Location-allocation models and new solution methodologies in telecommunication networks

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Abstract. When designing a telecommunications network topology, three types of interdependent decisions are combined: location, allocation and routing, which are expressed by the following design considerations: how many interconnection devices - consolidation points/concentrators should be used and where should they be located; how to allocate terminal nodes to concentrators; how should the voice, video or data traffic be routed and what transmission links (capacitated or not) should be built into the network. Including these three components of the decision into a single model generates a problem whose complexity makes it difficult to solve. A first method to address the overall problem is the sequential one, whereby the first step deals with the location-allocation problem and based on this solution the subsequent sub-problem (routing the network traffic) shall be solved. The issue of location and allocation in a telecommunications network, called "The capacitated concentrator location-allocation - CCLA problem" is based on one of the general location models on a network in which clients/demand nodes are the terminals and facilities are the concentrators. Like in a location model, each client node has a demand traffic, which must be served, and the facilities can serve these demands within their capacity limit. In this study, the CCLA problem is modeled as a single-source capacitated location-allocation model whose optimization objective is to determine the minimum network cost consisting of fixed costs for establishing the locations of concentrators, costs for operating concentrators and costs for allocating terminals to concentrators. The problem is known as a difficult combinatorial optimization problem for which powerful algorithms are required. Our approach proposes a Fuzzy Genetic Algorithm combined with a local search procedure to calculate the optimal values of the location and allocation variables. To confirm the efficiency of the proposed algorithm with respect to the quality of solutions, significant size test problems were considered: up to 100 terminal nodes and 50 concentrators on a 100 x 100 square grid. The performance of this hybrid intelligent algorithm was evaluated by measuring the quality of its solutions with respect to the following statistics: the standard deviation and the ratio of the best solution obtained.

1. Introduction

As telecommunication networks increase in size and complexity due to the constant progress of computational resources, the minimization of the total communication system cost continues to be an important research issue when designing the network topology. This is a decisional problem that combines three types of interdependent decisions: concentrators location, user/terminal nodes allocation and user layout, which are expressed by the following design considerations: how many interconnection devices - consolidation points/concentrators should be used and where should they be
located; how to allocate terminal nodes to concentrators; how should the voice, video or data traffic be routed and what transmission links (capacitated or not) should be built into the network.

This comprehensive question is addressed in a sequential manner:
- the first step deals with the integrated problem of concentrators’ location and user/terminal nodes allocation, called "The capacitated concentrator location-allocation – CCLA problem", that is formulated as an implementation of discrete location theory, where clients/demand nodes are the terminals and facilities are the concentrators;
- based on this solution the subsequent sub-problem (routing the network traffic) shall be solved.

In this study, the CCLA problem is modeled as a single-source capacitated location-allocation model whose optimization objective is to determine the minimum network cost consisting of fixed costs for establishing the locations of concentrators, costs for operating concentrators i.e. costs of using their capacity and costs for allocating terminals to concentrators.

The problem is known as a difficult combinatorial optimization problem that belongs to the class of NP-hard problems for which powerful algorithms are required [1]. The literature describes some variants and extensions of the basic CCLA problem:

Chardaire, Lutton and Sutter [2] describe a data network constructed as a two-level concentrator network, where several terminals are connected to a concentrator on the first level, which in turn is connected to a concentrator situated on a second level. This architecture represents an extension of the Simple Plant Location Problem – SPLP (which is a one-level location problem) towards a hierarchical formulation of the problem. Thus, the problem is expressed as a two-level SPLP from the discrete location theory. The corresponding integer programming formulation is solved by combining a Lagrangian relaxation with an algorithm based on simulated annealing.

Kapov [3] implemented another way of measuring the estimation of the optimality of the location criterion, namely covering the largest possible amount of clients at a minimal cost, criterion which was stated in the Maximal Covering Location-Allocation Problem - MCLAP from the location theory. The Capacitated Concentrator Covering problem uses a radial configuration of the network, where terminal nodes surround concentrator node locations. The objective is to decide the number and the location of concentrators and to allocate the remote sites to concentrators in order to maximize the total demand covered by concentrators at minimal cost, without violating their capacity limit. An extension of the coverage objective function deals with multiple coverage: Shetty, Sarathy and Sen [4] address the K-coverage concentrator location problem, where each terminal node is covered by k (k≥2) concentrators to prevent situations where the communication between the terminal and concentrator is interrupted: the link between them fails or even the concentrator fails.

