

Water Distribution Network Optimization Using a Gravitational Search Enhanced Memetic Algorithm

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Abstract: This study proposes a Gravitational Search enhanced Memetic Algorithm (GSMA) proposed for solving the Water Distribution Network (WDN) problem where the Gravitational Search Algorithm (GSA) will be the main optimizer for exploration capability and the local search method for exploitation is derived from the Simulated Annealing (SA) and Particle Swarm Optimization (PSO) methods. When one technique cannot handle a challenging problem on its own then, its performance can be enhanced by functionally integrated with another technique. Memetic algorithm is one such heuristic model where a meta-heuristic approach is combined with a local search technique. The GSA is proven as an elite method for thorough exploration of the search space. Similarly, SA and PSO methods when integrated and utilized properly with appropriate operators will prove to be a promising local search model. This new memetic algorithm model solves the WDN, a complex real time optimization problem which is NP-hard and requires robust solution techniques for obtaining optimum results. Numerical experiments on three benchmark WDN problems are executed and the result of the proposed GSMA method is compared with the other existing methods for WDN in the literature.

Key words: Gravitational Search Enhanced Memetic Algorithm, simulated annealing, particle swarm optimization, water distribution network, India

INTRODUCTION

In the recent past, the machine learning groups around the globe invested a huge amount of hard work and time to research, design and develop a new section of hybrid evolutionary algorithms named as Memetic Algorithms (MAs). Primarily, memetic algorithms are simply the hybridization of simple Genetic Algorithms (GA) with Local Search (LS) methods for the refinement of the final solution of the GA (Moscato and Cotta, 2003). Due to the advent of several new heuristics algorithms, the definition for MAs gradually changed as per the contributors aspiration. In general, the interest of MAs materialized due to the lack of exploitation nature of the evolutionary algorithms. To overcome this, a Local Search (LS) method is integrated in the course of run of the main algorithm. In contrast, this leads to loss of exploration capability, forcing the main algorithm converge to local optimum. Therefore, it necessitates a motivating research problem to improvise the performance of MAs, by proposing suitable diversity techniques (Nguyen *et al.*, 2007).

In general, MAs are basically understood as algorithms derived from gas functionally integrated with any local search mechanisms to improvise the solution

each time the main algorithm is allowed to run. This integration mechanism may be viewed logically as hybridization of heuristic and exact or hill climbing techniques together but still researchers distinguish MAs in a different perspective (Neri and Cotta, 2012). Although, hybridization of two algorithms is pretty old, MAs gained their attention only in the past two decades. As previously mentioned, genetic algorithms paved the way for designing MAs as the GAs are very powerful population based techniques that are named for the exploration strength but they are weak in exploitation towards the end of the run. Hence, most of the past literatures reviewed about the MAs are based only on GAs. And in this also most of them are used for addressing single objective continuous optimization problems. Thus, Elbeltagi *et al.* (2005) compares the formulation and results of five recent evolutionary-based algorithms: genetic algorithms, memetic algorithms, GSA, (PSO), Ant-Colony systems (ACO) and Shuffled Frog Leaping (SFL). Among the rapid growing body of literature, we would like to review only a few in particular.

In a new framework of MA which integrates the greedy crossover-based hill climbing and steepest mutation-based hill climbing (Wang *et al.*, 2009). In addition to improve, the convergence capability adaptive

dual mapping and triggered random immigrants is also discussed. In another development (El Fallahi *et al.*, 2008), the MA is designed based on a post-optimization phase with path relinking and additionally a Tabu Search (TS) method is integrated. In contradictory to GA (Neri and Mininno, 2010) proposes a Differential Evolution (DE) framework of MA which as an alternative process the statistical representation of the population which evolves over time. In addition, to enhance the performance of the DE it utilizes a stochastic local search algorithm. In another improvement of the DE based MA, the exploitative features of three local search algorithms namely the Hooke Jeeves algorithm, a Stochastic Local Search and Simulated Annealing (SA) with various pivot rules and neighborhood generating functions is proposed (Tirronen *et al.*, 2008).

A chaotic local search for DE to explore a large search space in the beginning of the run to overcome premature convergence and exploiting a small region at the end of the run to fine tune the final solutions is proposed (Jia, 2011). In a SFL based MA is proposed the virtual frogs of SFL act as memes and the algorithm performs simultaneously an independent local search in each memplex. The local search of MA is achieved using the PSO concise only on local search. Similarly in another attempt (Eusuff *et al.*, 2003, 2006), SFL uses memetic evolution in the form of infection of ideas from one individual to another in a local search such that a strategy for the exchange of information among local searches to go toward a global optimum is proposed. In a new MA is proposed combining the global search ability of PSO with a synchronous local search for tamed local refining of solution (Liu *et al.*, 2007). The particle updating model uses the fuzzy global-best to deal premature convergence and also to ensure diversity among the particle swarm.

