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Utilization-Based Optimal Placement Of Wavelength Converters In WDM Optical Network Using New Mutation Strategy In The Differential Evolution

Pratima.B. Kadekar[1] , M. Manoj Kumar[2], Manoj Kumar Singh[3*]

[1]Department of E & C, V T U - RRC Belagavi, Karnataka, India

[2]Department of E & C, P E S I T M, Shivamogga, Karnataka, India.

[3]Manuro Tech Research Pvt.Ltd, Bangalore,India

[1]*pratimakadekar@gmail.com,* [2]*manoj_kumarm1@rediffmail.com,*
[3]*mksingh@manuroresearch.com*

Abstract

In this paper, a new mutation strategy in the Differential Evolution has proposed for an optimal allocation of wavelength converters in the wavelength division multiplexing (WDM) optical network. Concerned objectives were to maximize the overall utilization performance of placed wavelength convertors along with handling the network conflict conditions of placement efficiently. Traffic handling by the different number of wavelength converters has considered in extracting the overall performance of converters placement. A better traffic handling model has also proposed as an objective function for efficient utilization of allocated convertors when there were multiple equivalent conditions of traffic load existed in the different parts of the network. To achieve the objectives, under the Differential Evolution a new mutation operator and formation of the efficient differential vector have proposed for faster convergence and better exploration for the solution. Convergence rate has improved by obtaining the differential vector under the guidance of the best solution or through the randomly selected solution from the population in a probabilistic way. The level of exploration has increased in the process of mutation vector formation by applying the logical XOR operation between the differential vector and the base vector. The proposed approach has applied over benchmark network model NSFNET and it has delivered a more effective performance in comparison to other forms of Differential Evolution as well as reasoning based results available in the past literature.

Keywords: *WDM optical network, Wavelength converter, Converter placement, Differential evolution, Utilization matrix.*

1. Introduction

The enormous bandwidth available in optical fibers for optical communication network has been utilized efficiently with the use of wavelength division multiplexing (WDM) technology. The problem of the electronic bottleneck due to slow switches has been successfully resolved by WDM technology. The appeared benefits have challenges in terms of involved design complexity and cost. There are many critical issues exists under the WDM network like routing and wavelength assignment and WDM network design problem [1]. A channel using a fixed wavelength through which communication takes place in a WDM network is defined as light-path. For a particular light path, defining the route and the wavelength in the network is considered as the RWA problem. The chosen route between source and destination has to assign the same wavelength which is a constraint in the light path and called continuity constraint [2]. There is another issue in terms of wavelength clash constraint which is defined as not having the same wavelength of two light paths share the same link. The main objectives concern with the WDM network design part is in terms of minimizing the blocking probability [3]. Continuity

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constraint in light-path is the main hurdle to minimize the blocking probability. The continuity constraint can be relaxed if the wavelength converters have deployed into an optical router. The wavelength converter is a device that converts the one wavelength to another wavelength. Deciding how many and where to locate these wavelength converters is a particular design problem known as the wavelength converter allocation (WCA) problem, which is an NP-hard problem [4] when dealing with irregular network topologies. Either all nodes or only selected nodes deployed the wavelength converters to increase the traffic capacity. There are two types of the wavelength converter, full range wavelength converter (FWC) and limited range wavelength converter (LWC) [5]. It has also seen that with proper placement to only a few numbers of nodes equipped with FWC's /LWC's acceptable level of blocking probability can be achieved. Hence, it is important that for a given number of FWC's, the allocation has to be done in such a manner that blocking probability could minimum as much as possible.

