the pressure to be positive.

The simulation model is linked to the Rao algorithm-based optimization procedure to fulfil optimization goals.

Optimization goals

The objective of this study, which is based on LR through ER in WDNs, considers the maximization of the normalized objective function of LR ratio and hourly ER. The objective can be achieved either by giving equal weights to both objectives or different weights (Suribabu 2017).

$$Z = \mathrm{Max}\left(w\left(\frac{\mathrm{ER}}{\mathrm{ER}_{\max}}\right) + (1-w)\left(\frac{\mathrm{LR}}{\mathrm{LR}_{\max}}\right)\right)(1 - \mathrm{Penalty}_1)\ (1 - \mathrm{Penalty}_2) \tag{1}$$

Z is the objective functions; w is the weight; ER and LR are the hourly ER and LR ratio for the solution set; $\mathrm{ER}_{\max}$ is the total excess energy of the network; $\mathrm{LR}_{\max}$ is the ratio corresponding to the maximum reduction in network leakage, which is equal to one when the leakage is zero; $\mathrm{Penalty}_1$ corresponds to the penalty for violating minimum head constraints (Jain & Khare 2021) and $\mathrm{Penalty}_2$ is equal to one when there is a repetition in pipe number for the solution set.

$$\mathrm{Penalty}_1 = Q_j\ (\max(0, H_{j,\min} - H_j)) \tag{2}$$

Q_j is the discharge (m^3/s), $H_{j,\min}$ is the minimum required pressure head and H_j is the available pressure head at node j.

Leakage reduction

LR in the system is the difference in the leakage volume before and after using an ERD. It can be represented in the form of an LR ratio (Bonthuys *et al.* 2020):

$$\mathrm{LR} = \frac{Q_{\mathrm{L0}} - Q_{\mathrm{L1}}}{Q_{\mathrm{L0}}} \tag{3}$$

Q_{L1} is the leakage after ERD installation and Q_{L0} is the initial leakage. The total leakage volume of the system can be calculated as:

$$Q_{\mathrm{L1}} = \sum_{k=1}^{np} Q_{lk} \tag{4}$$

Q_{lk} is the water leakage volume at pipe k; np is the total number of pipes in the network. Q_{lk} is calculated from a nonlinear relationship of pressure and leakage derived from the experimental data and represented as (Germanopoulos 1985):

$$Q_{lk} = C_k L_k H_k^{\alpha} \tag{5}$$

L_k is the length of the pipe; α is the leakage exponent; C_k is the coefficient that relates the leakage per unit length of pipe to available pressure and depends on the system characteristics (for example, the age and deterioration of the pipe and the soil properties, etc.); H_k is the average pressure head that can be approximated by the average pressure head relative to the ground level at two ends of the pipe:

$$H_k = \frac{H_i + H_j}{2} \tag{6}$$

H_i and H_j are the pressure heads at the nodes i and j connected to pipe k. For the flow through an orifice, the value of the leakage exponent is taken as 0.5. For measuring leakages, a higher exponent value (0.9–1.18) is used, which incorporates the difference in internal and external pressures of the pipes with joints or cracks (Jowitt & Xu 1990).

Energy recovery

Pressure management in the system is regarded as the best technique to reduce leakage due to the proportional relationship between leakage and pressure. In the past, PRVs and PCVs were used for pressure management. However, using these techniques results in the wastage of excess water pressure. On the other hand, inducing ERDs (e.g., hydro-turbines or PATs) utilize this excess pressure and provide an added benefit of energy production. This recovered energy can either be used directly to pump during high-demand conditions or supplied to the grid.

For the reliability of the system, the WDNs are usually designed by ensuring that the pressure head at each node is more than the minimum required pressure head (H_{min}). Whenever the available pressure head (H) is higher than the H_{min}, there is a possibility of potential ER due to the availability of the excess pressure. However, this excess pressure varies with time due to uncertainty in demand. The excess pressure head at any point can be calculated as (Samora *et al.* 2016):

$$H_{\mathrm{ex}} = \Delta H = H - H_{\mathrm{min}} \tag{7}$$

As hydropower energy is influenced by both head and flow rate, excess energy cannot be determined simply on the grounds of excess pressure head. The excess energy of the network, which is also the total excess energy ($\mathrm{ER}_{\mathrm{max}}$) of the network, can be calculated as:

$$\mathrm{ER}_{\max} = \sum_{j=1}^{nn} \rho g (H - H_{\min})_j \max(Q_{kj}) \Delta t \tag{8}$$

$$\mathrm{ER}_{\max} = \sum_{j=1}^{nn} \rho g \Delta H_j \max(Q_{kj}) \Delta t \tag{9}$$

Q_{kj} is the flow in the pipe k connected to node j (m^3/s); max (Q_{kj}) is the flow corresponding to the pipe k with the maximum flow, which is connected to node j; ρ is the density of water (kg/m^3); g is the gravitational acceleration (m^2/s); Δt is the time interval (h), that can be considered as the study state duration.

