Optimization of Reliability under Different flow state of Multistate Flow Network

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Abstract

This paper focuses on maximizing the reliability of multistate flow network(MFN) by meeting the demand to flow from source to destination. The reliability maximization problem is formulated considering the different flow state of the edges and their corresponding existence probabilities. A method based on genetic algorithm is proposed to maximize the reliability of MFN searching through the state space. Each step of the proposed method is illustrated by taking a suitable example network. The values of computed reliability by the proposed method is exactly same as computed by the deterministic approach. The reliability of some benchmark networks are evaluated under different demand levels. The reliability of a practical example network is evaluated and compared against the reliability value computed by some deterministic approaches of similar interest. The computational time of the proposed method is also compared with these methods. The comparison findings reveal that the proposed method surpasses existing methods on the basis of computed reliability values and computational time.

Keywords: reliability, minimal cutset, state space, genetic algorithm

1. Introduction

The reliability is a critical performance parameter to assess the operationality of many real-time networks like interconnection networks used in high-performance computing, computer networks, transportation system, mobile ad-hoc networks, wireless sensor networks, telecommunication networks to name a few. When it comes to determining how networks work, the binary network model has performed well in conventional reliability assessment. Even though, the binary network model has flaws because it assumes that network components can only be in one of two states: fully operational or completely failed [1-7]. In the last few years, researchers have expanded the binary network model to a multi-state network model for more practical applications where network components have more than two levels of performance. The success of such networks is mostly assessed by the amount of data or unit of products that can be successfully flowed across them. In other words, it's natural to assume that these networks have certain designated origins and destinations and that the links that connect them have a variety of flow states. Because the flows are stochastic, each one has a set of intrinsic probabilities. The success probability of transferring d units of product or d quantity of data from a specific pair of source nodes to a specific pair of destination nodes can be described as the reliability of such a multistate flow network at a given demand level d.

In the past, reliability evaluation of multistate networks drew a lot of attention, and it's still a matter of contention, especially when it comes to big networks that are explored in real-time. Multi-valued Decision Diagram (MDD)[8, 9], Monte-Carlo Simulation method (MCS)[10], State Space Decomposition method (SSD)[11- 13], Universal Generating Function (UGF) method[14], and d-MPs/d-MCs method[15-23] are the most commonly used approaches for evaluating MFN reliability. Chen et al.[15] presented an approach for fast enumeration of d-MPs. The work carried out in [16] searched for all d-MCs of multistate flow network and then the duplicate d-MCs were detected and discarded. The work presented in [17] evaluated the reliability of the stochastic flow network under budget and time constraints by using intersecting MPs. The work in [18] followed state-space decomposition method and recursively generated unique d-MPs. The problem of evaluating the reliability of an MFN with a cost constraint in terms of minimal cuts is addressed in the work[19]. Similar work can be found in [20].

Xu et al. [21] integrated a flow-max algorithm and enumeration algorithm to solve the d-MP problem of a multistate flow network. Niu et al. [22] introduced an approach to generate d-MCs more accurately after removing the redundant MCs. The authors in [23] combined the max-flow algorithm with the partition technique to generate the d-MPs. Rushdi et al. [24] evaluated the reliability of a multistate flow network using the map method.

The research [25] considers the cost and spoilage limitations when evaluating the reliability of a multi-state distribution network (MSDN). Under delivery spoilage and budget constraints, reliability is defined as the likelihood that the MSDN will be able to distribute a sufficient quantity of items to meet market demand.

The reliability of a multi-state delivery network with different suppliers, transfer stations, and marketplaces connected by branches of multi-state capacities, delivering a specific commodity or service between their end vertices is the focus of the work [26].

The network reliability of a multistate network is calculated using an efficient technique based on the sum of disjoint products (SDP) principle in [27]. In addition, to improve the efficiency of reliability evaluation, a recursive function with simplified methods is presented.

The above-mentioned studies demonstrated that numerous methodologies for evaluating MFN reliability were used to simplify the reliability evaluation process. In some circumstances, the reliability of small to medium-sized networks, and even large networks, is evaluated deterministically with a huge amount of computational time. Using various heuristic methods, this computational time can be reduced significantly, unless the estimated reliability values are compromised. The works [28-29] used a genetic algorithm to evaluate the reliability of the binary state networks. However, the application of heuristic techniques to multistate flow networks for their reliability evaluation is very limited[30-31]. The work carried out in this paper is an attempt to reduce the computational time for evaluating the reliability of a multistate flow network using a genetic algorithm. The rest of the paper is organized as follows:

In Section-2, the reliability maximization problem is formulated and GA based method is proposed to maximize the reliability of MFN. Secion-3 illustrates the proposed method by taking a suitable example. Simulated results are presented in Section-4. The reliability of a practical distribution network is computed and compared against some existing method in Section-5. Section-6 concludes the paper with future scope.