There were number researchers in the past who have given attention over this problem. A multi-objective optimization approach based on an evolutionary algorithm that simultaneously minimizes blocking and the number of wavelength converters has been proposed in [6]. Wavelength converters placement in an optical burst switching network (OBS) has been considered in [7]. Particle Swarm Optimization (PSO) technique to solve OWCA problem in [8]. Wavelength converter and routing problems have considered simultaneously in [9] as a multi-objective optimization approach under uncertain traffic conditions. Wavelength converters placement (WCP) in all-optical WDM networks belongs to the class of hard combinatorial optimization problems. So far, this problem has been solved by various heuristic strategies or by application of meta-heuristic approaches such as Bee Colony Optimization (BCO) [10], genetic algorithms (GA)[11], Particle swarm optimization (PSO), Differential Evolution (DE).The details of DE has discussed in [12]. Rule based converter placement has proposed in [13]. The use of all-optical wavelength converters has applied in [14][15] to reduce the number of required wavelength converter against optical-electrical-optical-conversion-based wavelength converters. Over the mesh network placement of converters has been discussed in [16]. Wavelength assignment in WDM with dynamic and static approach along with converter placement for mesh network has discussed in [17].The challenges and support for 5G wireless network by current advancement in optical network has discussed in [18].

In this paper there are two different areas where research attention has focused. First, a better traffic oriented objective function mathematical modeling has developed and second, significant improvement in the Differential Evolution algorithm with a new mutation strategy has proposed.

The paper structure has divided into number of sections .The mathematical model of problem formulation has presented in section2. Mathematical model of objective function has discussed in Section 3 while the proposed solution has presented in section 4. The detail experimental results and analysis have given in section5 while the conclusion has appeared in the end.

2. Problem modeling

The modeling to maximize the utilization of allocated FWCs can be considered as an optimization model. First, for the individual node, the use of an allocated corresponding number of FWCs estimated and later a summed form established over utilization of all nodes to define the total utilization [13]. Assuming that the utilization matrix of the network is available and the following parameters have been used to define the model.

Considering parameters nomenclature as $\mathrm{N}:$ Number of nodes in the WDM optical network; M_i : Number of FWC's required at the node ' i ' for complete wavelength conversion; $\mathrm{M}:$ Maximum value of $\{\mathrm{M_1}, \mathrm{M_2}, \ldots \mathrm{M_N}\}$; $\mathrm{T}:$ Total number of available FWCs to allocate over the network nodes; U : Utilization matrix having a dimension of $\mathrm{N} \times (\mathrm{M} + 1)$), in

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which the (i, j)-th entry (where, $1 \le i \le N, 0 \le j \le M)$ denotes the percentage of time that j number of FWC's are being utilized simultaneously at the i^{th} node.

So if there is 'K' number of wavelength converters available at the i^{th} node, then the total utilization of placed convertors at the i^{th} node is

$$\sum_{j=1}^{K} U_{i,j} \tag{1}$$

For the given the utilization matrix, U, the solution of allocation existed in the form of binary allocation matrix (X) of size $N \times M$ where a binary value in the $(i, j)th$ place carry the information of presence or absence of the j^{th} converter for the i^{th} node.

$$X_{i,j} = \begin{cases} 1 & ; \text{ if j number or more FWC are allocated for the } i^{th} \text{ node} \\ 0 & ; \text{ Otherwise} \end{cases} \tag{2}$$

Hence, the total utilization value of allocated FWC at i^{th} node is given as Eq.3

$$\sum_{j=1}^{M} U_{i,j} X_{i,j} \tag{3}$$

Then the final objective function can be model as the sum of utilization of all nodes as the sum of the total utilization and given as Eq.4.

$$\sum_{i=1}^{N} \sum_{j=1}^{M} U_{i,j} X_{i,j} \tag{4}$$

Subjected to the following constraints:

$$\begin{cases} \sum_{i=1}^{N} \sum_{j=1}^{M} X_{i,j} \\ X_{i,j} \ge X_{i,j+1} \end{cases}$$

$$, \quad i = 1,2 \ldots . N; \; j = 1,2, \ldots M - 1$$

$$X_{i,j} \in \{0,1\}$$

The first constraint ensures that the total number of allocated converters should be the same as the available number of converters. The second constraint makes sure that the solution should maintain the continuity in the assigning the convertors number to each node. The third constraint restricts the element of the solution to the binary domain only. This is obvious that to increase the total utilization of allocated FWC over the network, STU as given in Eq.4 has to maximize while satisfying all the constraints.