In another development (Bao *et al.*, 2013), the PSO is used for thorough search of space and capturing the potential regions containing optimum solutions, in addition a Pattern Search (PS) is enabled for effective exploitation of optimum regions discovered by the PSO. Likewise, PSO with a ring-shape topology and a fuzzy cognition combination method for designing MA for dynamic optimization is proposed (Wang *et al.*, 2010). Similarly, in the particles of PSO form sub-regions in the fitness landscape in parallel, for global exploration and an adaptive two different LS operators is used in a cooperative way for exploitation (Wang *et al.*, 2012). In another design the MA combines both GA and PSO such a way that each candidate of GA will be tuned by the PSO for qualifying into next generation (Marinakis and Marinaki, 2010). In a hybrid evolutionary PSO fusing PSO with fuzzy operators for aiding miniature aerial vehicle

controllers is proposed (Chiou *et al.*, 2015). A clonal based MA with the a simulated annealing based local search algorithm based on Nowicki and Smutnicki's neighborhood is proposed (Yang *et al.*, 2008). An ABC based MA is proposed in (Bansal *et al.*, 2013) such that ABC works as a local search algorithm a step size is required to update the best solution using a golden section search approach.

In a hybrid Differential Evolution Krill Herd (DEKH) method to overcome the drawbacks of Krill Hers algorithm is proposed (Wang *et al.*, 2014). The enhancement is done by adding a new Hybrid Differential Evolution (HDE) operator into the krill. In another advent (Wang *et al.*, 2013), a new improved meta-heuristic Simulated annealing-based Krill Herd (SKH) method is discussed. This Krill Selecting (KS) operator refines the krill behaviour to improve algorithms reliability and robustness. A recent optimization algorithm called Gravitational Search Algorithm (GSA) inspired from the law of gravity and mass interactions is presented in (Rashedi *et al.*, 2009). Here, candidates are a group of masses which cooperate together based on the Newtonian gravity and the laws of motion. Based on this (Mirjalili *et al.*, 2012), proposes a hybrid of PSO and GSA to training Feedforward Neural Networks (FNNs) in order to investigate the efficiencies of these algorithms. In continuation of the above several MAs proposed so far and to bets of our knowledge, there is still a vacuum of literature of the application of a GSA based MA for several optimization problems.

Optimization of WDN is attracted in the recent few decades due to its computational and complexity in getting quality solution. The majority of studies dealt with least-cost optimization (Cunha and Sousa, 1999; Geem, 2009; Vasan and Simonoric, 2010). Conversely, the reliability of network design in ensuring adequate head is also of prime importance. The complex relation between flow and head loss along with the presence of discrete variables makes any optimizer finds it difficult to find quality solutions. Many researcher applied several methods for minimizing the network cost applying a large variety of techniques which includes linear and non linear programming, mathematical optimization methods and also meta-heuristic techniques (Banos *et al.*, 2010). In a new version of PSO is presented for solving this problem (Aghdam *et al.*, 2014). In order to increase the convergence speed of the original PSO algorithm, some accelerated parameters are introduced to the velocity update equation. Thus, this research proposes a Gravitational Search enhanced Memetic Algorithm (GSMA) for solving a real world optimization called Water Distribution Network (WDN) problem.

Water distribution network; problem formulation: The water distribution network problem is formulated in this section. The WDN is a generalized formulation widely used by several researchers and is adopted from (Montesinos *et al.*, 1999; Lai and Schaake, 1969; Fujiwara *et al.*, 1987; Cunha and Ribeiro, 2004). The formulations are revisited for the sake of the readers benefit. The optimal design of a looped network based on gravity system is defined by the set of pipe sizes which results in the minimum installation cost of the entire network. The network cost optimization problem can be formulated mathematically in terms of pipe diameter, cost coefficients and unit length costs as follows. The objective function for cost minimization of the water distribution system is given by:

$$C = \sum_{i=1}^{NP} \sum_{j=1}^{NP} c_i L_{ij} D_i (\$) \quad (1)$$

Where:

D_i = Pipe diameter (in)

L_i = Pipe length (ft)

