ÖZGÜR BAŞKAN, Ph.D.[1]
(Corresponding author)
E-mail: obaskan@pau.edu.tr
CENK OZAN, Ph.D.[2]
E-mail: cenk.ozan@adu.edu.tr
MAURO DELL'ORCO, Ph.D.[3]
E-mail: mauro.dellorco@poliba.it
MARIO MARINELLI, Ph.D.[3]
E-mail: mario.marinelli@poliba.it
[1] Department of Civil Engineering, Faculty of Engineering, Pamukkale University, 20070, Denizli, Turkey
[2] Department of Civil Engineering, Faculty of Engineering, Aydın Adnan Menderes University, 09010, Aydin, Turkey
[3] Technical University of Bari, D.I.C.A.T.E.Ch. Via Edoardo Orabona 4, 70125 Bari, Italy

Science in Traffic and Transport
Original Scientific Paper
Submitted: 26 Oct. 2017
Accepted: 20 Sep. 2018

IMPROVING THE PERFORMANCE OF THE BILEVEL SOLUTION FOR THE CONTINUOUS NETWORK DESIGN PROBLEM

ABSTRACT

For a long time, many researchers have investigated the continuous network design problem (CNDP) to distribute equitably additional capacity between selected links in a road network, to overcome traffic congestion in urban roads. In addition, CNDP plays a critical role for local authorities in tackling traffic congestion with a limited budget. Due to the mutual interaction between road users and local authorities, CNDP is usually solved using the bilevel modeling technique. The upper level seeks to find the optimal capacity enhancements of selected links, while the lower level is used to solve the traffic assignment problem. In this study, we introduced the enhanced differential evolution algorithm based on multiple improvement strategies (EDEMIS) for solving CNDP. We applied EDEMIS first to a hypothetical network to show its ability in finding the global optimum solution, at least in a small network. Then, we used a 16-link network to reveal the capability of EDEMIS especially in the case of high demand. Finally, we used the Sioux Falls city network to evaluate the performance of EDEMIS according to other solution methods on a medium-sized road network. The results showed that EDEMIS produces better solutions than other considered algorithms, encouraging transportation planners to use it in large-scale road networks.

KEY WORDS

continuous network design; capacity enhancement; mutual interaction; user equilibrium;

1. INTRODUCTION

The continuous network design problem (CNDP) can be defined as "determining optimal capacity enhancements of selected links under budget constraints in a given road network". In this well-known transportation problem, the global optimum solution can be found by exact methods (for example, branch and bound) only for small-sized networks; in fact, difficulty in finding the optimal solution for CNDP increases with the dimensions of the network. CNDP can be generally formulated as a bilevel programming model since it has multiple objectives in which road users and local decision makers interact mutually. Due to the non-convex feature of the bilevel programming model of CNDP, it can be recognized as one of the significant problems in the transportation/optimization fields. The difficulty of the bilevel programming model of CNDP arises from the requirement of solving the traffic assignment problem at the lower level for each candidate solution at the upper level. On the other hand, solving the upper-level objective function requires finding equilibrium link flows, determined by solving a traffic assignment problem at the lower level. In CNDP, upper level can be formulated as the sum of total travel time and expenditures of investment for capacity enhancement in a given road network, while the lower level is defined as a deterministic (DUE) or stochastic user equilibrium (SUE) traffic assignment [1]. It is clear that SUE traffic assignment models may be used in the lower level problem of CNDP. A wide range of literature shows us that there is a limited number of studies in which the SUE traffic assignment is considered to determine users' reactions to the changes performed in terms of link capacity expansions at the upper level of CNDP. The reason is that the use of SUE traffic assignment models increases the computation burden of the bilevel solution of CNDP by introducing more paths than DUE traffic assignment. This issue is also clearly stated in the pioneer study by Farahani et al. [2]. It is also indicated in the same study that the SUE traffic assignment models have been used only in three studies in the late 2000s, which used metaheuristics to determine the solutions in the context of transportation network design problem. Therefore, we have used the DUE traffic assignment model at the lower level of CNDP with regards to some fundamental reasons: (1) to decrease the computational burden, and (2) to make a fair comparison with other studies about CNDP since almost all studies in the literature used the DUE traffic assignment models to take the users' reactions at the lower level.

In CNDP, we need to take into account the mutual interaction between road users and local decision-makers, when optimizing the upper-level objective function; in fact, modifications in terms of the capacity of the road network affect users' route choice. Users' responses to these modifications arise from the multiplicity of equilibrium link flows. Due to the mutual interaction between the two levels, the bilevel programming model of CNDP may be included in the class of non-convex problems; therefore, it is quite difficult to use gradient-based optimization algorithms for its solution [3].

Abdulaal and LeBlanc [4] first formulated the network design problem and drew attention to the results, in terms of increasing of practical capacity, using convex or concave investment functions in the model. After this first study, several variations of CNDP have been studied, and different solution techniques have been developed. Suwansirikul et al. [5] proposed a new method for finding an approximate solution and tested this method on different test networks. Afterwards, Marcotte [6] and Marcotte and Marquis [7] tried to solve CNDP using heuristic methods, easily applicable for small-sized road networks. Meng et al. [8] presented the augmented Lagrangian method to solve CNDP, especially for large networks. On the other hand, Chiou [9] presented a descent approach by using gradient-based algorithms and used several test networks to show the efficiency of the proposed algorithms. Ban et al. [10] transformed the bilevel solution of CNDP into a single level and achieved good results. Karoonsoontawong and Waller [11] proposed three well-known heuristic methods and found that the genetic algorithm (GA) produced better results than the others in terms of some performance measures. Gao et al. [12] formulated CNDP as single level and proposed a novel algorithm to solve this problem. Xu et al. [13] proposed simulated annealing (SA) and GA to achieve good results in solving CNDP. They found that the SA outperforms the GA especially for road networks faced with high demand. Unlike the study proposed by Xu et al. [13], Mathew and Sarma [14] reported that the GA model is more efficient for CNDP than the other compared algorithms available in the literature. Wang and Lo [15] tried to solve CNDP by considering it as a single level. Their results showed that the method is able to achieve the global solution for CNDP. Li et al. [16] presented a viable global optimization method for CNDP, converted into a set of single-level models. Recently, Baskan [17, 18] also attempted to solve the bilevel formulation of CNDP using three powerful heuristics in solving CNDP. Wang et al. [19] remarked that the multiple user classes should be taken into consideration for solving CNDP. Differently from the literature, Wang et al. [20, 21] presented a bilevel programming model to solve CNDP with a relaxation algorithm. Small and medium-sized networks have been used to show the capability of the proposed model.