3. Proposed New model of Traffic Oriented Objective Function

There may be the same value of percentage utilization for the different distribution of available numbers of FWC in the network. This causes the problem of multi-solution for a defined maximum number of FWC. Each solution in the domain of multi-solution has the same value of total utilization, but the different placement of FWC over available nodes. From the utilization point of view this is not a problem, but to handle the traffic in a better manner, nodes that handle high traffic must have the more FWC in compare with nodes with lesser traffic. This will help to reduce the blocking probability with available FWC as well as the solution will have better fault-tolerant.

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The problem is how to handle this issue in solution design? In [13], a reasoning based approach has been applied to tackle this issue. Reasoning based approach has the complication of design complexity as well as computation complexity. The number of times, condition checking has to done to understand the clarity of FWC placement over a node.

Meta-heuristic approaches have enough capability to explore the solution domain irrespective of the nature of the objective function. So, if the objective function carries a model about the desired way to handle traffic condition, optimal placement of FWC's can achieve. In this paper, a modified version of the objective function has proposed as shown in Eq.6.This objective function not only considers the sum form of total utilization value but also take care of the traffic handling condition by the previously available number of FWC. Considering the placement solution as X, first, the utilization of every placed FWC has achieved by multiplying with their corresponding utilization value in the utilization matrix U as given in Eq.5 and later the final fitness of the solution has achieved by Eq.6.

$$P_{ij} = [U_{ij}][X_{ij}] \quad ; i = 1 \dots N, j = 1,2, \dots M \tag{5}$$

$$f_m = \sum_{i=1}^{N}\left[\sum_{j=1}^{M} P_{ij} + \sum_{k=1}^{z-1}\left(\prod_{r=k}^{r+1} P_{kr}\right)\right] \tag{6}$$

Where 'z' is the nonzero number of elements in the row of P.

4. Proposed Solution: Differential Evolution with new mutation strategy (XLBDE)

In the standard version of differential evolution [14] the differential vector added with third member by arithmetic operator which may be useful for real value solution domain but exploration in binary domain becomes restricted after transformation of in binary base vector in terms of exploring the global solution and making the convergence faster. A binary version has developed by transforming the mutation vector through sigmoid function and the threshold has applied to get the outcomes. It was observed with experimental outcomes that there are limitations existed in terms of poor performance or premature convergence, with the standard differential evolution as well as self-adaptive Differential Evolution (SADE). Not only that, poor consistency in performance is the other major concern over the standard DE outcomes. To overcome these issues, a new form of mutation strategy has proposed which is a logical XOR operation between the differential vector and the base solution and called XBDE (XOR-based binary DE). The pseudo-code of the proposed mutation strategy has shown below.

<u>Development of Mutation vector in XBDE</u>

Inputs: $Q \leftarrow q^{th}$ member of the population for which offspring has to be generated;
mf ←mutation factor constant; Th ←a predefined threshold value;
Outcomes: M← Mutation vector corresponding to solution Q for cross-over operation

Step1: Select three solution members' m1, m2 & m3 randomly from population through uniform distribution except for the solution Q.
Step2: Obtain the differential vector; $v \leftarrow mf * [m2 - m3]$;
Step3: *For* each component dv_i of dv
(i) Limit the component dv_i value in the range of [0 1] by transformation through the unipolar sigmoid function: $Tdv_i \leftarrow sigmoid\,(dv_i)$;
(ii) Binary conversion of Tdv_i by comparison with threshold:

$$BTdv_i \leftarrow \begin{cases} 1 & if\ Tdv_i > Th \\ 0 & if\ Tdv_i \le Th \end{cases}$$

(iii) Obtain the i^{th} component M_i of mutation vector M by logical XOR operation:

$$M_i \leftarrow m1_i \oplus BTdv_i$$

End For

The proposed mutation strategy can deliver the high diversity in the mutation vector, which causes better and faster exploration. To increase the convergence speed of standard DE a new approach in the differential vector formation has also presented. It has two possibilities of differential change under the probabilistic environment. In the first case, differential change is defined through the best member and a randomly selected member from the population while in the second case two random members are selected from the population to obtain the differential change. A threshold value is defined to determine the selection of mode for a differential change. This threshold value should be less than 0.5 (in this paper taken as 0.2) to maintain the balance between exploration and exploitation. A higher value of more than 0.5 will cause of dominancy of exploitation over exploration. Best member-based differential change promotes the faster change while random member-based selection helps to prevent suboptimal convergence. The pseudo-code for the applied differential vector strategy has shown below.