2. Methods

2.1 Formulation of Reliability maximization problem under different flow states

2.1.1 Flow model of Multistate network

The multistate flow network (MFN) can be represented as a directed graph(G) with N vertices and E edges. The edges exhibit multiple states in terms of the different flow capacity states. The flow capacity state f_i for an edge $e_i \in E$ can be defined as a non-negative inter randomly selected from 0 to F_i. Since, f_i is the capacity state of e_i, the capacity vector f can be defined as follows:

$$f = (f_1,\ f_2,\ \cdots\ f_m) \text{ where, } f_i \in F_i \tag{1}$$

If (s, t) are the source and destination nodes respectively, the maximum amount of flow from s to t can be represented as $F(f: s \to t)$. For a capacity level (d), the following condition must hold:

$$F(f: s \to t) = d \tag{2}$$

2.1.2 Capacity vector space

The capacity vector space can be directly defined by using Eq(1) as

$$S(f) = \{(f_1, f_2, \cdots\ f_m) |\ 0 \le f_i \le F_i\ for\ 1 \le i \le m\} \tag{3}$$

The capacity state of an edge f_i occurs with a probability, say $p(f_i)$ or in other words, it can be stated that the edge e_i has the probability p to have the capacity state f_i.

2.1.3 Success state

As per the max-flow min-cut theorem [24], the capacity level (d) is attainable only when

$$\min\ [F(C_j)] \ge d \tag{4}$$

where, C_j is the jth minimal cut set with $j = 1, 2, \cdots K$ and K is the maximum number of cut sets between s and t. Since, each minimal cut set may contain one or more number of edges, sum of their capacity states must be greater than or equal to d and in turns the MC is termed as d-MC.

The state of a network in terms of different flows along the edges is said to be success if it satisfies Eq.(4) for each generated MCs. Mathematically,

$$s(f) = \begin{cases} if\ \min\ [F(C_j)] \ge d, & Success \\ else & No \end{cases} \tag{5}$$

The probability of the success state is calculated as:

$$p\big(s(f)\big) = \prod_{i=1}^{m} p(f_i) \tag{6}$$

Let, *Succ* be the set of all the successful state.

The reliability of the network permitting capacity level (d) is calculated from Eq. (4) and (5) as:

$$R(d) = \sum_{s \in Succ} p(s(f)) \tag{7}$$

2.1.4 Formulation of Reliability maximization problem

For a given multistate flow network with a set of edges whose flow distribution is governed by some probability measures, the Reliability maximization problem can be stated as finding the optimal flow state of each edge so that the overall reliability is maximized while meeting the capacity level d. Mathematically, this multi-objective problem can be formulated as:

$$\max\{R(d)\} \tag{8}$$

such that

$$(f: s \to t) = d \tag{9}$$

$$\min[F(C_j)] \geq d, j = 1, 2, \cdots K \tag{10}$$

$$f = (f_1, f_2, \cdots f_m) \text{ where, } f_i \in F_i \tag{11}$$

$$0 \leq f_i \leq F_i \ for\ 1 \leq i \leq m \tag{12}$$

2.2 Proposed GA based method to maximize the reliability of MFN under different flow states

2.2.1 Encoding scheme

The capacity of each edge $e_i \in E$ is represented by f_i and its occurrence is defined by the probability, $p(f_i)$. The following encoding scheme is adopted in this work to encode each edge:

$$e_i(f_i) = \begin{cases} f_i & if\ e_i \in C_j \\ 0 & otherwise \end{cases} \tag{13}$$

2.2.2 Initial population

The initial population can be defined directly from the capacity vector space by using Eq(3) as

$$Pop = \{e_1(f_1), e_2(f_2) \cdots e_m(f_m)\} \tag{14}$$

Where,

$$0 \leq e_i(f_i) \leq F_i \ for\ 1 \leq i \leq m\}$$

2.2.3 Generation of MCs

The minimal cutsets (C) are generated by using the method [32] such that

$$C = \cup_j\{C_j\}, j = 1, 2, \cdots K \tag{15}$$

2.2.4 Refinement of initial population

The initial population is checked for each MC, C_j and the chromosomes that satisfies condition (4) are kept in this list while discarding the rest.