In terms of CNDP based on SUE traffic assignment, the first study was presented by Davis [22], in which two different methods considering the effect of a stochastic user equilibrium were proposed for solving CNDP, and they were applied to several test networks. After almost two decades, Liu and Wang [23] considered CNDP with SUE traffic assignment by using the logit route choice model, aiming to determine the global optimum solution. Du and Wang [24] proposed the generalized geometric programming method to achieve the global solution for CNDP by considering both DUE and SUE assumptions. As another type of road network design problems, the discrete network design problem (DNDP) with SUE constraint has been studied by Chen and Alfa [25]. They used a heuristic solution algorithm based on the branch and bound method for solving the DNDP by considering SUE traffic assignment. Another point of view for the DNDP, the lane reallocation problem has been tackled with the SUE principle by using a heuristic solution algorithm based on the particle swarm optimization method by Zhang and Gao [26]. Similarly to this study, Wu et al. [27] proposed a bilevel programming model in which the upper level seeks to adopt reversible lanes by optimizing the total system cost and flow entropy while the lower level deals with a stochastic user equilibrium assignment. Long et al. [28] developed a bilevel programming model to solve the turning restriction design problem with SUE. Recently, Liu and Wang [29] proposed a mixed-integer nonconvex model to tackle the DNDP with SUE. On the other hand, a study about the combined version of CNDP and DNDP, called the mixed network design problem (MNDP), with the SUE constraint, was proposed by Dimitriou et al. [30]. They dealt with problems of road network design and pricing decisions by using a genetic algorithm with elastic demand. A recent study about the MNDP was conducted by Gallo et al. [31], in which an SUE traffic assignment is considered at the lower level while total travel time in the network is minimized at the upper level by the scatter search method.

Since metaheuristic methods do not guarantee reaching the global solution for CNDP, there are few applications of metaheuristics in solving CNDP compared to other types of road network design problems [2]. This issue may be considered as the most important disadvantage of the use of metaheuristics for CNDP, although some metaheuristic methods have valuable advantages, requiring less computational efforts and mathematical complexity. To reveal these advantages, this study aims to solve CNDP using an enhanced differential evolution algorithm based on multiple improvement strategies (EDEMIS). To do this, a bilevel programming model has been presented in which the upper level deals with minimizing the sum of total travel times and investment expenditures while the lower level problem is formulated by considering the DUE assumption.

The rest of the paper is presented as follows. The bilevel programming model for CNDP is given in Section 2. EDEMIS and its improvement strategies are presented in the next section. In Section 4, numerical experiments are performed on three different test networks. Finally, conclusions are given in Section 5.

Notations

A - set of links, $\forall a \in A$
K_{rs} - set of paths between O-D pair $rs \, \forall r \in R, s \in S$
R - set of origins
S - set of destinations
$\mathbf{D}$ - O-D demands, $\mathbf{D} = [D_{rs}] \forall r \in R, s \in S$
$\mathbf{f}$ - path flows, $\mathbf{f} = [f_k^{rs}] \forall r \in R, s \in S, k \in K_{rs}$
$\mathbf{t}$ - link travel times, $\mathbf{t} = [t_a(x_a, y_a)] \forall a \in A$
$\mathbf{u}$ - upper bound for link capacity expansions, $\mathbf{u} = [u_a], \forall a \in A$
$\mathbf{x}$ - equilibrium link flows, $\mathbf{x} = [x_a], \forall a \in A$
$\mathbf{y}$ - link capacity expansions, $\mathbf{y} = [y_a], \forall a \in A$
θ_a - link capacity, $\forall a \in A$
Z - upper-level objective function
z - lower level objective function
ρ - conversion factor
$\delta_{a.k}^{rs}$ - the link/path incidence matrix variable, $\forall r \in R, s \in S, k \in K_{rs}, a \in A$
α_a, β_a - the parameters of link cost function, $\forall a \in A$

2. BILEVEL PROGRAMMING MODEL

In case of using a bilevel programming model for CNDP, the upper level is usually defined as minimizing the sum of total travel times and expenditures of investment into capacity enhancement projects within a limited budget, whereas road users' reactions to these projects are determined at the lower level. In other words, mutual interaction between users and local decision makers is taken into consideration by using the bilevel programming model. It is clear that the use of such model can simplify the solution of CNDP, although it leads to some disadvantages (i.e., non-convexity) for the algorithms used in the solution. This mutual interaction can be formulated as follows:

$$\min_{y} Z(x,y) = \sum_{a \in A} (t_a(x_a, y_a) x_a + \rho g_a(y_a)) \quad (1)$$

$$\text{s.t. } 0 \le y_a \le u_a, \quad \forall a \in A \quad (2)$$

where x_a is flow on the link a under given capacity enhancement plan and determined at the lower level problem; $g_a(y_a)$ is the investment function. *Equation 2* guarantees that the expenditure of the capacity enhancement plan of a link is lower than its own budget. It also ensures that the decision variables are to be positive.

Users' reactions to the enhancement projects applied at the upper level are determined by solving a traffic assignment problem at the lower level. As known, a traffic assignment problem can be solved under DUE or SUE assumptions so that each of them has its own advantages and disadvantages. In this paper, DUE is applied to find the equilibrium link flows by considering Wardrop's first principle. Wardrop [32] argued that the travel times of all used paths between the same origin-destination (O-D) pair are equal and less than any unused paths. This hypothesis and its mathematical formulation stated by Beckmann et al. [33] are given as follows.

$$\min_{x} z = \sum_{a \in A} \int_{O}^{x_a} t_a(w, y_a) dw \quad (3)$$

$$\text{s.t. } \sum_{k \in K} f_k^{rs} = D_{rs} \quad \forall r \in R, s \in S, k \in K_{rs} \quad (4)$$

$$x_a = \sum_{rs} \sum_{k \in K_{rs}} f_k^{rs} \delta_{a,k}^{rs} \quad \forall r \in R, s \in S, a \in A, k \in K_{rs} \quad (5)$$

$$f_k^{rs} \ge 0 \quad \forall r \in R, s \in S, k \in K_{rs} \quad (6)$$

where *Equation 4* represents that the sum of the route flows between an O-D pair r-s is to be the demand between the same O-D pair. *Equation 5* shows that the flow on a link is to be the sum of the route flows which use this link. *Equation 6* is related to the non-negativity. Frank-Wolfe (FW) algorithm [34] is used to obtain DUE link flows in the lower level of CNDP.

3. ENHANCED DIFFERENTIAL EVOLUTION ALGORITHM

3.1 Classical DE for CNDP

DE is a strong and easily applicable algorithm introduced by Storn and Price [35] to solve various optimization problems. It guides the initial solution vectors towards the vicinity of the global or near-global optimum solution by means of a repeated cycle of mutation, crossover, and selection. DE takes the advantage of two parameters in the solution process apart from the number of populations (NP). One of them is the mutation factor (F), which is used to obtain mutant vector from selected three solution vectors in the population and recommended to be set between 0.5–1 by [35]. The second one is the crossover rate (CR), which represents the probability of consideration of the mutant vector. The recommended range of CR by [35] is [0.8, 1]. F and CR are chosen as 0.8 for all numerical experiments in this paper. The DE steps can be summarized as follows. Note that the DE solution process is described in the context of CNDP for the sake of brevity.