A differential vector development in the g^{th} generation

Inputs : mf ←mutation factor constant; Thr ←a predefined threshold value;
R ←U[0, 1]; a random number generated through uniform distribution;
BS←Fittest solution in the population over the g^{th} generation.
Outcomes: dv ← a differential vector used in mutation vector development;

Step1: Select three members $m1$,$m2$ & $m3$ randomly from population. Where $m1$ has been preserved for mutation vector development.
Step2: *If* *R* < *Thr*
$dv \leftarrow mf * [BS - m3]$;
Else
$dv \leftarrow mf * [m2 - m3]$;
End

The main title (on the first page) should begin 1 3/16 inches (7 picas) from the top edge of the page, centered, and in Times New Roman 14-point, boldface type. Capitalize the first letter of nouns, pronouns, verbs, adjectives, and adverbs; do not capitalize articles, coordinate conjunctions, or prepositions (unless the title begins with such a word) (*e.g.* **A Comparative Study of Privacy Protection Methods for Smart Home Environments**). Please initially capitalize only the first word in other titles, including section titles and first, second, and third-order headings (for example, “Titles and headings” — as in these guidelines). Leave two blank lines after the title.

In the standard as well as self-adaptive DE binary version, the proposed method of mutation and differential vector development have been applied and called as XBDE, XLBDE, XBSADE and XLBSADE. The complete functional block diagram of XLBDE has shown in Fig.1 (X stands for XOR-based mutation operation, L stands for the best solution included differential vector under probabilistic environment and B stands for binary version). In the proposed model of DE, as in the standard DE, initially, a binary solution population is defined randomly through uniform distribution. Let's assume that at any point in solution evolution at present g^{th} generation is available and a solution has selected for the evolution. Three members’ m1, m2 and m3 among the solution population have selected randomly through uniform distribution. A random number ‘R’ generated through uniform distribution in the range of [0 1]. If R is less than a predefined threshold *Thr*, then the differential vector will be created by the best member BS (has maximum fitness in the current population) and m3 otherwise m2 and m3 will form the

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differential vector. This differential vector multiplied with mutation factor mf and transformation in binary domain takes through the unipolar sigmoid function followed by a thresholding process. The XOR operation has taken place between final differential vectors with the m1 to form the mutation vector MV. An offspring has created through the crossover operation between P and MV. Finally, the fitness-oriented selection process decides the winner among parents and corresponding offspring who will be part of $(g+1)^{th}$ generation population.