The total excess energy of the system is not the potentially recoverable energy, as at some nodes, excess energy is essential to guarantee the minimum required pressure at other nodes. The ER potential can be defined as the excess energy extracted from the system by ensuring pressure higher than the $H_{\min}$ at any other point. The ER potential for each set of solutions can be calculated by adding the energy potential of each ERD location.

$$\mathrm{ER} = \sum_{j=1}^{M} \rho g \Delta H_j \max(Q_{kj}) \Delta t \tag{10}$$

where M is the number of ERDs installed.

The LR potential cannot be predicted per ERD location as it is governed by the combined effect of installing ERDs at all locations.

Optimum site location

Even if potentially recoverable energy is identified in a network, the optimal location of ERDs within a network is not easily identified. It is attributed to several factors, including the pipe flow rate and velocity constraints that vary on a daily basis, the head, which is determined by the minimum required pressures and the size of ERD, and the network geometry, which governs the flow distribution within its closed network. To solve this problem, a search algorithm was developed that employed the Rao algorithm to maximize the objective function based on ER, LR and weighted penalty, as discussed in the 'optimization goals' section.

Minor head loss

The operation of the ERD is simulated as a head loss at the pipe position associated with a certain node (Bonthuys *et al.* 2020). This head loss is reflected by a minor loss coefficient (k_m) derived using the equation:

$$k_m = \frac{2g\Delta H}{V^2} \tag{11}$$

V is the flow velocity (m/s).

Rao algorithm

The optimization procedure to find the location of ERDs for LR through ER is written in Python language using the Rao algorithm. Rao algorithms were introduced by Rao (2020). The major advantage of using Rao algorithms is that they are algorithm-specific parameter-less algorithms and hence do not require tuning such parameters. In addition, the concept of Rao algorithms is straightforward and easy to understand (Rao & Pawar 2020). Rao algorithms work by moving closer to the best solution for the entire population and moving away from the worst. Figure 1 outlines a flowchart that describes the optimization procedure utilizing the Rao algorithm.

The optimization parameters like population size, the number of iterations and examined number of ERDs are specified in the Python code. The optimization variable for the procedure is the location of an induced head loss at the link with maximum pressure connected to a specific node within the system.