Marin, Canovas and Landete [5] suggest an uncapacitated multiple allocation version of the problem which does not require the limitation of one hub per route; authors consider a general transportation cost structure with discount factor between hubs, costs being proportional with travel distances or not.

Gouveia and Saldalha-da-Gama [6] consider a discretized model of the capacitated concentrator location-allocation problem with modular interfaces; the problem considers several interfaces of different sizes that can be located in any possible location and must determine the number of interfaces of each type to be located in each potential concentrator location.

The surveys in [7, 8, 9] offer a more comprehensive study of location-allocation problems which have applications in computer network planning & design and telecommunications, considering papers since the beginning of the 80s.

This study proposes a Fuzzy Genetic Algorithm combined with a local search procedure to calculate the optimal values of the location and allocation variables for the CCLA problem. To demonstrate the relevance of the suggested approach, a computational analysis is performed on several randomly generated test problems of different size.
2. Mathematical formulation of the CCLA problem

The CCLA problem is similar to the capacitated fixed charge location-allocation - CFCLA problem in discrete location theory. This decisional problem is a classic Operations Research (OR) cost minimization problem that aims to optimally allocate \( n \) user nodes/clients to some facilities whose locations are selected from a set of \( m \) possible sites such that all clients’ demands are satisfied by the selected facilities, without violating the capacity level on the demand they can serve. It should be noted that we do not know, a priori, how many facilities should be opened, which makes the problem even more difficult to solve.

To formulate this problem we introduce the following notation [10, 11]:

- \( I = \{T_1, T_2, \ldots, T_n\} \) is the set of terminal nodes with known locations
- \( J = \{1, \ldots, j, \ldots, m\} \) is the set of potential concentrator sites
- \( f_j \) is a fixed cost of installing a concentrator at site \( j \), \( j \in J \)
- \( c_{ij} \) is the communication cost i.e. the cost of connecting terminal node \( T_i \) with a concentrator located at site \( j \), \( i \in I, j \in J \)
- \( d_j \) is the cost of using one unit of processing capacity for a concentrator located at site \( j \), \( j \in J \)

A concentrator located at site \( j \) is limited by two constraints: actual processing limit (\( P_j \)) and the number of terminals capable of being connected (\( K_j \)):

- \( P_j \) is the maximum capacity (actual processing limit) of a concentrator that can be located at site \( j \), \( j \in J \)
- \( R_j \) is the number of connection ports for a concentrator that can be located at site \( j \), \( j \in J \)
- \( a_{ij} \) is the fraction of concentrator capacity that would be needed to handle demand traffic from terminal node \( T_i \) if this node is assigned to a concentrator located at site \( j \), \( i \in I, j \in J \)

Decision variables:

- \( Y_{ij} \) and \( X_j \) are the 0-1 allocation and respectively location decision variables with the following interpretation:

\[
Y_{ij} = \begin{cases} 
1, & \text{if user node } T_i \text{ is assigned to a concentrator located at site } j, i \in I; j \in J \\
0, & \text{otherwise}
\end{cases}
\]

\[
X_j = \begin{cases} 
1, & \text{if a concentrator is located at site } j, j \in J \\
0, & \text{otherwise}
\end{cases}
\]

Objective function:

\[
\text{Min } \left[ \sum_{i \in I} \sum_{j \in J} c_{ij} \cdot Y_{ij} + \sum_{i \in I} \sum_{j \in J} d_j \cdot a_{ij} \cdot Y_{ij} + \sum_{j \in J} f_j \cdot X_j \right] 
\]

Constraints:

\[
\sum_{j \in J} Y_{ij} = 1, \forall i \in I
\]

\[
\sum_{i \in I} Y_{ij} \leq R_j, \forall j \in J
\]

\[
\sum_{i \in I} a_{ij} \cdot Y_{ij} \leq P_j, \forall j \in J
\]

\[
Y_{ij} - X_j \leq 0, \forall i \in I, j \in J
\]

\[
X_j \in \{0,1\}, \forall j \in J
\]

\[
Y_{ij} \in \{0,1\}, \forall i \in I, j \in J
\]