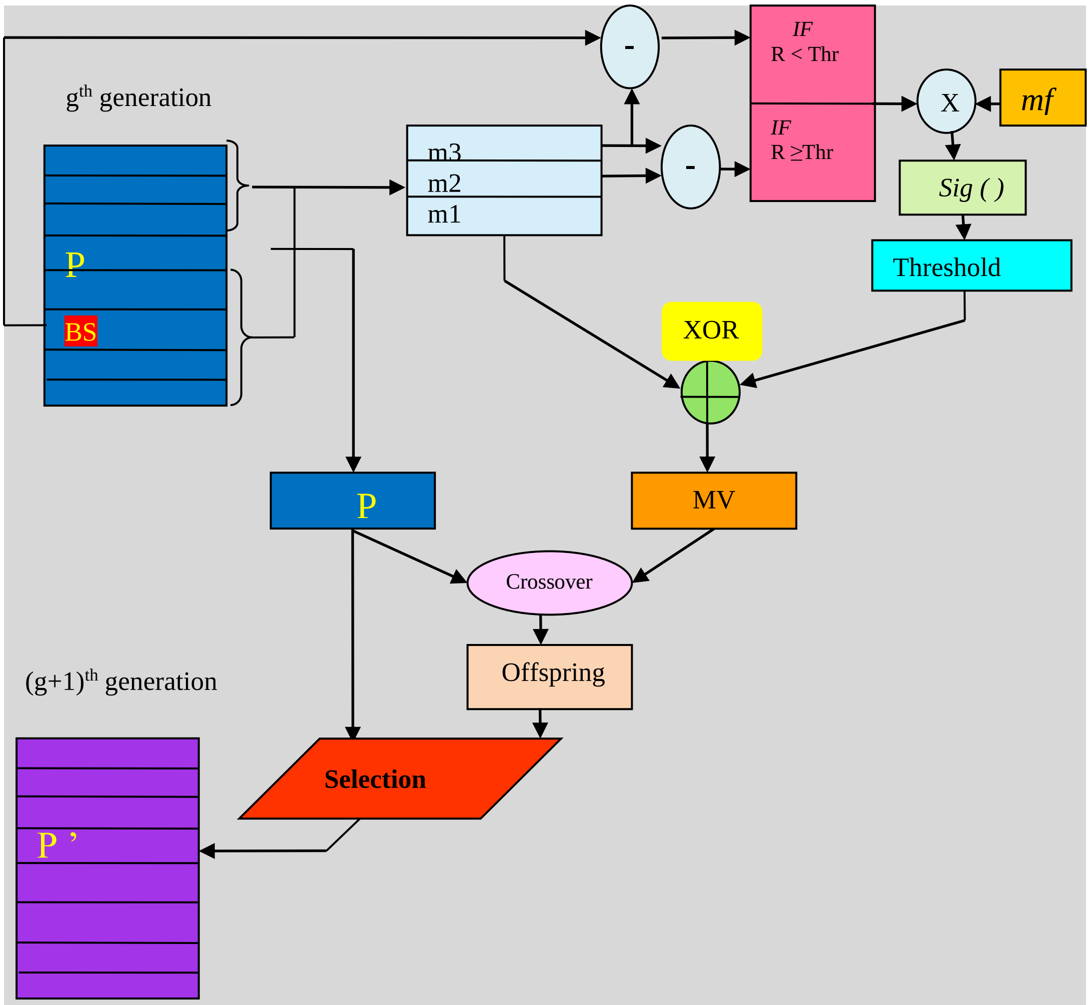

Figure.1 Functional model of XLBDE

5. Simulation Results

We have selected the NSFNET backbone network for experimental purposes. The corresponding network is shown in Fig.2. It has 14 nodes and 21 bi-directional links. The node numbers assumed are pointed inside the corresponding node-circles. The utilization matrix (U) for the selected network has given in Table1 and the same is considered in [13] so that comparison over performances can be evaluated.

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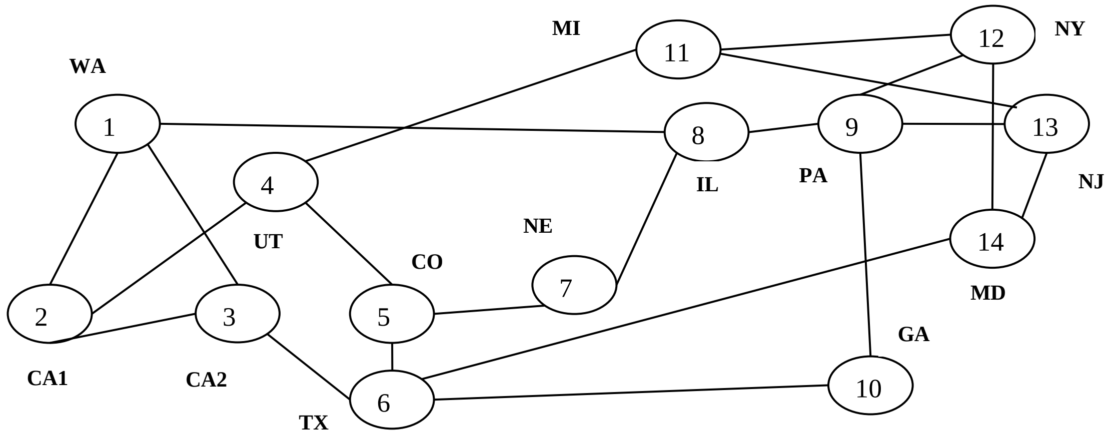