Generation of the initial population: At generation t, the initial population ($\mathbf{y}^t$) is created with capacity enhancements values for a set of selected links as shown in *Equation 7*. Considering the generated upper-level decision variables, equilibrium link flows are determined for each solution vector (i.e., target vector) in the population by solving DUE traffic assignment problem at the lower level. Following this, the fitness values (f_j^t) for each target vector are calculated by using *Equation 1*.

$$\mathbf{y}^t = \begin{bmatrix} y_1^{1,t}, y_2^{1,t}, & \cdots & y_{i-1}^{1,t}, y_i^{1,t} \\ y_1^{2,t}, y_2^{2,t}, & \cdots & y_{i-1}^{1,t}, y_i^{2,t} \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ y_1^{j-1,t}, y_2^{j-1,t}, & \cdots & y_{i-1}^{j-1,t}, y_i^{j-1,t} \\ y_1^{j,t}, y_2^{j,t}, & \cdots & y_{i-1}^{j,t}, y_i^{j,t} \end{bmatrix} \Rightarrow \begin{bmatrix} f_1^t \\ f_2^t \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ f_j^t \end{bmatrix} \quad (7)$$

where $i \in \{1,2,...,N\}$, $j \in \{1,2,...,NP\}$ and N is the number of links for capacity enhancement projects.

Mutation: First, two randomly selected solution vectors subtract from each other; afterwards, a third vector is added to the difference vector, multiplied by the mutation factor (F). Thus, the mutant vector ($\mathbf{m}^t$) is created, and its each member can be determined as shown in *Equation 8*.

$$m_i^{j,t} = y_i^{1,t} + F\left(y_i^{2,t} - y_i^{3,t}\right) \quad (8)$$

where $y_i^{1,t}, y_i^{2,t}$, and $y_i^{3,t}$ are randomly selected capacity enhancement values within the range $[0,NP]$ at generation t, and $y_i^{1,t} \neq y_i^{2,t} \neq y_i^{3,t}$.

Crossover: The crossover mechanism is used to diversify the target vector with the mutant vector. The vector created by using crossover operator is called trial vector ($\mathbf{r}^t$), and its each member is chosen either from the mutant vector or from the target vector as given in *Equation 9*.

$$r_i^{j,t} = \begin{cases} m_i^{j,t}, & \text{if rand}(0,1) \leq CR \quad or\ i = i_{rand} \\ y_i^{j,t} & \text{otherwise} \end{cases} \quad (9)$$

The crossover rate, CR, is compared with a randomly generated value between 0 and 1. If CR is greater, the trial vector is created from the mutant vector, otherwise from the target vector. In addition, the statement, $i=i_{rand}$, where i_{rand} is the randomly selected integer number in the range $[1,N]$, ensures that at least one member of the trial vector is taken from the mutant vector to make the trial vector different from the target vector at each generation.

Selection: Each DE generation is finalized by applying this step. First, the fitness value of each trial vector is calculated by using *Equation 1*. Then the trial vector is compared with the target vector according to their fitness values, and the best one deserves to enter to the next generation as shown in *Equation 10*.

$$\mathbf{y}^{t+1} = \begin{cases} \mathbf{r}^t, & \text{if } f(\mathbf{r}^t) < f(\mathbf{y}^t) \\ \mathbf{y}^t, & \text{otherwise} \end{cases} \quad (10)$$

3.2 DE improvement strategies

Although DE is considered as one of the powerful heuristic algorithms, probably better solutions for CNDP can be obtained by improving it in different ways. Thus, we developed the EDEMIS algorithm which has three improvements to increase the performance of the DE as given below. The flowchart of EDEMIS for CNDP is given in *Figure 1*.

Improvement 1: More than one mutation strategies are simultaneously taken into account by means of a parameter called mutation strategy selection rate (MSSR). If the MSSR is greater than the random number generated between 0 and 1, the classical mutation strategy is used as shown in *Equation 11*. Otherwise, the second mutation strategy, in which the best solution vector found in the previous generation is considered, is used to obtain a mutant vector.

$$m_i^{j,t} = \begin{cases} y_i^{1,t} + F\left(y_i^{2,t} - y_i^{3,t}\right), & \text{if rand}(0,1) < \text{MSSR} \\ y_i^{1,t} + F\left(y_i^{best,t-1} - y_i^{2,t}\right) & \text{otherwise} \end{cases} \quad (11)$$

By means of this improvement, the proposed algorithm may have the potential to faster achieve the global or near global optimum solution of a given optimization problem. It should be noted that the value of MSSR strongly affects the solution quality of EDEMIS. If the value of MSSR is too small, this may lead to premature convergence, since the best solution vector is taken into account more than it is needed. Therefore, the value of 0.95 for the MSSR is used in solving CNDP in this paper.

Improvement 2: The second improvement strategy may provide a chance to improve the quality of the target vector when its fitness value is less than that of the trial vector at the end of the selection process. In other words, the target vector is diversified by means of the difference vector ($\mathbf{dv}$) when it could not be improved with the trial vector. The difference vector is created by multiplying the difference between the trial and target vectors with the random number generated within the range of 0–1. After that, the difference vector is added to the target vector or subtracted according to whether the random number generated is less or equal than the value of 0.5 or not, and the new vector ($\mathbf{nv}$) is created. In case an improvement has been obtained after determining fitness values according to the adding or subtracting of difference vector, the target vector has been replaced with the $\mathbf{nv}$ vector. The basic formulation of the difference vector and its application can be shown in *Equations 12–14.*