NP = Number of pipes in the system subject to

Continuity constraint: For each junction node (other than the source), a continuity constraint should be satisfied as:

$$\sum_{i=1}^{LK} Q_i - \sum_{j=1}^{LK} Q_j = Q_{kt} \quad (2)$$

Energy conservation constraint: the total head loss within a loop must be equal to 0:

$$\sum_{i \in \text{Loop}} \Delta H_i = 0, \forall i \in \text{NL} \quad (3)$$

Where:

ΔH_i = Head loss in the pipe i and

NL = Total number of loops in the system and each pipes diameter should be within its prescribed minimum and maximum limits:

$$d_{\min} \leq d_i \leq d_{\max} \quad (4)$$

$i = 1, 2, 3, \dots, NP$

Each pipes pressure limit should be within its prescribed minimum and maximum limits:

$$P_{\min} \leq P_j \leq P_{\max} \quad (5)$$

$j = 1, 2, 3, \dots, NP$

Each pipes speed of water flow should be within its prescribed minimum and maximum limits:

$$V_{\min} \leq V_i \leq V_{\max} \quad (6)$$

$i = 1, 2, 3, \dots, NP$

Reliable loops are considered when the connected pipes to a node do not vary widely in diameter, thus a node termed as “node uniformity coefficient.” If and (where) are the diameters of three pipes connected to a node j , then the uniformity coefficient of the node is given by:

$$C_j = \frac{(D_1 + D_2 + D_3)}{3D_1} \quad (7)$$

This formulation assumes that all systems are a gravity fed system without pumping stations and other driving devices. Thus the objective function (1) conveys the cost minimization of the water distribution network that is formulated to be a function of the pipe diameters “ D ” (the decision variables), with the pipe length “ L ” and the unit cost “ c ” to be known. The total cost to lay the pipes is a complex problem and declared as NP-Hard as it includes both continuous and discrete variables. In the next study, we discuss the proposed methodology called Memetic algorithm basically derived from the GSA.

MATERIALS AND METHODS

This study describes the details of the proposed solution methodology, the Gravitational Search enhanced Memetic Algorithm (GSMA) where the Gravitational Search Algorithm (GSA) will be the main optimizer for exploration capability and the local search method for exploitation is derived from the Simulated Annealing (SA) (Kirkpatrick *et al.*, 1983) and Particle Swarm Optimization (PSO) (Eberhart and Kennedy, 1995) methods. The GSA is proven as an elite method for thorough exploration of the search space. Similarly, SA and PSO methods when integrated and utilized properly with appropriate operators will prove to be a promising local search model.

Gravitational search algorithm: The GSA is inspired by the natural interaction forces between masses (Rashedi *et al.*, 2009). The Newton’s law of gravity paves the expression for the gravitational force between any two particles as follows:

$$f_G = \delta \frac{\mu_1 \mu_2}{\partial^2} \quad (8)$$

Where;

μ_1 and μ_2 = The mass for particles 1 and 2

δ = The gravitational constant

∂ = The distance between the particles 1 and 2

According to the Newton's second laws of motion, the gravitational force shall also be expressed as; $f_G \propto \mu \alpha$ which may be re-written:

$$\alpha = \frac{f_G}{\mu} \quad (9)$$

where, α is the acceleration of the particles mass. Let us consider a swarm of particles (or population), P , of size n . P is represented such a way that each component represents a potential solution for a given optimization problem as follows:

$$P_i = [p_1, p_2, p_3, \dots, p_n]$$

In the above vector P_i , each potential solution p_i is considered as the particle position in the solution search space. The force between any two particles i and j , for dimension m and iteration j is expressed as given in Eq.3:

$$f_{ij}^m = \delta(k) \frac{\mu_i(jk)\mu_j(k)}{\partial_{ij}(k) + \xi} (p_j^m(k) - p_i^m(k)) \quad (10)$$

where, ξ is a positive constant (typically 1) and the gravitational constant is expressed by:

$$\delta(k) = \delta(k_0) \frac{k_0^\epsilon}{k} \quad \text{where, } \epsilon < 1 \quad (11)$$