2.2.5 Fitness function

The fitness function evaluates the reliability of the network by using the Eq. (7).

2.2.6 Selection

The reliability of each chromosome belonging to the population is evaluated and the parents are selected from them having the best two values of reliability.

2.2.7 Crossover

The crossover is a single-point random operation performed on the parents (P1, P2).
Let CP be if the randomly selected crossover point. The algorithm for crossover operation is presented below:

Algorithm I:

Cross_over (CP)
for i = 1 to CP-1
C1[i]=P1[i]
C2[i]=P2[i]
for j= CP to m
C1[j]=P2[i]
C1[j]=P1[i]
return (P1, P2, C1, C2)

The steps of the proposed GA based method are presented in the flowchart

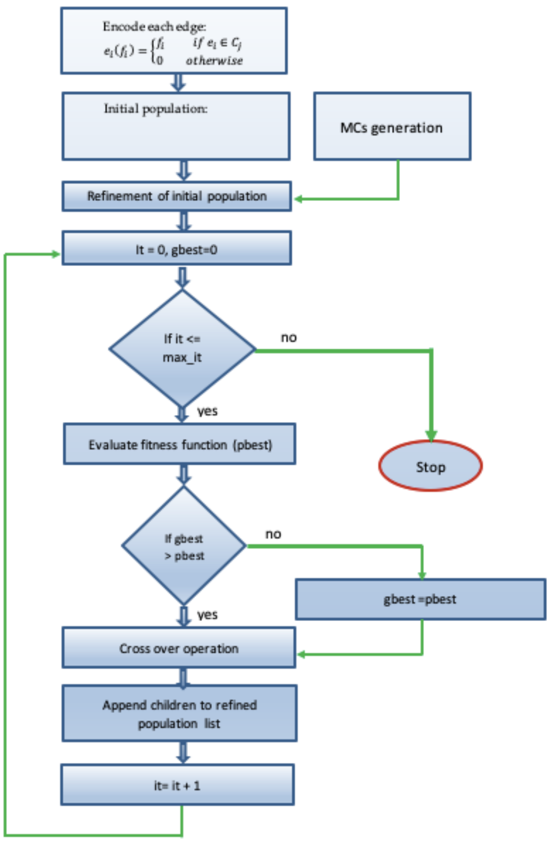


Figure 1: Flowchart of the proposed GA based method

3. Illustration

To illustrate the proposed GA-based approach, the following sample network is considered as an example.

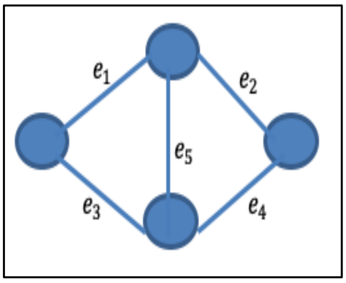


Figure 2: Example network [24]

The states and their corresponding state probabilities are presented in Table 1.

Table 1: *States and state probability of edges of Fig.2 (as per [24])*

Edge	Capacity state	Probability state
e_1	0	0.2
	2	0.8
e_2	0	0.1
	2	0.9
e_3	0	0.2
	3	0.4
	4	0.4
e_4	0	0.3
	2	0.7
e_5	0	0.1
	2	0.9

The size of the initial population is 48 and the flow for each edge satisfies Eq(13) and (14).
The MCs are generated by using method [32] and are enlisted below:

$C_1 = \{e_1, e_3\}$
$C_2 = \{e_2, e_4\}$
$C_3 = \{e_1, e_4, e_5\}$
$C_4 = \{e_2, e_3, e_5\}$

The chromosome must satisfy Eq.(4) for each the above mentioned MCs.
For example:
Chromosome =[2, 0, 4, 2, 0] does not satisfy (4), since

$e_1 = 2, e_2 = 0, e_3 = 4, e_4 = 2, e_5 = 0$
$F(C_1) = f_1 + f_3 = 6 > 4$
$F(C_2) = f_2 + f_4 = 2 \ngtr 4$
$F(C_3) = f_1 + f_4 + f_5 = 4$
$F(C_4) = f_2 + f_3 + f_5 = 4$