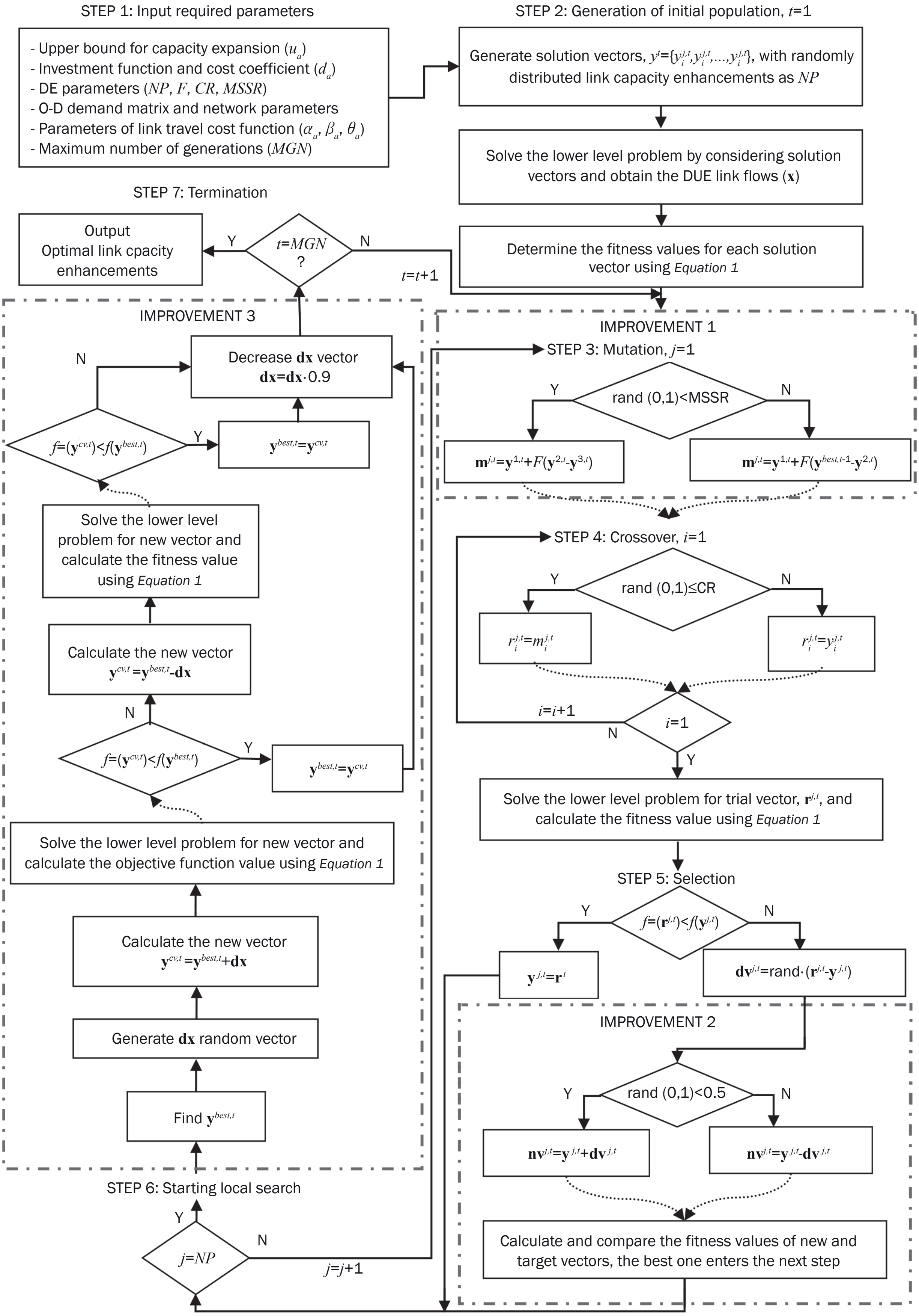

Figure 1 – Flowchart of EDEMIS for CNDP

$$dv_i^{j,t} = rand(0,1) \cdot \left(r_i^{j,t} - y_i^{j,t} \right) \tag{12}$$

$$nv_i^{j,t} = \begin{cases} y_i^{j,t} + dv_i^{j,t}, & \text{if } \mathrm{rand}(0,1) \leq 0.5 \\ y_i^{j,t} + dv_i^{j,t}, & \text{otherwise} \end{cases} \tag{13}$$

$$y_i^{j,t} = \begin{cases} nv_i^{j,t}, & \text{if } f(nv_i^{j,t}) < f(y_i^{j,t}) \\ y_i^{j,t}, & \text{otherwise} \end{cases} \tag{14}$$

Improvement 3: The last improvement strategy is the addition of a local search to the end of each generation. The aim of the local search is to push the best solution towards the global or near-global optimum at the end of each generation. In this process, the algorithm generates the $\mathbf{dx}^t$ vector from the range of (γ_1^t, γ_2^t) which is selected according to the upper and lower bounds of decision variables of the given optimization problem, as shown in *Equation 15*. After the $\mathbf{dx}^t$ vector is generated, it is added to the best solution vector, and then the candidate vector ($\mathbf{y}^{cv,t}$) is created. If the candidate vector's fitness value is better than that produced by the vector of the best solution, it is replaced with the best solution in the population. Otherwise, the $\mathbf{dx}^t$ vector is subtracted from the vector of the best solution in order to search for possible better solutions in other direction. The basic statement for creating the candidate vector can be seen in *Equation 16*. After the local search is ended, the $\mathbf{dx}^t$ vector is multiplied with 0.9 to reduce the search space around the best solution step by step, as given in *Equation 17*.

$$\mathbf{dx}^t = rand(\gamma_1, \gamma_2) \tag{15}$$

$$\mathbf{y}^{cv,t} = \mathbf{y}^{best,t} \pm \mathbf{dx}^t \tag{16}$$

$$\mathbf{dx}^{t+1} = \mathbf{dx}^t \cdot 0.9 \tag{17}$$

4. NUMERICAL APPLICATION

4.1 5-link network

Before applying the EDEMIS algorithm to small and medium-sized networks, a 5-link network is considered in order to demonstrate the capability of EDEMIS. This network consists of four nodes and five links, as given in *Figure 2*. The travel demand is taken as 100 from node 1 to 4. The link cost function is defined as given in *Equation 18*. Link parameters, demand data, and cost coefficients are adopted from Suwansirikul et al. [5].

$$t_a(x_a, y_a) = \alpha_a + \beta_a \left(\frac{x_a}{\theta_a - y_a} \right)^4 \tag{18}$$

The objective function of CNDP for this network is presented as:

$$\min_y Z(x,y) = \sum_{a \in A} \left(t_a(x_a, y_a) x_a + 1.5 d_a y_a^2 \right) \tag{19}$$

where d_a is the cost coefficient; upper bound for capacity enhancement is set to 10. The performance of EDEMIS in solving CNDP is compared with solutions from four algorithms given in the literature. The results from solving the 5-link network are given in *Table 1*.

The solution obtained by GA is reported as the global optimum value for this network. In [14], a complete enumeration is conducted to obtain the global optimum solution for CNDP. As shown in *Table 1*, MINOS, GA, and EDEMIS are able to achieve to the global optimum solution. On the other hand, the objective function values obtained by EDO and HJ algorithms are slightly far from the global solution. This experiment shows the ability of EDEMIS to obtain the global optimum solution in solving CNDP at least in this hypothetical network. Note that MINOS, GA, and EDEMIS algorithms produce slightly different link capacity enhancements despite the fact that their objective function values are the same. This property stems from the non-convexity of CNDP.