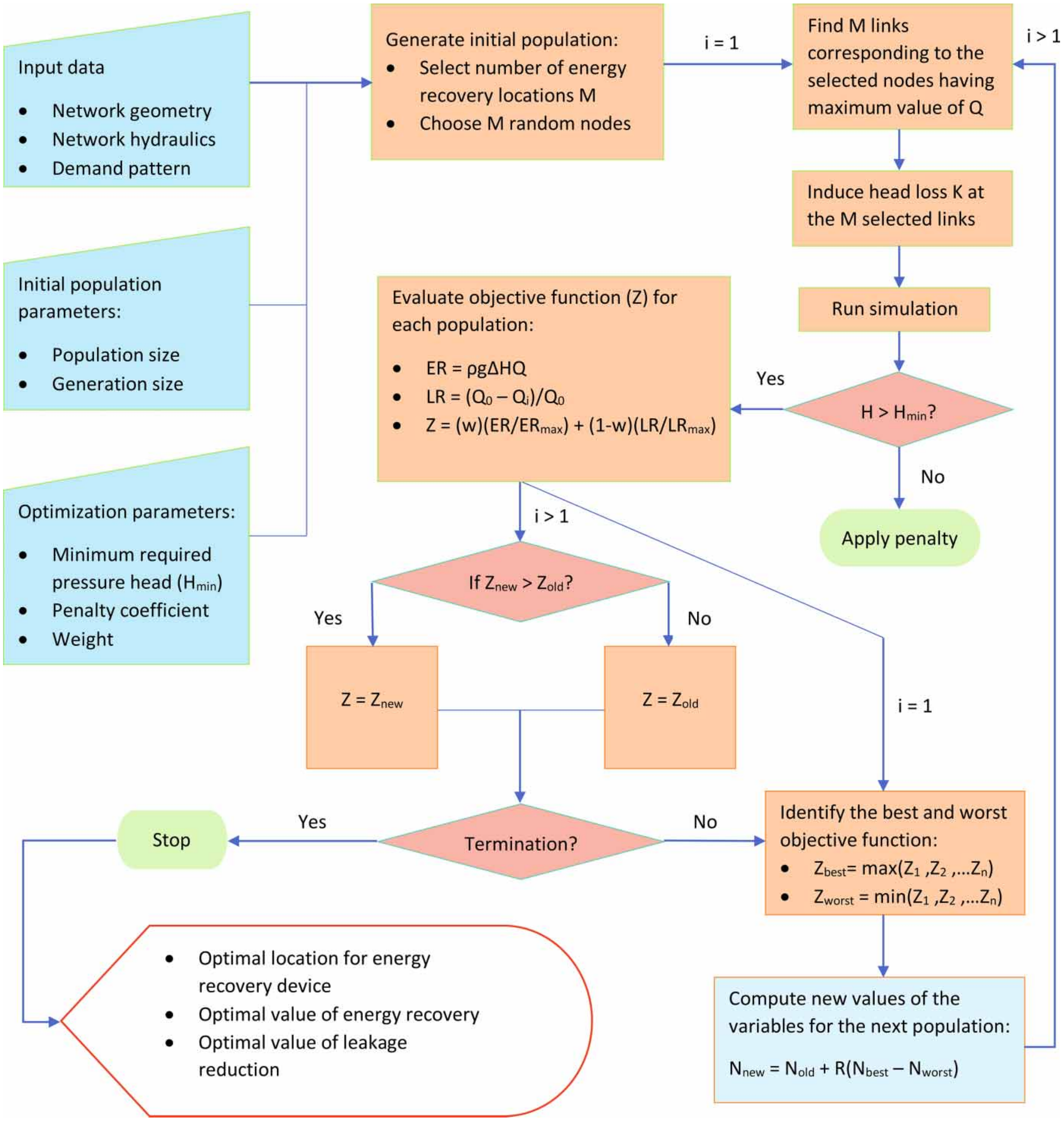


Figure 1 | Flowchart of leakage reduction through energy recovery in water distribution network using the Rao algorithm.

The initial population of the variables, which is the node location of ERDs, is generated randomly. The pipe locations associated with the selected node location, that is, the pipe flow rate as the maximum flow rate among the pipes connected to a node, are identified. For each pipe location, the minor loss coefficient (k_m) equivalent to a head loss of excess pressure is induced (Bonthuys *et al.* 2020). This process is repeated to get the n number of solutions, where n is the population size. Calculate LR, ER and the normalized objective function (Z) for each population.

The size of the ERD or the induced head loss changes with its location. The initial locations of the ERDs are determined through a randomly selected initial population. Subsequently, the optimization variables are modified using the Rao algorithm. To generate a new population, identify the best and worst solutions from the entire population with the corresponding objective function value and the node connected to the specific pipe location. These function variables are then used to generate a new population using the Rao algorithm as:

$$N_{\text{new}} = N_{\text{old}} + R(N_{\text{best}} - N_{\text{worst}}) \tag{12}$$

R is a random number [0, 1]; N_{new} is the node number for the new population; N_{old} is the node number for the old population; N_{best} and N_{worst} are the node numbers corresponding to the best and worst solutions, respectively.

The obtained value of N is then rounded off to the closest integer value to create a new population. Creating a new population is repeated until the convergence criteria (maximum number of iterations) are completed.

CASE STUDY NETWORKS

A hypothetical 5-node network, a well-known 25-node network and a 46-node network are used to evaluate the performance of this methodology. Figure 2 shows the layouts of all network cases. Complete link-node details of all networks are given in Supplementary Data.

The 5-node network

The theoretical 5-node network model is a gravity-fed system consisting of one reservoir and four junctions connected by five pipes. The reservoir had an assumed constant head of 100 m. The network input data such as pipe diameter, network topology and nodal demands are taken from Corcoran *et al.* (2016).