Also, $\delta(k_0)$ is the randomly preset initial gravitational constant and is the Euclidian distance (distance in multi-dimensional space) between any two particles. Thus, the total force f_G that acts upon particle i in a particular dimension, m , is expressed as follows in Eq. 5 by:

$$f_i^m(k) = \sum_{s \in S_{\text{best}}, j \neq i}^n \Psi_{ij} f_{ij}^m(k) \quad (12)$$

in which, Ψ_{ij} denotes an uniform distribution of randomly generated number in the interval $[0,1]$ and S_{best} is the best particles selected based on their fitness based on the objective of the optimization problem undertaken with size set to S_0 (in this case $S_0 = n$) at the beginning of the GSA run and the value is linearly decreased as the iteration progress. The α_i is the acceleration of the particles mass is thus calculated using:

$$\alpha_i = \frac{f_{Gi}^d(k)}{\mu_i(k)} \quad (13)$$

with μ_i denotes the inertia mass for particle i , which is estimated using:

$$\mu_i = \frac{\phi_i(k)}{\sum_{d=1}^n \phi_d(k)} \quad (14)$$

and:

$$\phi_i(k) = \frac{ff_i(k) - f_w(k)}{f_b(k) - f_w(k)} \quad (15)$$

Where:

$ff_i(k)$ = The fitness function value for particle i in iteration k

$f_i(k)$ = The worst fitness function value among all particles in iteration k

$F_b(k)$ = The best fitness function value among all particles in iteration k

After estimation of all above parameters, the new velocity and the new positions of each particle are updated as per the following equations:

$$v_i^m(k+1) = \Psi_{2j} v_i^m(k) + \alpha_i^m(k) \quad (16)$$

$$p_i^m(k+1) = p_i^m(k) + v_i^m(k+1) \quad (17)$$

Where:

$V_i^m(k+1)$ = The new velocity calculated from the previous velocity $V_i^m(k)$

$p_i^m(k+1)$ = The new position calculated from the previous position

Ψ_{2j} = A random number uniformly generated between $[0, 1]$

The local search framework: The local search part is the prime segment in a MA. The exploration capability of the GSA should be appropriately tamed by a local search subroutine which should be designed with care so that the newly explored solution regions must be thoroughly exploited for attaining quality solutions (Pirlot, 1996). This study proposes a new local search framework deriving the features of two algorithms. One is the simulated annealing and the other is the particle swarm optimization. Both are individually proven heuristics for solving wide variety of problems. Perhaps, both algorithms are designed based on two different principles, they have a similarity when the algorithm tends to reach an end. Accordingly:

- In simulated annealing, the algorithms tries to avoid the acceptance criterion as the temperature gradually reaches the cooling point thereby, it only fine-tunes the final solution region (Kirkpatrick *et al.*, 1983)
- In particle swarm optimization, the inertia weight controls the algorithms global and local search capabilities, thus when the inertia weight is kept low, then it only fine-tunes the final solution region (Eberhart and Kennedy, 1995)

Thus, these two features of the two algorithms are functionally placed into the GSA and a new MA is designed. The next section describes this proposed solution method for WDN.

The Gravitational Search enhanced Memetic Algorithm (GSMA):

The Gravitational search algorithm will be the main optimizer used for exploring the solution space to find better solution region. Meantime, the proposed local search framework designed using the local search capabilities of SA and PSO will be used to exploit the better solution regions discovered by the GSA. The pseudocode the proposed GSMA is as follows:

- Step 1: Initialize the iteration count and randomly set values for mass, velocity and position
- Step 2: Initialize the masses and evaluating using the fitness function (objective function of the problem)
- Step 3: Update the best and worst positions based on the fitness values
- Step 4: Estimation of acceleration of all the particles mass using Eq. 13-15
- Step 5: Invoke the local search subroutine
- Step 6: Initialize the inertia weight w^k = small range and Temperature T^k = large range
- Step 7: Route 1; perform the local search using the PSO with the best position obtained so far

- Randomly find the neighborhood of the $f_b(k)$ and calculate:

$$q_i^{k+1} = w^k \cdot q_i^k + \text{rand}_2(G_{besti} - p_i^k)$$

such that:

$$p_{ps0}^k = q_i^{k+1} + p_i^k$$

- Estimate p_{ps0}^k and p_i^k is the position corresponding to $f_b(k)$
- Step 8: Route 2; perform the local search using the SA with the worst position obtained so far
- Randomly find the neighborhood of the $f_w(k)$ estimate f_{md} and check for
- If $\exp[(f_w(p_i^k) - f_{md}(p_j^k))/T_k] \geq \text{rand}(0, 1)$, once satisfied, perform till the temperature reaches its final set value
- Estimate p_{SA}^k and p_j^k is the position corresponding to $f_w(k)$
- Step 9: Compare the fitness values of p_{ps0}^k and p_{SA}^k and replace the best with the best position of GSA
- Step 10: If termination criterion is not satisfied, go to step 3

Thus, the best positions of the GSA as well as the worst are exploited for better improvement in the solution independently by both the PSO and SA algorithms. When the local search subroutine could able to find a better position, that position will guide the entire GSA for rest of the run. The flowchart of the proposed GSMA is shown in Fig. 1.