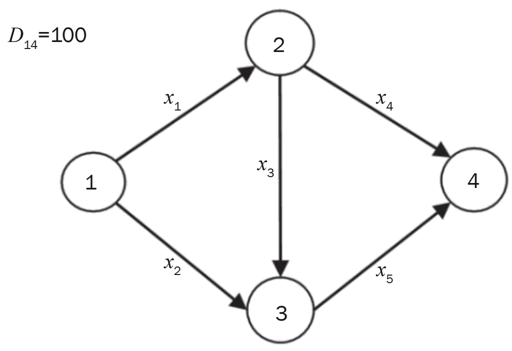

Figure 2 – 5-link network

Table 1 – Comparison of results from solving the 5-link network

	MINOS [5]	EDO [5]	HJ [5]	GA [14]	EDEMIS
y_1	1.34	1.31	1.25	1.33	1.33
y_2	1.21	1.19	1.20	1.22	1.22
y_3	0.00	0.06	0.00	0.02	0.00
y_4	0.97	0.94	0.95	0.96	0.97
y_5	1.10	1.06	1.10	1.10	1.09
Z	1200.58	1200.64	1200.61	1200.58	1200.58

4.2 16-link network

EDEMIS is applied to a 16-link network which has 16 links and 6 nodes, as given in *Figure 3*. For this network, two demand scenarios are considered, as given in *Table 2*. All data are taken from Suwansirikul et al. [5]. The fitness function for the 16-link network is given as:

$$\min_{y} Z(x,y) = \sum_{a \in A} (t_a(x_a, y_a)x_a + d_a y_a) \qquad (20)$$

Upper bounds for capacity enhancements were set to 10 and 20 for scenarios 1 and 2 for a fair comparison with other algorithms. Since the EDEMIS algorithm is a stochastic search method, the results obtained from this algorithm are given as the best output of different trials. Results for scenario 1 are compared with those obtained by other major algorithms, as

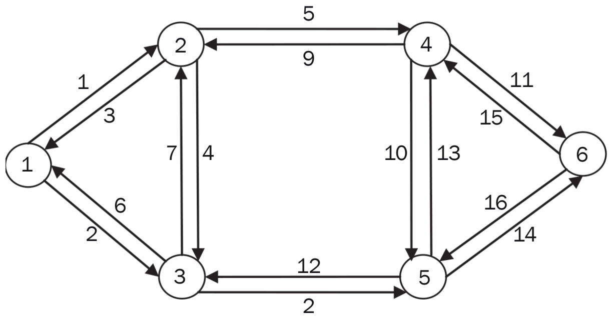

Figure 3 – 16-link network

Table 2 – Travel demand scenarios for the 16-link network

Scenario	D_{16}	D_{61}	Total demand
1	5	10	15
2	10	20	30

Table 3 – Comparison of results from solving the 16-link network for scenario 1

	MINOS [5]	HJ [5]	EDO [5]	IOA [36]	SA [37]	CS [17]
y_1	0	0	0	0	0	0
y_2	0	0	0	0	0	0
y_3	0	1.2	0.13	0	0	0
y_4	0	0	0	0	0	0
y_5	0	0	0	0	0	0
y_6	6.58	3.00	6.26	6.95	3.1639	5.1894
y_7	0	0	0	0	0	0
y_8	0	0	0	0	0	0
y_9	0	0	0	0	0	0
y_{10}	0	0	0	0	0	0
y_{11}	0	0	0	0	0	0
y_{12}	0	0	0	0	0	0
y_{13}	0	0	0	0	0	0
y_{14}	0	0	0	0	0	0
y_{15}	7.01	3.00	0.13	5.66	0	0
y_{16}	0.22	2.80	6.26	1.79	6.7240	7.6076
Z	211.25	215.08	201.84	210.86	198.10	199.32
#	-	54	10	9	18300	3
	SAB [38]	GP [9]	CG [9]	QNEW [9]	MILP [15]	EDEMIS
y_1	0	0	0	0	0	0
y_2	0	0	0	0	0	0
y_3	0	0	0	0	0	0
y_4	0	0	0	0	0	0
y_5	0	0	0	0	0	0
y_6	5.8352	5.8302	6.1989	6.0021	4.41	5.1597
y_7	0	0	0	0	0	0
y_8	0	0	0	0	0	0
y_9	0	0	0	0	0	0
y_{10}	0	0	0	0	0	0
y_{11}	0	0	0	0	0	0
y_{12}	0	0	0	0	0	0
y_{13}	0	0	0	0	0	0
y_{14}	0	0	0	0	0	0
y_{15}	0.9739	0.87	0.0849	0.1846	0	0
y_{16}	6.1762	6.1090	7.5888	7.5438	7.70	7.6164
Z	204.70	202.24	199.27	198.68	199.78	199.32
#	6	14	7	12	-	5

Note: Z describes the objective function value, # denotes the number of Frank-Wolfe iterations performed

Table 4 – Comparison of results from solving the 16-link network for scenario 2

	MINOS [5]	HJ [5]	EDO [5]	IOA [36]	SA [37]	AL [8]	CS [17]
y_1	0	0	0	0	0	0	0
y_2	4.61	5.40	4.88	4.55	0	4.6153	4.6144
y_3	9.86	8.18	8.59	10.65	10.1740	9.8804	9.9419
y_4	0	0	0	0	0	0	0
y_5	0	0	0	0	0	0	0
y_6	7.71	8.10	7.48	6.43	5.7769	7.5995	7.3821
y_7	0	0	0.26	0	0	0.0016	0
y_8	0.59	0.90	0.85	0.59	0	0.6001	0.5922
y_9	0	0	0	0	0	0.001	0
y_{10}	0	0	0	0	0	0	0
y_{11}	0	0	0	0	0	0	0
y_{12}	0	0	0	0	0	0.1130	0
y_{13}	0	0	0	0	0	0	0
y_{14}	1.32	3.90	1.54	1.32	0	1.3184	1.3152
y_{15}	19.14	8.10	0.26	19.36	0	2.7265	0
y_{16}	0.85	8.40	12.52	0.78	17.2786	17.5774	20
Z	557.14	557.22	540.74	556.61	528.50	532.71	522.40
#	-	134	12	13	24300	4000	4
	GP [9]	CG [9]	QNEW [9]	MILP [15]	LMILP [39]	PMC [16]	EDEMIS
y_1	0.1013	0.1022	0.0916	0	0	0	0.0002
y_2	2.1818	2.1796	2.1521	4.41	2.722	4.6905	1.3621
y_3	9.3423	9.3425	9.1408	10.00	9.246	9.9778	11.1298
y_4	0	0	0	0	0	0	0
y_5	0	0	0	0	0	0	0
y_6	9.0443	9.0441	8.8503	7.42	8.538	7.5554	5.5616
y_7	0	0	0	0	0	0	0
y_8	0.008	0.0074	0.0114	0.54	0	0.6333	0.5901
y_9	0	0	0	0	0	0	0
y_{10}	0	0	0	0	0	0	0
y_{11}	0	0	0	0	0	0	0
y_{12}	0.0375	0.0358	0.0377	0	0	0	0
y_{13}	0	0	0	0	0	0	0
y_{14}	0.0089	0.0083	0.0129	1.18	0	1.7664	1.2902
y_{15}	1.9433	1.9483	1.9706	0	0	0	1.9979
y_{16}	18.9859	18.986	18.575	19.50	20.000	19.6737	18.82564
Z	534.02	534.11	534.08	523.63	526.49	522.75	518.69
#	31	16	11	-	-	-	8

Note: Z describes the objective function value, # denotes the number of Frank-Wolfe iterations performed

given in *Table 3*. EDEMIS achieved the value of 199.32 as its best output, and this result is same as that produced by CS. Among all compared algorithms, SA produces the best solution but needs much more computational efforts in terms of the number of Frank-Wolfe iterations. It is clear that EDEMIS is able to produce good results with less computational efforts in comparison with EDO, SA, CG, QNEW, and MILP in solving CNDP.