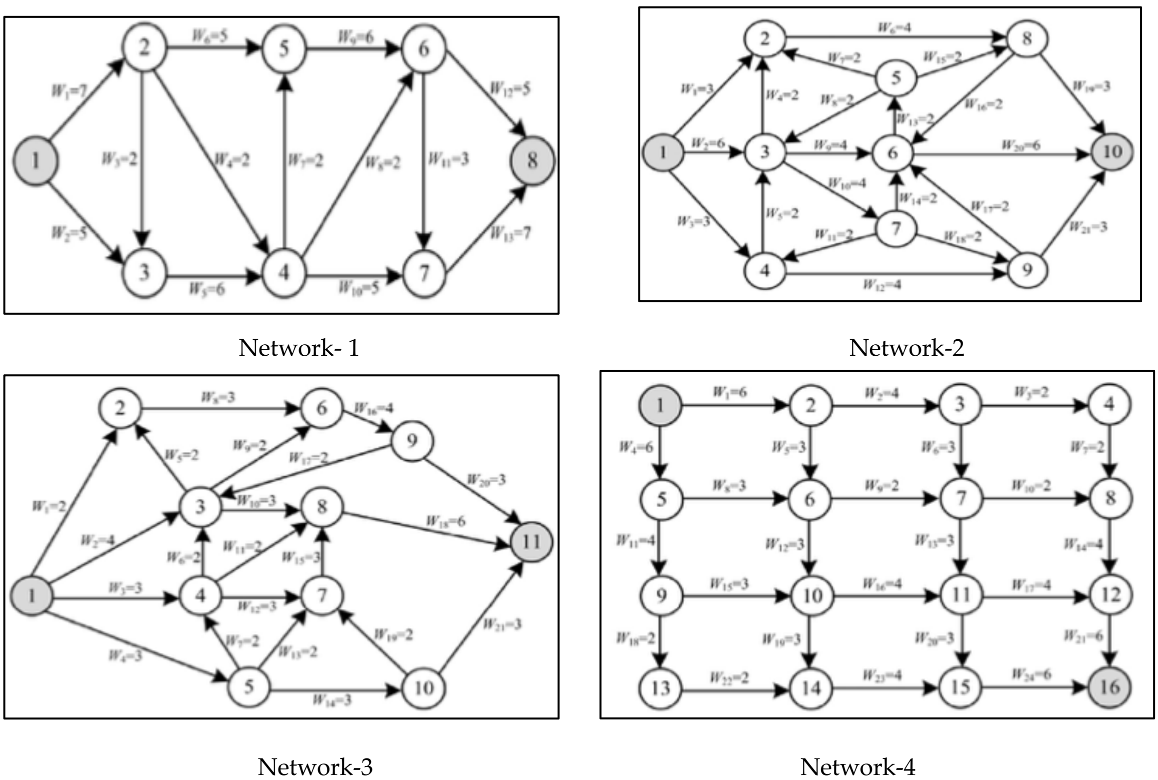
Such chromosomes must be discarded from the population.
The fitness of the chromosome is evaluated using Eq. (6) in the following manner:
Let's assume that chromosome contains the capacity vector i.e. [2, 2, 4, 2, 0]. The probability vector associated with the flow for each edge is [0.8, 0.9, 0.4, 0.7, 0.1].
The reliability of this chromosome can be computed as:

$R(c) = p(f_i) \times p(f_2) \times p(f_3) \times p(f_4) \times p(f_4)$
= 0.02016

Thus, the overall reliability of the network is calculated by summing over the feasible states (chromosome). The selection function extracts two chromosomes of having best and next to best reliability values.
The working cross over function is exemplified below:
Let P1 ([2, 2, 4, 2, 4]) and P2 ([2, 2, 3, 2, 0])be the parents and the cross over point be 2. The two children are generated as follows:
c1=[2, 2, 4, 2, 0] and c2=[2, 2, 3, 2, 4]
Since, both c1 and c2 satisfy condition (5). Both are added to the population. After performing all these steps, the computed reliability is 0.44856 (which is the same to the value of computed reliability in the work [24]).
The resultant capacity vectors are presented below:
[2, 2, 3, 2, 4], [2, 2, 3, 2, 0], [2, 2, 4, 2, 4], [2, 2, 4, 2, 0], [0, 2, 4, 2, 4]

4. Results

The simulation is carried out by using Python in Google colab environment. The generated MCs are stored in a matrix format with one MC per row. The refinement step of the proposed method is performed by element-wise multiplication of each chromosome of the population with each row of the matrix containing the MCs. The reliability of some benchmark networks are evaluated by the proposed method.