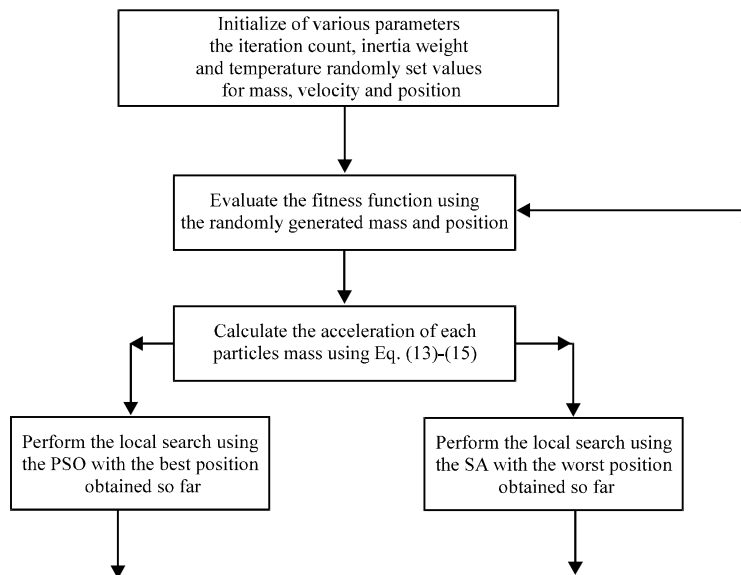


Fig. 1: Continue

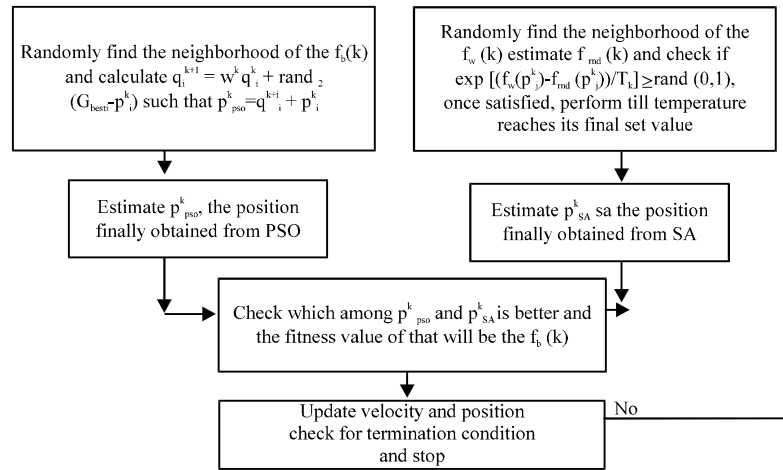


Fig. 1: Flowchart of the proposed GSMA for WDN optimization

Table 1: Parameter settings for the PSO and GSA methods

Methods	PSO	GSA	SA
Particle size	20	20	1
Parameter	Inertia weight= 0.9-0.4	Pos. constant = 0.01	Temp = 400-300F
Total iterations	300		100
Termination criteria	No change in fitness for 20 iterations		Not applicable
Total number of trials	30 trials		Not applicable

RESULTS AND DISCUSSION

Numerical simulations: The proposed GSMA method for WDN is experimented using some well-known test networks from the literature (Montesinos *et al.*, 1999; Lai and Schaake, 1969; Fujiwara *et al.*, 1987; Cunha and Ribeiro, 2004). Three standard WDN is evaluated using three different optimization techniques PSO, GSA and the proposed GSMA to solve least-cost design water distribution network problems. The proposed GSMA algorithm and other algorithms are used with the parameters as summarized in Table 1. The WDN used for simulations is studied in three different cases.

Case 1; Hanoi Water Distribution system: The Hanoi water distribution network shown in Fig. 2 is adopted widely by several researchers and tested for demonstrating the application of proposed techniques. The network consists of 32 nodes and 34 links arranged in three loops, fed from a single fixed head reservoir with an overall head of 100 m. The system data adopted from (Fujiwara *et al.*, 1987; Cunha and Ribeiro, 2004) and is not reproduced as several literature uses this. Since, a total of six discrete pipe sizes for the network design make the optimization problem complex and NP-hard and makes any search procedure to find the optimal solution in a cumbersome procedure.