The 25-node network

Following the theoretical five-node network analysis, a more complex benchmark network of 25-node was analysed. As the name suggests, 25-node network consists of 25 nodes, 37 pipes and 3 reservoirs. The value of Hazen Williams roughness coefficient (C_{hw}) is between 6 and 140, the total base demand is 150 L/s and the emitter coefficient for the leakage is 1.18 and

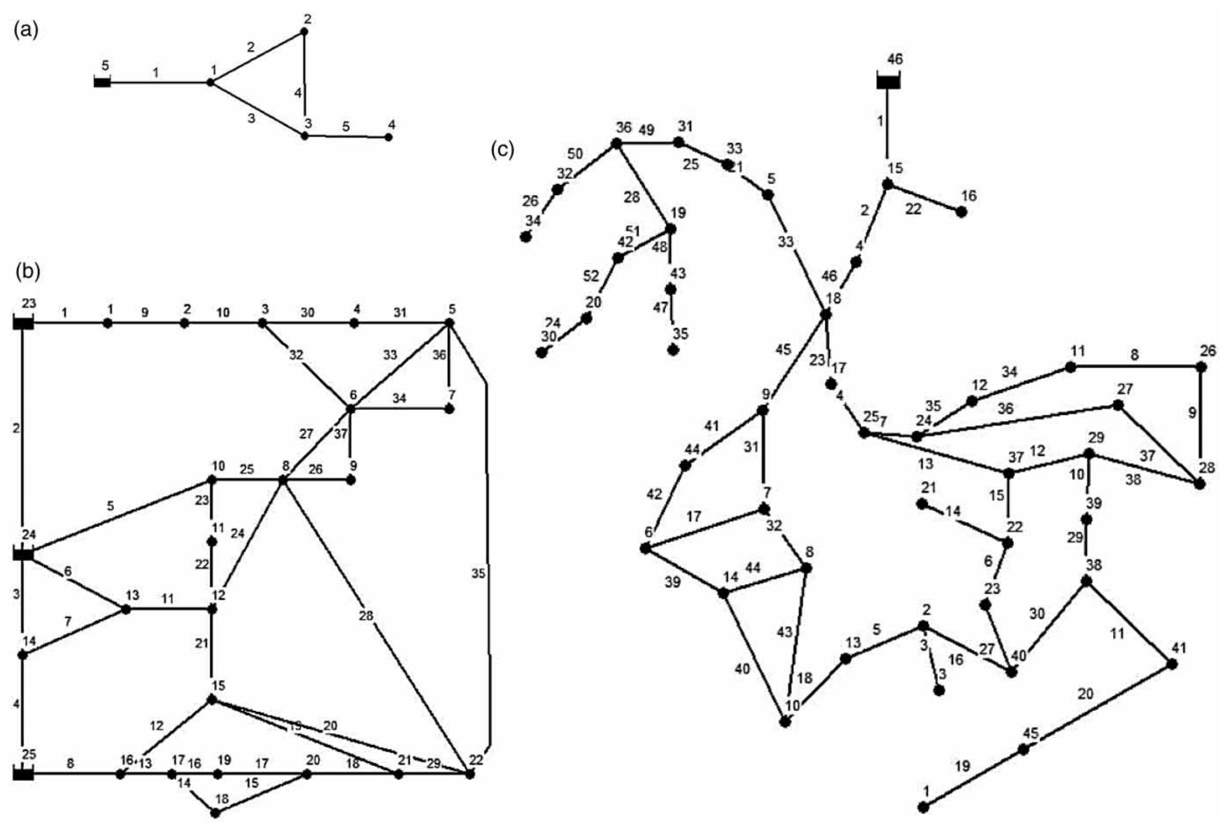


Figure 2 | Layout of case study networks: (a) 5-node network, (b) 25-node network and (c) 46-node network.

H_{min} is 30 m. Further network details can be found in Creaco & Pezzinga (2015). Three demand conditions as per Nicolini & Zovatto (2009) for minimum, base and maximum flow are considered to find the optimal results.

The 46-node network

The third case study network was used as a benchmark in the Battles of Water Networks. The network details are taken from Creaco & Pezzinga (2018), which consists of 46 nodes, 52 pipes and 1 reservoir. The three operating conditions for this network are in Table 1, along with the leakage parameters. The leakage coefficient varies from 0.2×10^{-8} to 2×10^{-8} $m^{2.1}/s$, the emitter coefficient for leakage is 0.9 and C_{hw} varies between 86.3 and 120 (Creaco & Pezzinga 2018).