Figure. 2 NSFNET backbone network

Table1. Utilization Matrix

	No. of Convertors busy simultaneously					
Node No.	0	1	2	3	4	5
1	0.44	0.41	0.13	0.02	0.00	0.00
2	0.41	0.38	0.16	0.03	0.02	0.00
3	0.52	0.44	0.03	0.01	0.00	0.00
4	0.11	0.51	0.22	0.10	0.04	0.02
5	0.64	0.25	0.07	0.04	0.00	0.00
6	0.59	0.32	0.09	0.00	0.00	0.00
7	0.12	0.54	0.22	0.07	0.03	0.02
8	0.47	0.43	0.08	0.01	0.01	0.00
9	0.71	0.21	0.08	0.00	0.00	0.00
10	0.21	0.57	0.12	0.04	0.03	0.03
11	0.46	0.38	0.13	0.03	0.00	0.00
12	0.39	0.51	0.09	0.01	0.00	0.00
13	0.35	0.43	0.12	0.09	0.01	0.00
14	0.67	0.28	0.03	0.02	0.00	0.00

It has assumed that considered WDM network follows the characteristics of the connected graph where there is a path available between any pair of nodes in the network graph. The existed link between nodes pair is bi-directional and contains ‘W’ different wavelength channels. The nature of placed converters is Full range wavelength converters which can convert any input wavelength to any other wavelengths available. Since there are six columns in Table1, so it is obvious that M =5.Considering the NSFNET backbone network as test network, six variants of DE (BDE, XBDE, XLBDE, BSADE, XBSADE, and XLBSADE) have been applied to obtain the placement solutions for three different cases of available wavelength converters as 18, 21, and 24. Modeling and experiments have been simulated under the MATLAB environment. Population size in all algorithms has taken as 100 while the mutation factor and crossover probabilities have taken as 0.2 and 0.4. Outcomes of sigmoid function transform into binary domain by applying threshold value as 0.5. For each value of available FWC’s, all algorithms have been evolved up to 500 generations and 20 independent trials have given to estimate the performance. A penalty concept has applied to construct the unfeasible solution by decreasing

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the solution fitness by $n \times PF$, where n is the total number of constraints violation and PF is the penalty factor constant (generally considered as a high value, here equal to 10000). Performance comparison for all the three cases with the available number of FWC's has been evaluated to identify the quality of algorithms. To obtain the comparative performances between different algorithms, the outcomes achieved over 20 trials from each algorithm have presented in terms of maximum, minimum and mean values of fitness through f_m as well as the STU model. The standard deviation has also presented to estimate the reliability of outcomes. The convergence quality in terms of the required number of iterations has estimated by finding the iteration number which has delivered the best-obtained value of fitness f_m and remains constant after that. The success rate has decided by out of 20 trials for how many trials the obtained global best fitness value has achieved by a particular algorithm.

Allocation and Performance outcomes for all the 20 trials with available FWC equal to 24 have shown in Table2 and Table3. The best fitness value in terms of is 7.6512 while the STU value is 7.04. It can observe from Table4 that XBDE and XLBDE have given the same fitness value 7.6512 (U=7.04) for all the 20 trials while BDE has delivered only a 75% success rate to achieve the best value. It can also be observed that XBDE has taken a lesser number of iterations in achieving the best value. But XLBDE has taken the even lesser number of iterations compared to XBDE as it was expected because of the best member-oriented differential vector. An interesting and surprising part of results are performances of self-adaptive differential evolution based variant XBSDE and XLBSDE has inferior performances over standard DE variant XBDE and XLBDE. Even though XBSDE and XLBSDE have achieved 100% success but have taken a large number of iterations comparatively.