As already mentioned, the three methods including the proposed GSMA is simulated for 30 different trial runs with independent random initialization of variables. For one simulation run (the best possible for our knowledge) the results are tabulated in Table 2. The convergence plot for all the three methods are shown in Fig. 3. From the simulation results, it can be inferred that, the proposed GSMA produced 6,322,214 (US \$) in comparison of 6,387,457 (US \$) produced by PSO and 6,338,445 (US \$) as produced by the GSA. It was also observed the GSMA consistently produced close to this results for all the 30 trial runs.

Case 2; New York water supply system: The simplified one line diagram of the New York water supply system is shown in Fig. 4. This system also studied and analysed by several researchers as standard case study. The pipe input data including discrete set of available diameters and minimum head and demand at each node are simply adopted from (Lai and Schaake, 1969). It is assumed that, due to pipe aging in nodes 16-20 the existing gravity flow tunnels cannot accommodate extra pressure. Hence, the network it is proposed by adding new pipes parallel to the existing pipes it is proposed to meet the minimum pressure head requirements (Vasan and Simonoric, 2010). Since, a total of sixteen discrete pipe sizes for the network design make the optimization problem complex and NP-hard and makes any search procedure to find the optimal solution in a cumbersome procedure.

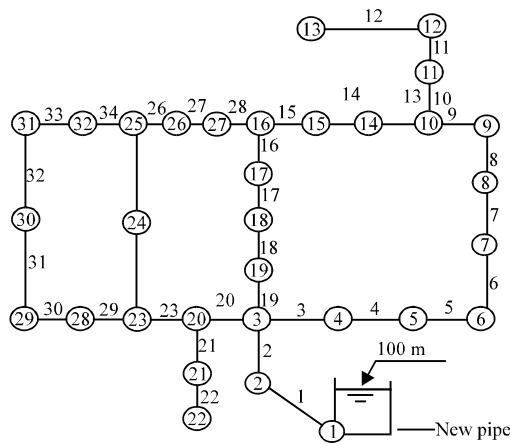


Fig. 2: Hanoi water distribution system

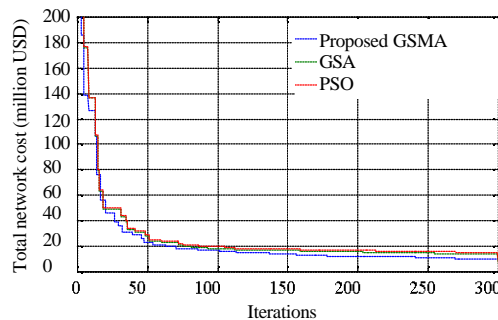


Fig. 3: Convergence plot for the cost optimization of Hanoi water distribution system

In this case also, the three methods including the proposed GSMA is simulated for 30 different trial runs with independent random initialization of variables. For this case also, a unique simulation run (the best possible for our knowledge) the results are tabulated in Table 3. The convergence plot for all the three methods are shown in Fig. 5. From the simulation results, it can be inferred that the proposed GSMA produced 38562 (Million US \$) in comparison of 38247 (Million US \$) produced by PSO and 38187 (Million US \$) as produced by the GSA. In this case also, it was also observed the GSMA consistently produced close to these results for all the 30 trial runs.

Case 3; water supply system as adopted from Cunha and Ribeiro (2004): Another standard system as shown in Fig. 6 is also simulated for demonstrating the superiority of the GSMA method. This system also studied and analysed by researchers as standard case study. The network consists of 17 nodes and 25 links arranged in three loops, fed from a