RESULTS AND DISCUSSION

The above three case study networks were used to show the potential of this work in searching for the optimal location of ER in WDNs. The initial leakage for all the network studies was calculated using Equation (5). For the 5-node and 25-node networks, minimum flow, base flow and maximum flow conditions were considered to find the leakage with 0.6, 1 and 1.4 demand multipliers, respectively. For the 46-node network, three operating conditions provided by Creaco & Pezzinga (2018) were used. Table 1 shows the leakage parameters, operating conditions and initial leakage values for all networks. For comparative reasons, the values of these parameters are taken the same as those of the referred study. Therefore, the initial leakage in the 46-node network is much lower than the other two networks because of the difference in leakage coefficient and emitter coefficient.

Table 2 shows the network and algorithm characteristics for all networks. The network complexity increases with the number of decision variables and the search space. The algorithm takes negligible time to complete one simulation and is fast even for higher search spaces. The number of ERDs which can be installed is proportional to the number of decision variables. However, the optimal number of ERDs depends on various factors, mainly the cost of ERD and profit from ERD. The cost is proportional to the number of ERDs installed; however, profit depends largely on the location and does not guarantee to increase with the increase in number. Initially, all the networks were estimated for one ERD installation. The number of ERDs was increased until a significant increase in objective function value was observed. Further increase in ERD will increase the cost without an increase in the profit.

The 25-node network was initially used by Jowitt & Xu (1990) and later by various researchers in the optimization of LR in WDNs. For validation, the results obtained using this technique are compared to those of past studies, as shown in Table 3. The LR results (pipe locations 1, 5 and 11) were similar to those obtained by three past studies. The solutions obtained by giving more weightage to the ER gave the best ER value compared to the past studies. In this study, the efficiency of the ERD is assumed as 100%, while some researchers assumed it to be 40, 65 or even 100%.

Figure 3 represents the value of LR and ER for all network cases for the three operating conditions. The benefit from a particular solution can be measured and compared with other solutions by the triangle size. In Figure 3(a) and 3(b), two solutions came out as the optimal solution for the 5-node network with 58.2% LR and 19.83 kW power retrieval for 1 ERD at pipe location 1 and 61.1% LR and 25.17 kW power retrieval for 2 ERDs at pipe locations 1 and 2. In this case, with the increase in ERDs, both LR and ER increase. For 25-node and 46-node networks, the solutions corresponding to maximum

Table 1 | Initial leakage in 5-node, 25-node and 46-node network

Network	Total length (m)	Average daily demand (L/s)	Leakage coefficient (C_L)	Leakage index (α)	Operating condition	Demand multiplier	Time (h)	Leakage (L/s)
5-Node	6,000	42.5	10^{-5}	1.18	Min flow	0.6	8	10.061
					Base flow	1	8	8.393
					Max flow	1.4	8	6.123
25-Node	44,261	150	10^{-5}	1.18	Min flow	0.6	8	30.284
					Base flow	1	8	28.889
					Max flow	1.4	8	26.142
46-Node	12,813.71	21.11	10^{-8}	0.90	Condition 1	0.67	4	3.324
					Condition 2	0.98	13	3.192
					Condition 3	1.23	7	3.132

Table 2 | Network and algorithm characteristics for LR through energy recovery

Benchmark network	5-Node	25-Node	46-Node
Reference	Corcoran *et al.* (2016)	Jowitt & Xu (1990)	Creaco & Pezzinga (2015)
No. of decision variables	6	36	52
No. of energy recovery devices	{1, 2}	{1, 2, 3}	{1, 2, 3, 4}
Size of total search space	21	7,806	294,203
No. of runs	10	10	10
Population size	20	20	20
Maximum iterations	100	200	500
Average computational time (s)	200	700	2,000
Number of ERD corresponding to maximum value of objective function	2	3	4
Maximum LR (%)	61.1	18.1	16.70
Power corresponding to maximum LR (kW)	25.07	24.14	4.15
ERD location corresponding to maximum LR	{1, 2}	{1, 5, 11}	{18, 27, 29, 38}
Maximum power (kW)	25.07	34.70	6.51
LR corresponding to maximum power (%)	61.1	13.6	6.80
ERD location corresponding to maximum power	{1, 2}	{11, 24, 27}	{17, 25, 27, 37}

Table 3 | Literature survey on optimal pipe locations for inducing pressure reduction in the 25-node network