Table2. FWC allocation by XLBDE

	24 FWC placement					21FWC placement					18 FWC placement				
Node No.	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
1	1	1	0	0	0	1	1	0	0	0	1	0	0	0	0
2	1	1	0	0	0	1	1	0	0	0	1	1	0	0	0
3	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0
4	1	1	1	0	0	1	1	0	0	0	1	1	0	0	0
5	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0
6	1	1	0	0	0	1	0	0	0	0	1	0	0	0	0
7	1	1	0	0	0	1	1	0	0	0	1	1	0	0	0
8	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0
9	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0
10	1	1	0	0	0	1	1	0	0	0	1	1	0	0	0
11	1	1	0	0	0	1	1	0	0	0	1	0	0	0	0
12	1	1	0	0	0	1	0	0	0	0	1	0	0	0	0
13	1	1	0	0	0	1	1	0	0	0	1	0	0	0	0
14	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0

Table3. Performances over 20 trials with 24 FWC

Algorithm	fm Max.	fm Min.	fm Mean	Std.Dev.	STU Max	STU Min.	STU Mean	Std.Dev.	% Success	Mean Itr No.
BDE	7.6512	7.5940	7.6464	0.0133	7.0400	7.0000	7.0355	0.01	75	278.6
XBDE	7.6512	7.6512	7.6512	0.0	7.0400	7.0400	7.0400	0.0	100	244.1
XLBDE	**7.6512**	**7.6512**	**7.6512**	**0.0**	**7.0400**	**7.0400**	**7.0400**	**0.0**	**100**	**219.5**
BSADE	7.6512	7.6436	7.6506	0.0019	7.0400	7.0200	7.0385	0.0049	90	361.5
XBSADE	7.6512	7.6512	7.6512	0.0	7.0400	7.0400	7.0400	0.0	100	307.4
XLBSADE	7.6512	7.6512	7.6512	0.0	7.0400	7.0400	7.0400	0.0	100	296.7

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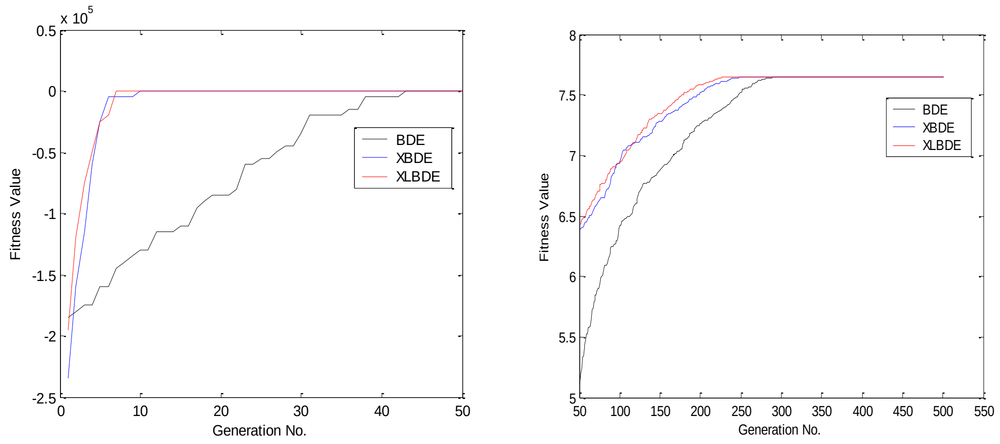

Figure.3. (a) Initial and (b) later stage Convergence characteristics with 24 FWC in BDE variant

The convergence characteristics for BDE algorithm based variants have shown in Fig.3(a) and Fig.3(b). It is observed from both figures that, in comparison to BDE and SBDE, there are sharp improvements in the solution fitness quality of the proposed algorithm that has appeared at the initial stage of evolution itself. BDE and SBDE move from unfeasible region to feasible region with a nearly linear manner while jump change has appeared for XOR mutation-based variant. This change appeared because the high exploration capability existed with the proposed logical XOR-based mutation strategy. In later stages also convergence characteristics are much better for proposed solutions.