In order to investigate the performance of EDEMIS under different demand levels, scenario 2 is considered and results are given in *Table 4*.

It can be clearly seen that EDEMIS is able to produce the best solution in comparison with other 13 algorithms, as well as with less computational efforts. By means of this experiment, the performance of EDEMIS has been demonstrated for solving CNDP, especially in heavier demand conditions.

4.3 Sioux Falls network

In order to show the ability of EDEMIS on middle-sized networks, the city of Sioux Falls is used, which has 24 nodes and 76 links. As in the previous numerical experiments, the relevant data of the network are taken from Suwansirikul et al. [5]. The dashed links are candidates for capacity enhancement projects as shown in *Figure 4*. The fitness function for the Sioux Falls network is formulated as in *Equation 21*. The upper bound for y_a was set to 25 for a fair comparison with other algorithms.

$$\min_{y} Z(x,y) = \sum_{a \in A} \left(t_a(x_a, y_a) x_a + 0.001 d_a y_a^2 \right) \qquad (21)$$

The results obtained by EDEMIS on the Sioux Falls network are evaluated and they are given in *Table 5*. From the table, it can be observed that the EDEMIS algorithm is able to produce the best solution among the compared major algorithms, except SA and CS. Although SA and CS slightly outperformed EDEMIS, the objective function values obtained by these algorithms are quite close. In addition, EDEMIS produced good results with a much lower number of Frank-Wolfe iterations in comparison with SA and CS. It should be noted that AL, HJ, and GA algorithms also has the potential to achieve good results for solving CNDP, but they require much more computational efforts as compared to EDEMIS.

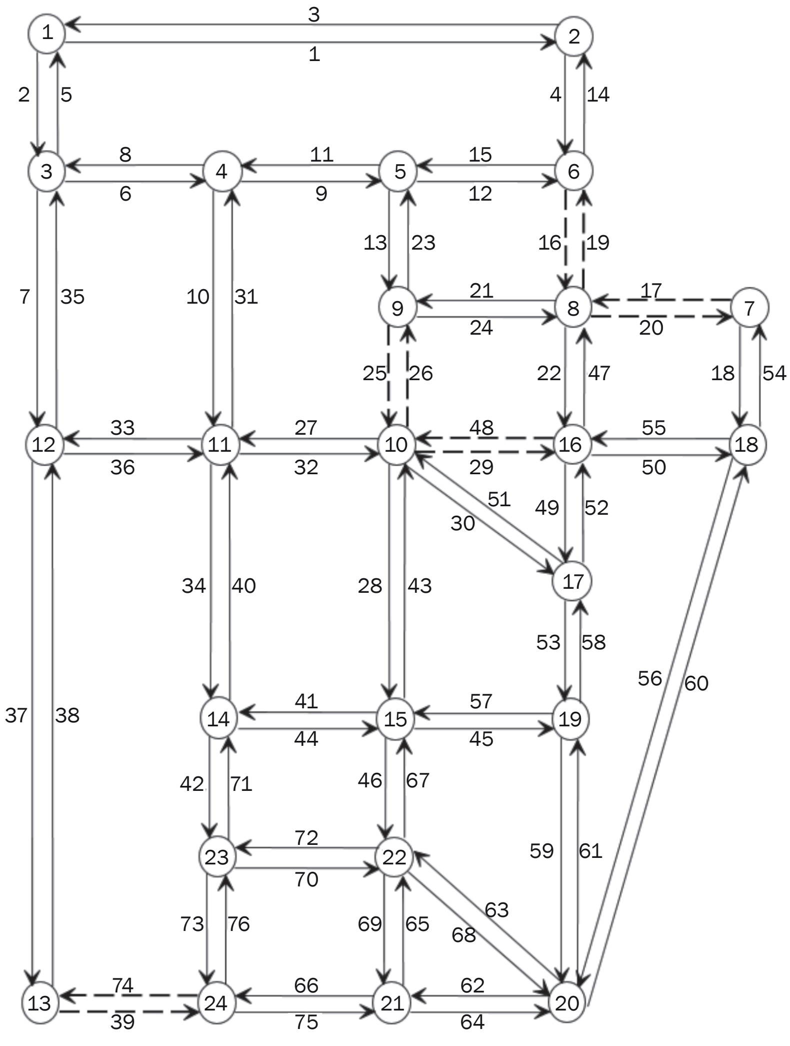

Figure 4 – Sioux Falls network

Table 5 – Comparison of results from solving the Sioux Falls network

	HJ [5]	EDO [5]	SA [37]	AL [8]	IOA [36]	CS [17]
Initial value of y_a	1.0	12.5	6.25	12.5	12.5	-
y_{16}	3.8	4.59	5.38	5.5728	4.6875	5.0916
y_{17}	3.6	1.52	2.26	1.6343	3.9063	1.3515
y_{19}	3.8	5.45	5.50	5.6228	1.2695	6.4903
y_{20}	2.4	2.33	2.01	1.6443	1.6599	2.2995
y_{25}	2.8	1.27	2.64	3.1437	2.3331	2.9074
y_{26}	1.4	2.33	2.47	3.2837	2.3438	2.0515
y_{29}	3.2	0.41	4.54	7.6519	5.5651	3.6725
y_{39}	4.0	4.59	4.45	3.8035	4.6862	5.2202
y_{48}	4.0	2.71	4.21	7.3820	5.4688	3.4230
y_{74}	4.0	2.71	4.67	3.6935	6.2500	4.8798
Z	81.77	83.47	80.87	81.75	87.34	81.51
#	108	12	3900	2700	31	36
	GP [9]	CG [9]	HS [1]	PT [9]	GA [14]	EDEMIS
Initial value of y_a	12.5	12.5	-	12.5	-	-
y_{16}	4.8693	4.7691	4.4482	5.0237	5.17	5.5415
y_{17}	4.8941	4.8605	1.2926	5.2158	2.94	1.9202
y_{19}	1.8694	3.0706	5.4675	1.8298	4.72	5.2428
y_{20}	1.5279	2.6836	2.3064	1.5747	1.76	1.7973
y_{25}	2.7168	2.8397	0.6453	2.7947	2.39	2.8978
y_{26}	2.7102	2.9754	2.7100	2.6639	2.91	2.8391
y_{29}	6.2455	5.6823	4.1596	6.1879	2.92	3.5865
y_{39}	5.0335	4.2726	3.6761	4.9624	5.99	3.9184
y_{48}	3.7597	4.4026	4.9047	4.0674	3.63	3.5828
y_{74}	3.5665	5.5183	4.3878	3.9199	4.43	4.9844
Z	82.71	82.53	81.83	82.53	81.74	81.60
#	9	6	-	7	77	18