Author	Objective	Pipe location	Assumed efficiency of turbine or PAT	Leakage reduction (%)	Power (kW) at avg demand	Energy (kWh/day)
Jowitt & Xu (1990)	PR	11, 21, 29	*	20	*	*
Araujo *et al.* (2006)	PR	11, 21, 29	*	15	*	*
Fecarotta *et al.* (2015)	ER + PR	11, 21, 29	40	14.65	2.75	32
Giugni *et al.* (2014)	PR	1, 11, 13	100	29.5	8.62	206.9
Giugni *et al.* (2014)	ER	1, 5, 11	100	28	13.62	327
Corcoran *et al.* (2016)	ER	1, 5, 11	100	*	16.43	270.5
Creaco & Pezzinga (2015)	PR	1, 8, 11	*	33	*	*
Fecarotta & McNabola (2017)	ER[a]	1, 5, 8, 11	65	30	13.4	321.6
Gupta *et al.* (2017)	PR	1, 8, 11	*	20.64	*	*
Bonthuys *et al.* (2020)	PR	11, 21, 28	*	24	*	*
Fernández García & Mc Nabola (2020)	ER	1, 5, 11	65	*	8.48	156

PR, pressure reduction; ER, energy recovery.
*Values not available.
[a]Considering four energy recovery location.

LR of 18.1 and 16.8% gave 24.14 and 2.98 kW power retrieval when high weightage is given to the LR. The solutions with a maximum power of 34.7 and 5.77 kW gave 13.6 and 8.6% LR when high weightage is given to ER. When equal weightage is given to both LR and ER, the solutions resembled those of high ER weightage, in many cases. The Rao algorithm converged to the optimal solutions in only 2,000, 4,000 and 10,000 function evaluations for the 5-node, 25-node and 46-node networks, respectively, in much less computational time. The optimal number of ERDs was estimated as 2, 3 and 4 for 5-node, 25-node and 46-node networks, respectively.

In Figure 3(c), the highest percentage of LR is observed for pipe locations 1, 5 and 11. However, in Figure 3(d), the highest energy is recovered for pipe locations 11, 24 and 27. The second highest ER is observed with 2 ERDs at pipe locations 11 and