Network- 1   Network-2   Network-3   Network-4

Figure 3: The networks of [16]

The maximum flow for each edge is shown in the respective networks (Fig. 3). The probabilities of the occurrence of corresponding capacities are presented in Table 2.

Table 2: *State probability of different flow state*

pl	0	1	2	3	4	5	6	7
[0,2]	0.3	0.3	0.4	-	-	-	-	-
[0,3]	0.25	0.25	0.25	0.25	-	-	-	-
[0,4]	0.2	0.2	0.2	0.2	0.2	-	-	-
[0,5]	0.16	0.16	0.16	0.16	0.16	0.2	-	-
[0,6]	0.14	0.14	0.14	0.14	0.14	0.14	0.16	-
[0,7]	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.14

The reliability of networks (Fig. 3) are calculated under different capacity levels like 2, 3, 5, 7, 9, and 11 and are presented in Table 3. Table 3 also contains the number of d-MC generated for each capacity level.

Table 3: *Evaluation of reliability*

Network	#MC	d-MC	#d-MC	Reliability
1	16	2-MC	8202	0.9999
		3-MC	6491	0.7913
		5-MC	2652	0.4533
		7-MC	401	0.1488
		9-MC	192	0.0324
		11-MC	30	0.0036
2	58	2-MC	35355	0.9933
		3-MC	21522	0.6046
		5-MC	15433	0.4335
		7-MC	10231	0.2874
		9-MC	5600	0.1573
		11-MC	616	0.0173
3	110	2-MC	97223	0.9999
		3-MC	83435	0.8097
		5-MC	75340	0.7345
		7-MC	64457	0.6509
		9-MC	29531	0.5099
		11-MC	260	0.0002
4	330	2-MC	132910	0.9999
		3-MC	121023	0.6902
		5-MC	110334	0.3429
		7-MC	105049	0.1908
		9-MC	12834	0.0988
		11-MC	6904	0.0189

The following observations can be drawn from Table 3:

1. All the networks are robust in terms of reliability to accommodate the capacity level of 2 and 3.

2. A demand 5 can be reached to the destination through Network 3 with a high reliability value of 0.73 while this possibility falls to less than 50% for networks 1 and 2 respectively. Network 4 is the least competent network to cope with this demand.
3. Network 3 has a reliability value of 0.5 to meet the demand 9 which is satisfactory. However, other networks fall far away from meeting this demand.
4. None of the networks show satisfactory values of reliability for demand 11. Hence, the demand 11 cannot be achieved by any of these networks.

5. Discussion

The network depicted in Fig 4 is a practical distribution network [16] (or [23]). The details of the network can be found in [16] (or [23]). The capacity states and the probability states of each edge are as per [16] (or [23]) and are presented in Table 4. Both methods have evaluated the reliability of this network using the minimal cutset methods.

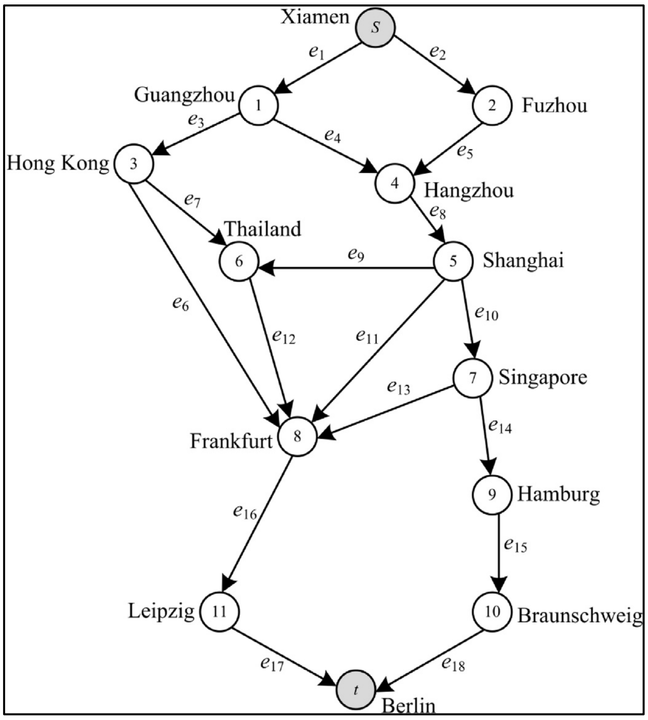


Figure 4: The networks of [16]