Note: Z describes the objective function value, # denotes the number of Frank-Wolfe iterations performed

5. CONCLUSIONS

In this paper, the EDEMIS algorithm has been presented to solve CNDP, which is formulated as a bilevel programming model. In this model, the upper level seeks to find the optimal capacity enhancements of selected links while the lower level is used to solve the DUE traffic assignment problem. To solve this bilevel model, EDEMIS has been developed by adding three improvement mechanisms to the classical DE algorithm. In order to test EDEMIS in solving CNDP, the first numerical experiment has been carried out on a hypothetical test network. This application has demonstrated that EDEMIS has the ability to achieve the global optimum solution, at least on this small network. The second experiment is carried out by using the 16-link network under different demand levels. The results obtained from EDEMIS were compared with those produced by other methods. From the results, it has been found that EDEMIS is able to produce good results for solving CNDP, especially under heavier demand conditions. As a last experiment, EDEMIS was applied to the Sioux Falls network. In comparison with the results obtained by the other major algorithms, except SA and CS, EDEMIS achieved the best solution. Although SA and CS slightly outperform EDEMIS, they need a higher number of Frank-Wolfe iterations, which increases the computational cost of the methods used in the solution. It is clear that EDEMIS gives promising results in terms of the fitness value and required computational efforts and can be used for large-scale road networks in solving CNDP.

Dr. **ÖZGÜR BAŞKAN**[1]
E-posta: obaskan@pau.edu.tr
Dr. **CENK OZAN**[2]
E-posta: cenk.ozan@adu.edu.tr
MAURO DELL'ORCO, Ph.D.[3]
E-mail: mauro.dellorco@poliba.it
MARIO MARINELLI, Ph.D.[3]
E-mail: mario.marinelli@poliba.it

[1] İnşaat Mühendisliği Bölümü, Mühendislik Fakültesi
Pamukkale Üniversitesi, 20070, Denizli, Türkiye
[2] İnşaat Mühendisliği Bölümü, Mühendislik Fakültesi
Aydın Adnan Menderes Üniversitesi, 09010, Aydın, Türkiye
[3] Politecnico di Bari, D.I.C.A.T.E.Ch.
Via Edoardo Orabona 4, 70125, Bari, Italia

SÜREKLİ ULAŞIM AĞ TASARIM PROBLEMİNİN İKİ SEVİYELİ ÇÖZÜM PERFORMANSININ İYİLEŞTİRİLMESİ

ÖZET

Kentiçi yol ağlarındaki sıkışıklığı azaltmak ve ek kapasiteyi ulaşım ağındaki bağlar arasında dengeli bir şekilde dağıtmak için Sürekli Ulaşım Ağ Tasarım (SUAT) problemi üzerinde araştırmacılar uzun yıllardır çalışmaktadırlar. Diğer taraftan SUAT probleminin ele alınması yerel yöneticilerin kısıtlı bütçelerle trafik sıkışıklığını azaltma çabaları noktasında oldukça önem taşımaktadır. SUAT problemi yerel yöneticiler ve kullanıcılar arasındaki karşılıklı etkileşim nedeniyle genellikle iki seviyeli modelleme tekniği kullanılarak çözülebilmektedir. Üst seviyede seçilen bağlara ait en uygun kapasite genişletmelerinin bulunması amaçlanırken alt seviyede ise trafik atama problemi çözülmektedir. Bu çalışmada, SUAT probleminin çözülmesi amacıyla Çoklu İyileştirme Stratejilerine Dayalı İyileştirilmiş Diferansiyel Gelişim algoritması geliştirilmiştir. Önerilen algoritmanın SUAT probleminin çözümünde global optimum çözüme ulaşabildiğini göstermek amacıyla algoritma ilk olarak küçük bir test ağına uygulanmıştır. Sonrasında önerilen algoritmanın özellikle ağır talep şartları altındaki performansını test etmek amacıyla 16 bağdan oluşan bir ulaşım ağı uygulaması yapılmıştır. Son olarak Sioux Falls şehir ağı uygulaması ile literatürdeki algoritmaların sonuçları ile karşılaştırmalar yapılmıştır. Sonuçlar geliştirilen algoritmanın karşılaştırma yapılan diğer algoritmalardan çoğunlukla daha iyi sonuçlar verebildiğini ve büyük ölçekli ulaşım ağlarında karar vericiler tarafından kullanılabileceğini göstermiştir.

ANAHTAR KELİMELER

Sürekli Ulaşım Ağ Tasarımı; Kapasite Genişletme; Karşılıklı Etkileşim; Kullanıcı Dengesi;

REFERENCES

[1] Baskan O. Harmony search algorithm for continuous network design problem with link capacity expansions. *KSCE Journal of Civil Engineering*. 2014;18(1): 273-283. Available from: doi:10.1007/s12205-013-0122-6

[2] Farahani RZ, Miandoabchi E, Szeto WY, Rashidi H. A review of urban transportation network design problems. *European Journal of Operational Research*. 2013;229: 281-302. Available from: doi:10.1016/j.ejor.2013.01.001

[3] Baskan O, Ceylan H. Modified Differential Evolution Algorithm for the Continuous Network Design Problem. *Procedia-Social and Behavioral Sciences*. 2014;111: 48-57. Available from: doi:10.1016/j.sbspro.2014.01.037

[4] Abdulaal M, LeBlanc L. Continuous equilibrium network design models. *Transportation Research Part B*. 1979;13(1): 19-32. Available from: doi:10.1016/0191-2615(79)90004-3

[5] Suwansirikul C, Friesz TL, Tobin RL. Equilibrium decomposed optimisation: A heuristic for the continuous equilibrium network design problem. *Transportation Science*. 1987;21(4): 254-263.