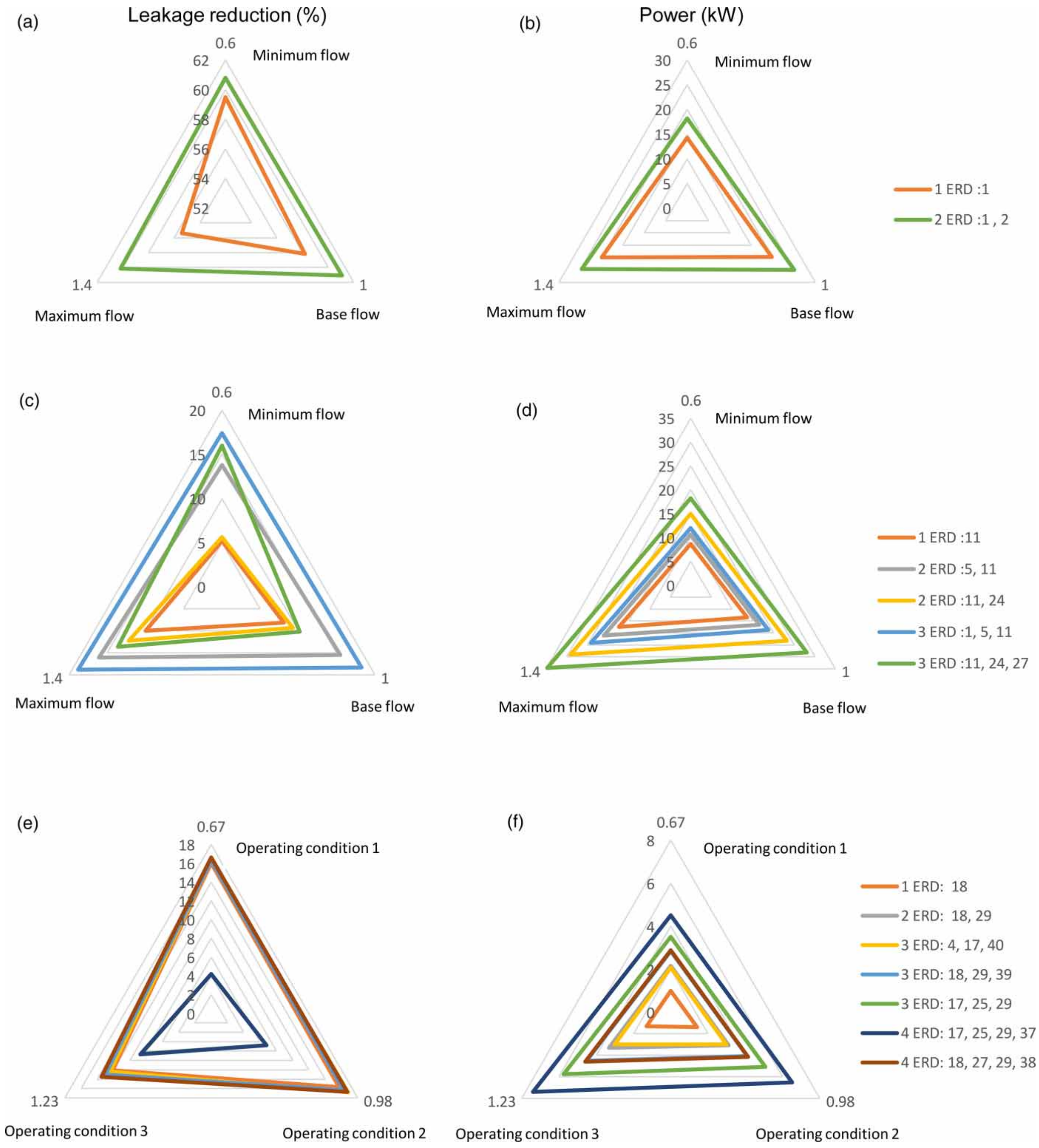


Figure 3 | Leakage reduction percentage ((a) 5-node; (c) 25-node; (e) 46-node network) and recoverable power (kW) ((b) 5-node; (d) 25-node; (f) 46-node network) at different operating conditions for all optimal solution.

24. It is essential to note that the ER for the third solution (2 ERDs) is more than the fourth solution (3 ERDs). In Figure 3(e), the value of LR is smallest for the solution with 3 ERDs at pipe locations 17, 25 and 29, for which ER is highest (Figure 3(d)). Here also, the ER value is more significant for 2 ERDs at pipe locations 18 and 29 than the 3 ERDs at pipe locations 4, 17 and 40. Thus, the location for the placement of ERDs is more important than finding the number of ERDs.

Figure 4 represents the installation of ERDs at the pipe locations for the solutions with the optimal number of turbines and optimal LR and ER for all network cases. The maximum ER was measured as 543.46, 648.24 and 154.58 kWh/day, and the maximum volume of water-saving was 430, 468 and 43.5 m^3/day for the 5-node, 25-node and 46-node network, respectively,