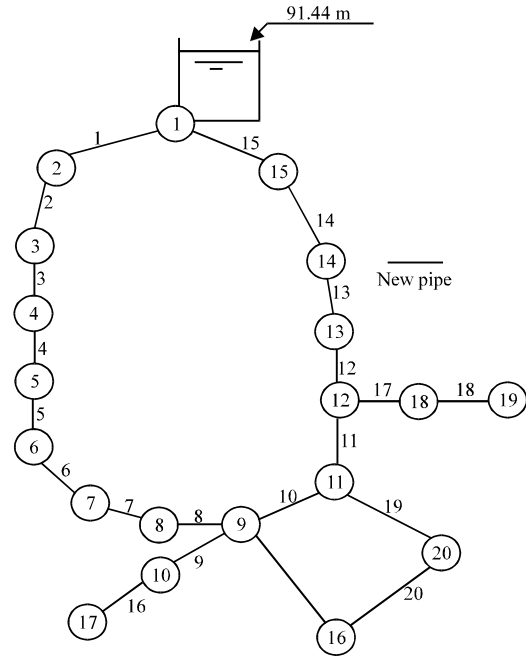


Fig. 4: New York water supply system

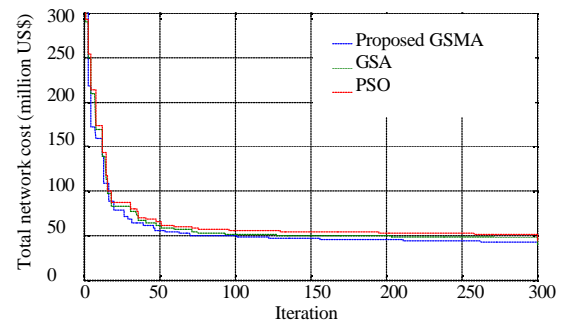


Fig. 5: Convergence plot for the cost optimization of New York water supply system

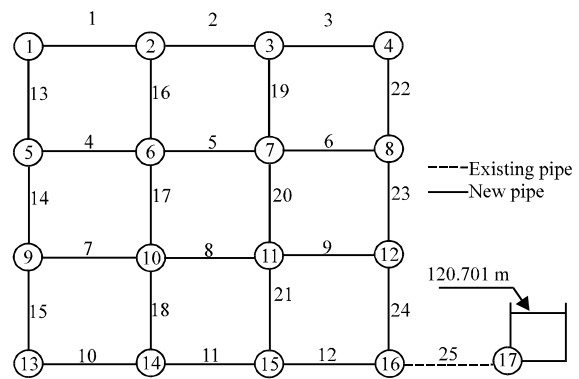


Fig. 6: Water supply system as adopted from Cunha and Ribeiro (2004)

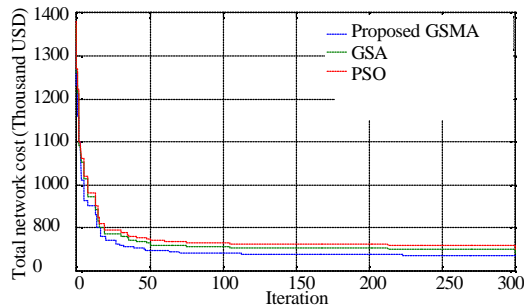


Fig. 7: Convergence plot for the cost optimization of case 3 WDN

Table 2: Optimum cost generated by various methods for the case 1 WDN

Index of pipe	Length of each pipe (km)	Pipe diameters (inch)		
		PSO	GSA	GSMA
1	0.100	40.000	40.0000	40.0000
2	1.350	40.000	40.0000	40.0000
3	0.900	40.000	40.0000	40.0000
4	1.150	40.000	40.0000	40.0000
5	1.450	40.000	40.0000	40.0000
6	0.450	40.000	40.0000	40.0000
7	0.850	38.1051	37.7989	38.4981
8	0.850	37.1718	36.4428	36.2596
9	0.800	35.2960	35.0287	35.5113
10	0.950	29.0486	29.2338	29.0095
11	1.200	26.7962	26.2222	26.7818
12	3.500	23.2752	22.9488	23.2528
13	0.800	19.2726	19.0853	19.7795
14	0.500	15.7921	15.8668	15.5489
15	0.550	12.0000	12.0000	12.0000
16	2.730	22.3046	22.8537	22.3412
17	1.750	24.9297	25.3336	25.2741
18	0.800	28.7034	29.0066	29.2371
19	0.400	29.4622	29.6798	29.0893
20	2.200	38.3828	38.9016	38.9185
21	1.500	17.4017	17.5049	17.4281
22	0.500	12.3009	12.9680	12.5204
23	2.650	32.7879	32.7502	32.7927
24	1.230	21.9384	21.9020	22.1066
25	1.300	18.7000	18.1297	18.2849
26	0.850	12.0000	12.0000	12.0000
27	0.300	22.4646	22.6501	22.6457
28	0.750	24.6913	24.2430	24.8073
29	1.500	21.5848	21.7697	20.9265
30	2.000	19.7968	19.1114	18.8518
31	1.600	16.5426	16.2723	16.9139
32	0.150	12.0000	12.0000	12.0000
33	0.860	12.0000	12.0000	12.0000
34	0.950	22.430	22.3800	22.5100
Optimum cost (\$)		6,387,457	6,338,44	56,322,214

single fixed head reservoir with an overall head of 120.701 m. The pipe input data including discrete set of available diameters and minimum head and demand at each node are simply adopted from . Since, a total of sixteen discrete pipe sizes for the network design make the optimization problem complex and NP-hard and makes any search procedure to find the optimal solution in a cumbersome procedure.