[6] Marcotte P. Network optimization with continuous control parameters. *Transportation Science*. 1983;17(2): 181-197. Available from: doi:10.1287/trsc.17.2.181

[7] Marcotte P, Marquis G. Efficient implementation of heuristics for the continuous network design problem. *Annals of Operational Research*. 1992;34(1): 163-176. Available from: doi:10.1007/BF02098178

[8] Meng Q, Yang H, Bell MGH. An equivalent continuously differentiable model and a locally convergent algorithm for the continuous network design problem. *Transportation Research Part B*. 2001;35(1): 83-105. Available from: doi:10.1016/S0191-2615(00)00016-3

[9] Chiou SW. Bilevel programming for the continuous transport network design problem. *Transportation Research Part B*. 2005;39(4): 361-383. Available from: doi:10.1016/j.trb.2004.05.001

[10] Ban XG, Liu HX, Lu JG, Ferris MC. Decomposition scheme for continuous network design problem with asymmetric user equilibria. *Transportation Research Record*. 2006;1964: 185-192. Available from: doi:10.3141/1964-20

[11] Karoonsoontawong A, Waller ST. Dynamic continuous network design problem-Linear bilevel programming and metaheuristic approaches. *Transportation Research Record*. 2006;1964: 104-117. Available from: doi:10.3141/1964-12

[12] Gao Z, Sun H, Zhang H. A globally convergent algorithm for transportation continuous network design problem. *Optimization and Engineering*. 2007;8(3): 241-257. Available from: doi:10.1007/s11081-007-9015-1

[13] Xu T, Wei H, Hu G. Study on continuous network design problem using simulated annealing and genetic algorithm. *Expert Systems with Applications*. 2009;36(2): 1322-1328. Available from: doi:10.1016/j.eswa.2007.11.023

[14] Mathew TV, Sharma S. Capacity expansion problem for large urban transportation networks. *Journal of Transportation Engineering*. 2009;135(7): 406-415. Available from: doi:10.1061/(ASCE)0733-947X(2009)135:7(406)

[15] Wang DZW, Lo HK. Global optimum of the linearized network design problem with equilibrium flows. *Transportation Research Part B*. 2010;44(4): 482-492. Available from: doi:10.1016/j.trb.2009.10.003

[16] Li C, Yang H, Zhu D, Meng Q. A global optimization method for continuous network design problems. *Transportation Research Part B*. 2012;46(9): 1144-1158. Available from: doi:10.1016/j.trb.2012.05.003

[17] Baskan O. Determining Optimal Link Capacity Expansions in Road Networks Using Cuckoo Search Algorithm with Lévy Flights. *Journal of Applied Mathematics*. 2013;2013: 1-11. Available from: doi:10.1155/2013/718015

[18] Baskan O. An evaluation of heuristic methods for determining optimal link capacity expansions on road networks. *International Journal of Transportation*. 2013;2(1): 77-94. Available from: doi:10.14257/ijt.2014.2.1.05

[19] Wang GM, Gao ZY, Xu M. An MPEC formulation and

its cutting constraint algorithm for continuous network design problem with multi-user classes. *Applied Mathematical Modelling.* 2014;38: 1846-1858. Available from: doi:10.1016/j.apm.2013.10.003

[20] Wang GM, Gao Z, Xu M, Sun H. Models and a relaxation algorithm for continuous network design problem with a tradable credit scheme and equity constraints. *Computers & Operations Research.* 2014;41: 252-261. Available from: doi:10.1016/j.cor.2012.11.010

[21] Wang GM, Gao Z, Xu M, Sun H. Joint link-based credit charging and road capacity improvement in continuous network design problem. *Transportation Research Part A*. 2014;67: 1-14. Available from: doi:10.1016/j.tra.2014.05.012

[22] Davis GA. Exact local solution of the continuous network design problem via stochastic user equilibrium assignment. *Transportation Research Part B*. 1994;28(1): 61-75. Available from: doi:10.1016/0191-2615(94)90031-0

[23] Liu H, Wang DZW. Global optimization method for network design problem with stochastic user equilibrium. *Transportation Research Part B*. 2015;72: 20-39. Available from: doi:10.1016/j.trb.2014.10.009

[24] Du B, Wang DZW. Solving Continuous Network Design Problem with Generalized Geometric Programming Approach. *Transportation Research Record*. 2016;2567: 38-46. Available from: doi:10.3141/2567-05

[25] Chen M, Alfa AS. A Network Design Algorithm Using a Stochastic Incremental Traffic Assignment Approach. *Transportation Science*. 1991;25(3): 215-224. Available from: doi:10.1287/trsc.25.3.215

[26] Zhang H, Gao Z. Two-Way Road Network Design Problem With Variable Lanes. *Journal of Systems Science and Systems Engineering*. 2007;16(1): 50-61. Available from: doi:10.1007/s11518-007-5034-x

[27] Wu JJ, Sun HJ, Gao ZY, Zhang HZ. Reversible lane-based traffic network optimization with an advanced traveller information system. *Engineering Optimization*. 2009;41(1): 87-97. Available from: doi:10.1080/03052150802368799

[28] Long J, Gao Z, Zhang H, Szeto WY. A turning restriction design problem in urban road networks. *European Journal of Operational Research*. 2010;206: 569-578. Available from: doi:10.1016/j.ejor.2010.03.013

[29] Liu H, Wang DZW. Modeling and solving discrete network design problem with stochastic user equilibrium. *Journal of Advanced Transportation*. 2016;50: 1295-1313. Available from: doi:10.1002/atr.1402

[30] Dimitriou L, Tsekeris T, Stathopoulos A. Genetic computation of road network design and pricing Stackelberg games with multi-class users. In: Giacobini, M, et al. (eds.) *Applications of Evolutionary Computing*. Berlin, Heidelberg: Springer: 2008. p. 669-678. Available from: doi:10.1007/978-3-540-78761-7_73

[31] Gallo M, D'Acierno L, Montella B. A meta-heuristic approach for solving the Urban Network Design Problem. *European Journal of Operational Research*. 2010;201: 144-157. Available from: doi:10.1016/j.ejor.2009.02.026

[32] Wardrop JG. Some theoretical aspects of road traffic research. *Proceedings of the Institution of Civil Engineers*. 1952;1(3): 325-362. Available from: doi:10.1680/ipeds.1952.11259

[33] Beckmann M, McGuire CB, Winsten CB. *Studies in the Economics of Transportation*. New Haven: Yale University Press; 1956.

[34] Frank M, Wolfe P. An algorithm for quadratic programming. *Naval Research Logistics Quarterly*. 1956;3(1-2): 95-110. Available from: doi:10.1002/nav.3800030109

[35] Storn R, Price K. Differential evolution: *A simple and efficient adaptive scheme for global optimization over continuous spaces*. ICSI, USA. Tech. Rep: TR-95-012, 1995.

[36] Allsop RE. Some possibilities for using traffic control to influence trip distribution and route choice. In: *Proceedings of the 6th International Symposium on Transportation and Traffic Theory, 26-28 August 1974, Sydney, Australia*. New York, USA: Elsevier Publishing Company; 1974. Vol. 6. p. 345-373.

[37] Friesz TL, Cho HJ, Mehta NJ, Tobin RL, Anandalingam G. A simulated annealing approach to the network design problem with variational inequality constraints. *Transportation Science*. 1992;26(1): 18-26. Available from: doi:10.1287/trsc.26.1.18

[38] Yang H, Yagar S. Traffic assignment and signal control in saturated road networks. *Transportation Research Part A*. 1995;29(2): 125-139. Available from: doi:10.1016/0965-8564(94)E0007-V

[39] Luathep P, Sumalee A, Lam WHK, Li ZC, Lo HK. Global optimization method for mixed transportation network design problem: a mixed-integer linear programming approach. *Transportation Research Part B.* 2011;45(6): 808-827. Available from: doi:10.1016/j.trb.2011.02.002