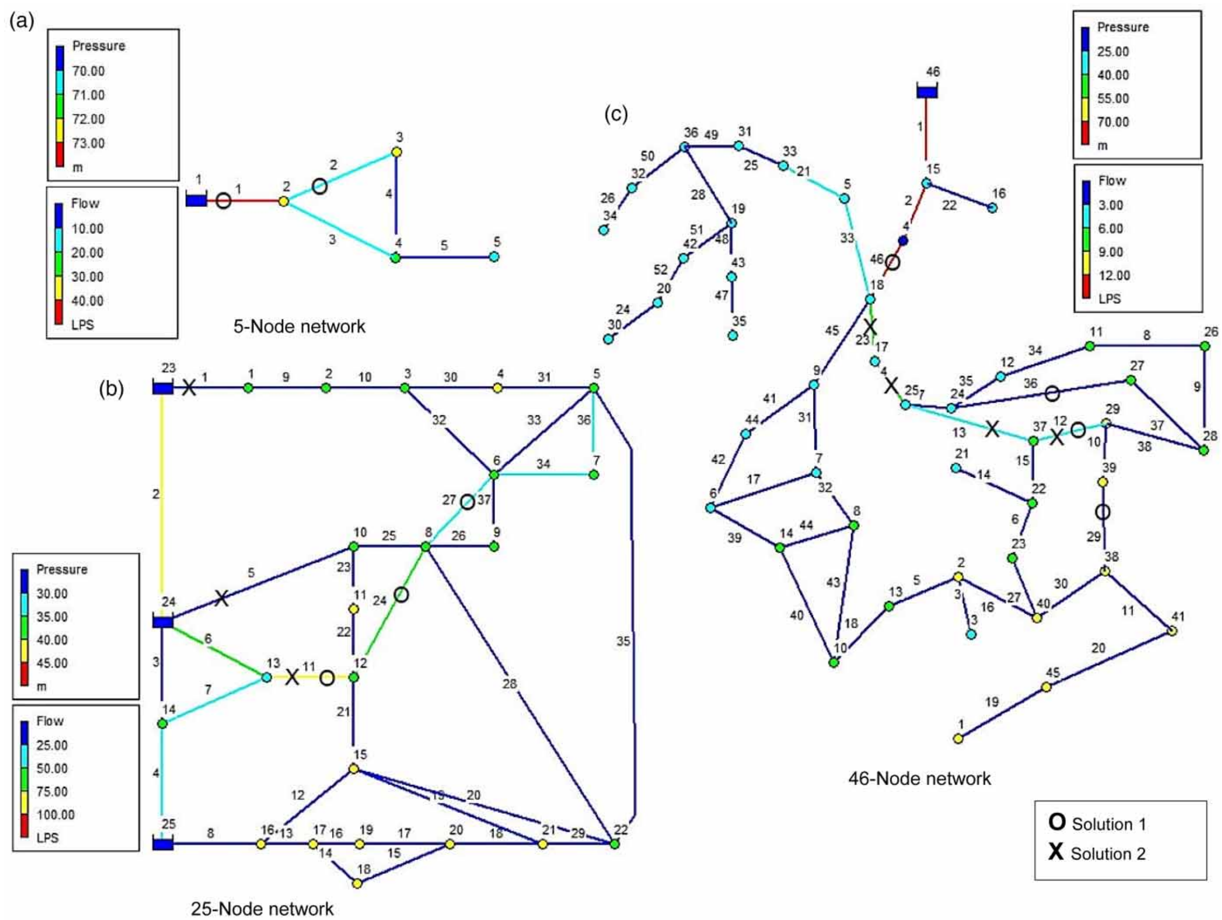


Figure 4 | Optimal pipe locations for installing ERD for leakage reduction: (a) 5-node network; (b) 25-node network; (c) 46-node network.

Table 4 | Amount of water saved and energy recovered per day using the Rao algorithm-based optimization procedure for 5-node, 25-node and 46-node network

Network	No. of ERDs	Weight (w)	Pipe location	Volume of water saved (m^3/day)	Power at average demand condition (kW)	Energy recovery (kWh/day)
5 Node	1	0, 0.5 and 1	1	410.8	19.83	432.52
	2	0, 0.5 and 1	1, 2	430.0	25.07	543.46
25 Node	1	0, 0.5 and 1	11	200.0	13.59	317.20
	2	0	5, 11	389.7	16.61	386.40
	2	0.5 and 1	11, 24	232.6	23.26	538.72
	3	0	1, 5, 11	468.0	18.80	439.12
	3	0.5 and 1	11, 24, 27	343.0	28.10	648.24
46 Node	1	0, 0.5 and 1	18	40.7	1.40	31.32
	2	0, 0.5 and 1	29, 18	42.3	3.09	72.04
	3	0	4, 17, 40	42.4	2.98	68.11
	3	0.5	18, 29, 39	42.7	4.09	96.14
	3	1	17, 25, 29	19.0	5.07	120.26
	4	0 and 0.5	18, 27, 29, 38	43.5	4.15	97.55
	4	1	17, 25, 27, 37	19.0	6.51	154.48

as shown in Table 4. The simulation was conducted for 10 runs by changing the seed number (initial population) for each benchmark network. Ten out of 10 runs gave the same results for the 5-node network, 8 for the 25-node network and 7 for the 46-node network. Hence the sensitivity of the seed number which decides the initial population of the optimization increases with the size of the search space.

CONCLUSIONS

The main aim of this study is to develop a straightforward methodology to estimate the ER potential of a WDN and the location of installation of ERDs. The results were obtained for the normalized objective function which maximizes ER and minimizes leakage (or maximizes LR). This method uses weightage factors and penalty functions based on pressure and discharge in the network member. The methodology was tested on three network cases of different sizes and characteristics. Acceptable results were obtained for each network with significantly less computational effort. The variation in solution (optimal pipe location) was observed when weightage for LR and ER was varied. For the 5-node network, two optimal solutions were obtained, and both LR and ER have increased by increasing the number of ERDs. For both 25-node and 46-node networks, it is observed that the solution with well-located 2 ERDs gave better ER than the solution with the poorly located 3 ERDs. Thus, finding the optimal location of ERD installation is crucial while using microturbines or PATs for ER and LR in WDNs. The algorithm's success rate was 100, 80 and 70%, for benchmark networks, respectively. This methodology is verified to give optimal ER locations and can be applied to any WDN regardless of size and location with slightly higher computation time for large and complex networks with more service reservoirs.

AUTHOR'S CONTRIBUTION

Priyanshu Jain wrote the paper and did the modelling and hydraulic analysis. Ruchi Khare collected the data and monitored and enhanced the manuscript.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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