Table 3: Optimum cost generated by various methods for the case 2 WDN

Index of pipe	Length of each pipe (km)	Pipe diameters (inch)		
		PSO	GSA	GSMA
1	3.5355	52.1605	51.7191	51.9435
2	6.0347	49.6091	49.6987	49.9155
3	2.2249	63.2898	63.5714	63.2440
4	2.5297	55.8733	55.3744	55.5229
5	2.6212	57.4308	57.2192	56.9759
6	5.8214	59.1511	58.7548	59.2698
7	2.9259	59.1278	59.5483	59.3204
8	3.8098	55.2442	55.0328	54.9798
9	2.9259	50.0000	50.0000	50.0000
10	3.4136	50.0000	50.0000	50.0000
11	4.4194	116.1220	115.7692	116.7001
12	3.7184	125.4946	125.3529	125.5389
13	7.3453	126.6379	126.4203	126.8087
14	6.4310	133.0099	132.9854	133.0683
15	4.7242	126.9534	126.3250	126.2340
16	8.0463	19.7033	19.8944	19.6635
17	9.5093	91.5426	91.3450	91.6500
18	7.3148	73.0992	73.0280	73.2201
19	4.3889	72.7388	73.0808	72.8366
20	11.7037	50.0000	50.0000	50.0000
21	8.0463	54.8200	54.4538	54.5271
Optimum cost (million \$)		38562.0	38247.0	38187.0

Table 4: Optimum cost generated by various methods for the case 3 WDN

Index of pipe	Length of each pipe (km)	Pipe diameters (inch)		
		PSO	GSA	GSMA
1	0.3657	51.2943	50.8751	50.4536
2		50.7398	50.7514	50.9756
3		50.6400	50.3439	50.9992
4		203.0142	202.7272	203.4275
5		50.6651	50.6127	50.7784
6		101.4932	101.1129	101.6548
7		50.8915	50.6840	50.4210
8		101.2197	101.7831	101.5508
9		50.3381	50.3928	51.0159
10		50.7586	50.3353	51.1928
11	0.2438	203.5699	203.3124	202.9731
12		203.6342	203.3085	202.9548
13		202.9644	202.7158	203.5656
14		50.4603	50.3164	50.5324
15		51.1729	50.4901	51.1049
16		50.5379	50.8869	51.2084
17		203.3458	202.7576	202.9319
18		203.6669	203.0676	202.9393
19		101.7649	101.7315	101.1498
20		51.1704	51.0176	50.3784
21	0.9144	101.1099	101.7927	101.7408
22		50.4370	50.3841	50.4909
23		101.9188	101.5544	101.9439
24		101.5302	101.5418	101.2739
25		254.3903	253.8533	253.6708
Optimum cost (\$)		812,784	809,452	807,214

In this case also, the three methods including the proposed GSMA is simulated for 30 different trial runs with independent random initialization of variables. For this case also, a unique simulation run (the best possible for our knowledge) the results are tabulated in Table 4. The convergence plot for all the three methods are shown in Fig. 7. From the simulation results, it can be inferred

that the proposed GSMA produced 812,784 (US \$) in comparison of 809,452 (US \$) produced by PSO and 807,214 (US \$) as produced by the GSA. In this case also, it was also observed the GSMA consistently produced close to this results for all the 30 trial runs.

CONCLUSION

This study proposes a Gravitational Search enhanced Memetic Algorithm (GSMA) where the Gravitational Search Algorithm (GSA) will be the main optimizer for exploration capability and the local search method for exploitation is derived from the Simulated Annealing (SA) and Particle Swarm Optimization (PSO) methods. The GSA is proven as an elite method for thorough exploration of the search space. Similarly SA and PSO methods when integrated and utilized properly with appropriate operators will prove to be a promising local search model. This new memetic algorithm model is proposed for solving the Water Distribution Network (WDN), a complex real time optimization problem, which is NP-hard and requires robust solution techniques for obtaining optimum results. Numerical experiments on three benchmark WDN problems are executed and the result of the proposed GSMA method is compared with the other existing methods for WDN in the literature. Numerical results demonstrate that the proposed GSMA method is superior in producing quality network cost for laying the water distribution system. The robustness of the algorithm is proven by simulating the solution methods for 30 different trial runs with independent random initialization of variables. In all the trials, the GSMA method produced better solutions than the other two methods. The newly proposed local search framework could prove itself as a better alternative to aid the GSA in exploiting the better solution regions. In future, additional constraints considering networks with electric pumps, additional reservoirs, etc., will be considered.

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