The method presented in [16] claimed of generating the exact number of d-MC by discarding duplicate d-MC while the work carried out in [23] also found the correct d-MC after removing the duplicate d-MCs. However, the number of 5-MCs (with d=5) generated for the practical network by methods [16] and [23] is different, and hence their estimated reliability values are likewise different. Both the methods use the state enumeration technique to evaluate the reliability of searching over the entire search space. In contrast to their methods, the proposed method uses a genetic algorithm to maximize the reliability by performing a heuristic search over the state space. The proposed method also results in distinct d-MCs by validating all the generated MCs. The number of d-MCs and the computed reliability values are presented in Table 5 for d=5. It can be observed from this table that the computed reliability value by the proposed method is 5% more than methods [16] and [23].

Table 4: *Capacity of edges and their corresponding probability (Fig. 4)*

Edges	Capacity of edges					State probability of different flow state				
e_1	0	1	2	3	4	0.002	0.003	0.008	0.05	0.937
e_2	0	1	2	3	-	0.002	0.002	0.05	0.946	-
e_3	0	1	2	3	-	0.015	0.022	0.023	0.94	-
e_4	0	1	2	3	-	0.001	0.022	0.03	0.947	-
e_5	0	1	2	3	-	0.002	0.22	0.04	0.936	-
e_6	0	1	2	3	-	0.001	0.026	0.05	0.923	-
e_7	0	1	2	3	-	0.002	0.003	0.05	0.945	
e_8	0	1	2	3	4	0.002	0.0050	0.008	0.017	0.968
e_9	0	1	2	3	-	0.012	0.023	0.03	0.935	-
e_{10}	0	1	2	3	-	0.011	0.024	0.03	0.935	-
e_{11}	0	1	2	3	-	0.005	0.008	0.016	0.971	-
e_{12}	0	1	2	3	4	0.001	0.001	0.005	0.005	0.943
e_{13}	0	1	2	3	4	0.001	0.001	0.005	0.005	0.988
e_{14}	0	1	2	3	-	0.012	0.012	0.04	0.936	-
e_{15}	0	1	2	3	-	0.003	0.011	0.011	0.975	-
e_{16}	0	1	2	3	4	0.003	0.007	0.01	0.02	0.96
e_{17}	0	1	2	3	4	0.001	0.006	0.01	0.014	0.969
e_{18}	0	1	2	3	-	0.002	0.004	0.01	0.984	-

Table 5: *Comparison of computed reliability*

Method	Number of d-MCs	Reliability
Method [22]	104	0.716992
Method [23]	135	0.802607
Proposed method	167	0.850135

In order to compare the computational time, the computational time to evaluate the reliability of the said network using SDP approach is considered for method[16] and [23](the time to generate the d-MCs is excluded). The computational time required by [16], [23] and the proposed method are shown in Fig. 5. Fig. 5 displays the proposed method, which saves approximately 82% of the computing time compared to methods [16] and [23].

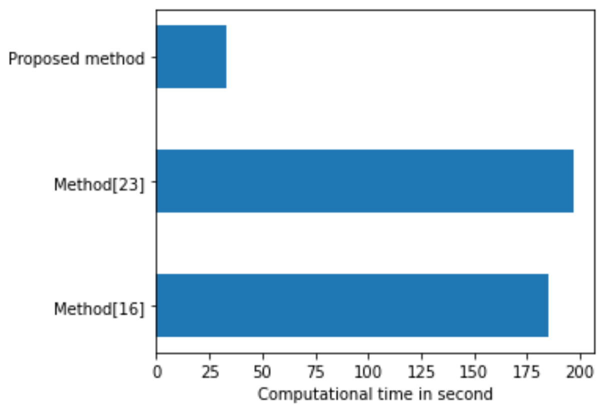


Figure 5: Comparison of computational time

6. Conclusion

In this paper, the reliability maximization problem is formulated under different flow states of a multistate flow network. A genetic algorithm-based method is proposed to maximize the reliability of the multistate flow network. The proposed method is well illustrated by taking a suitable example. The reliability of four different benchmark networks are evaluated under different demand levels. The reliability of a practical distribution network is evaluated and compared against some existing methods. The comparison ensures the robustness of the proposed method in terms of computed reliability values as well as the required computational time. Further, the work carried out in this paper may be extended to include cost and time constraints.

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