5.1 Comparison with previous work

The benefit of the proposed model over the STU and reasoning based approach(RBA) [13] in extracting the traffic condition efficiently for optimal placement of FWC's have been analyzed. Considering the available FWC over the NSFNET backbone network as 18(T=18) for the specified utilization matrix as given in Table1. The obtained placement solutions by XLBDE and reasoning based approach RBA have shown in Table4 and their corresponding fitness value has shown in Table5. To understand the involved complication with allocation over the node1 and node10, consider the traffic status over these nodes as shown in Table6. Node1 has 13% of all time where 2 FWC's are busy which 1% busier in compare to Node10. If STU has considered as an objective function, then this situation is clear to place the 2 FWC's at node1 and 1FWC at node10. But this allocation does not consider the traffic condition at node10 properly, it can observe that there is 16% more busy condition with 1 FWC, 2% more busy condition with 3 FWC's in comparison to conditions at node1, not only that node10 has 3% busy condition with 4 and 5 FWC's correspondingly while node1 doesn't have condition were 4 and 5 FWC's were simultaneously busy. Hence it is not a practical choice to place 2 FWC's at node1 and 1 FWC at node10. When the proposed objective function f_m has applied, even though STUXLBDE < STURBA, there is a high value of the objective function (fmXLBDE > fmRBA) has obtained. In result appeared solution by the proposed method has placed 1 FWC at node1 while 2 FWC's at node10. The solution obtained by RBA doesn't have such kind of sensitivity towards handling the traffic hence fails to deliver the optimal placement of FWC.

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Table4. FWC allocation with T equal to18

	XLBDE					RBA [13]				
Node No.	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
1	1	0	0	0	0	1	1	0	0	0
2	1	1	0	0	0	1	1	0	0	0
3	1	0	0	0	0	1	0	0	0	0
4	1	1	0	0	0	1	1	0	0	0
5	1	0	0	0	0	1	0	0	0	0
6	1	0	0	0	0	1	0	0	0	0
7	1	1	0	0	0	1	1	0	0	0
8	1	0	0	0	0	1	0	0	0	0
9	1	0	0	0	0	1	0	0	0	0
10	1	1	0	0	0	1	0	0	0	0
11	1	0	0	0	0	1	0	0	0	0
12	1	0	0	0	0	1	0	0	0	0
13	1	0	0	0	0	1	0	0	0	0
14	1	0	0	0	0	1	0	0	0	0

Table5. Fitness value with proposed model (f_m) and STU (T=18)

	f_m	STU
XLBDE	6.7402	6.38
RBA[13]	6.7351	6.39

Table6. Utilization value for node 1 and 10

	FWC					
Node No.	0	1	2	3	4	5
1	0.44	0.41	**0.13**	0.02	0.00	0.00
10	0.21	**0.57**	0.12	**0.04**	**0.03**	**0.03**

Conclusion & Future work

The proposed work in this paper has taken care of traffic oriented FWC assignment problem in three-dimensional approaches using a modified version of DE: delivery of optimal placement, faster convergence of solution and high reliability. The proposed strategy contents a new mutation operator which is based on logical XOR operation and cause of the increased level of exploration. Providing the chance to the fittest member under the probabilistic environment to define the differential vector has helped in faster convergence. A new model of utilization value that understands the traffic characteristic has also presented and shown with detail analysis that it has a better allocation of FWC in compare to the sum of utilization value as presented in past literature. When logical XOR-based mutation operator had applied with standard DE as well as with self-adaptive DE, there was a significant improvement appeared in terms of a success rate as well as the required number of iterations. There was a faster transformation observed from unfeasible solutions to feasible solutions with the use of the proposed mutation strategy. The placement performances obtained from the proposed method were compared and analyzed with a reasoning based approach proposed in the past and observed that the proposed method solution was superior. There are several ways where the presented work can be extended in the future like, considering the different types of network topology for test cases which may be regular and

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irregular. Instead of considering the static utilization matrix as taken in this work, the inclusion of a dynamic utilization matrix could be closer to the practical scenario.

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