The objective is to minimize total communication cost, which consist of the following components:
\[
\sum_{i \in I} \sum_{j \in J} c_{ij} \cdot Y_{ij}
\]
represent the cost of assigning terminal nodes to concentrators;
\[
\sum_{i \in I} \sum_{j \in J} d_{ij} \cdot a_{ij} \cdot Y_{ij}
\]
represent the cost for operating concentrators i.e. the cost of using concentrators at their operational capacity;
\[
\sum_{j \in J} f_j \cdot X_j
\]
represent the fixed installation cost for locating concentrators in the chosen sites.

The first constraint guarantees demand satisfaction, requiring that each terminal node is allocated to exactly one concentrator.

The second constraint limits the number of terminals that can be allocated to a concentrator according to the specified limit.

The third constraint requires that the concentrator processing capacity is not exceeded.

The fourth constraint associates location with the allocation decision: a terminal node may be allocated only to a site that was chosen as the location for a concentrator.

The last two constraints impose binary values for decision variables.

Remark: as noted in [12], an equivalent formulation can be obtained by replacing the third and the fourth constraints by the following constraint:
\[
\sum_{i \in I} a_{ij} \cdot Y_{ij} \leq P_j \cdot X_j, \quad \forall j \in J
\]  
(8)

3. Proposed Genetic Algorithm with fuzzy crossover controller
In this paper, we designed a hybridization of a genetic algorithm with a local search technique to ensure a proper equilibrium between intensification and diversification through the search procedure.

The algorithm also includes a fuzzy mechanism that adaptively controls the crossover rates. This enhancement is based on our previous experience in working with fuzzy logic technique to fine-tune the parameters of genetic and particle swarm algorithms [13, 14].

The specific implementation features of the genetic algorithm are described below.

3.1 Encoding scheme and initialization
Whereas the problem involves two concurrent decisions i.e. location of concentrators and allocation of terminal nodes to these concentrators, each chromosome is a structure that encodes decision variables in two data fields.

Because the traffic from a terminal node can be handled by exactly one concentrator, we assume an integer-based chromosome representation; U is a n-dimensional vector of integers in the set \{1,\ldots,m\}:

vector U: U[i], i \in I – indicates the concentrator site where terminal node i is allocated

One should remark that by this representation the first constraint of the mathematical model is automatically satisfied.

Concentrators’ location is binary represented by a vector of length m; V is a m-dimensional vector of binary digits:

vector V: V[j], j \in J – where V[j]=1 denotes that a concentrator is located at site j.

In order to generate the initial population, the components of vector U are generated as random integers from \[1, m\] and the components of vector V are generated as random binary digits.
\[
\text{for } k=1, \ldots, \text{PS} \quad \text{// Population Size}
\]
\[
\text{for } i=1, \ldots, n
\]
\[
\text{chromosome}[k].u[i] \leftarrow \text{rand}(\{1,2, \ldots, m\})
\]
\[
\text{repeat}
\]
\[
\text{for } j=1, \ldots, m
\]
\[
\text{chromosome}[k].v[j] \leftarrow \text{rand}(\{0,1\})
\]
\[
\text{repeat}
\]
\[
\text{repeat}
\]

Infeasible individuals (for which the capacity constraints are violated) generated by crossover and mutation operators were handled by an additive penalty-based approach:

\[
\text{chromosome}[k].\text{total}_{-}\text{value} \leftarrow \text{objective}_{-}\text{value} + \text{penalty}
\]

where “objective_value” is the total cost, calculated according to equation (1) and ”penalty” is calculated based on equations (3) and (8), by the following procedure:

\[
\text{for } k=1, \ldots, \text{PS} \quad \text{// Population Size}
\]
\[
\text{penalty} \leftarrow 0;
\]
\[
\text{for } j=1, \ldots, m
\]
\[
\text{load}[j] \leftarrow 0; \quad // \text{load}[j] \text{ calculates the load of the concentrator located at site } j
\]
\[
\text{nr} \leftarrow 0; \quad // \text{nr calculates the number of terminals allocated to a concentrator located at site } j
\]
\[
\text{for } i=1, \ldots, n
\]
\[
\text{if chromosome } [k].u[i] = j \text{ then}
\]
\[
\text{load}[j] \leftarrow \text{load}[j] + a[i][j];
\]
\[
\text{nr} \leftarrow \text{nr} + 1;
\]
\[
\text{endif}
\]
\[
\text{repeat}
\]
\[
\text{if load}[j] > P[j] \text{ then penalty } \leftarrow \text{penalty } + (\text{load}[j] - P[j])
\]
\[
\text{endif}
\]
\[
\text{if nr} > R[j] \text{ then penalty } \leftarrow \text{penalty } + (\text{nr} - R[j])
\]
\[
\text{endif}
\]
\[
\text{repeat}
\]
\[
\text{chromosome}[k].\text{total}_{-}\text{value} \leftarrow \text{objective}_{-}\text{value} + \text{penalty}
\]
\[
\text{chromosome}[k].\text{fitness} \leftarrow 1/\text{chromosome}[k].\text{total}_{-}\text{value}
\]
\[
\text{repeat}
\]

Genetic operators: the algorithm uses a roulette wheel selection scheme. A two-point crossover and a „bit-flip” mutation were used for both encoding vectors U and V.

Local search: is performed around the best individual in the current population and it is implemented by a minimal mutation for a randomly chosen gene; this will actually generate a minimal change in the chromosome.

3.2 Characteristic parameters of the Fuzzy Logic Controller
The probability of the crossover operator is automatically adjusted by a Fuzzy Logic Controller (FLC) that uses as inputs two performance measures, according to the current state of the search in the current population: the genotypic and the phenotypic diversity.

As described in [13], the genotypic diversity is expressed by evaluating the distances between the best chromosome of the current population, (C\text{best}) and the rest of the chromosomes (C_{k}):
The distance between two chromosomes is determined by the number of differing genes in their structure.

For the phenotypic diversity, we propose a measure defined in [15]:

\[
GD = \frac{\bar{d} - d_{\text{min}}}{d_{\text{max}} - d_{\text{min}}} \tag{9}
\]

\[
d = \frac{1}{PS} \sum_{i=1}^{PS} d(C_{\text{best}}, C_k), \text{PS is population size} \tag{10}
\]

\[
d_{\text{max}} = \max\{d(C_{\text{best}}, C_k) \mid C_k \in \text{current population}\} \tag{11}
\]

\[
d_{\text{min}} = \min\{d(C_{\text{best}}, C_k) \mid C_k \in \text{current population}\} \tag{12}
\]

The values for GD and FD are in the range [0,1].

When the GD value tends to 1, the chromosomes \( C_k \) are spread away from \( C_{\text{best}} \); when the GD value tends to 0, the chromosomes \( C_k \) are located around \( C_{\text{best}} \). When the FD value tends to 1, convergence was achieved and when FD is close to 0 population is very diversified.

The fuzzy input variables (GD and FD) have the following linguistic values: VL - very low, L - low, M - medium, H - high, VH - very high and the output variable (crossover probability) has three linguistic labels (D - decrease, UM - unmodified, I - increase). The triangular type membership functions for the inputs and for the output are represented in figure 1:

![Membership functions](image)

(GD and FD) (crossover probability)

**Figure 1.** The membership functions for the inputs and for the output.

We used the Mamdani fuzzy inference and the weighted average defuzzification method. The rules of the Mamdani FLC are described in table 1:

| DG | VL | L  | M  | H  | VH |
|----|----|----|----|----|----|
| VL | D  | D  | UM | UM | UM |
| L  | D  | D  | UM | UM | UM |
| M  | UM | UM | UM | I  | I  |
| H  | UM | UM | I  | I  | I  |
| VH | UM | UM | I  | I  | I  |
The algorithm was implemented with a population size of 50 to 200 individuals (for large size instances). Mutation probability was set at 0.05 and for the crossover probability the initial value was set at 0.70.

4. Simulation study and computational results
The algorithm described above was used first on a network with \( n=m=15 \) i.e. 15 locations for terminal nodes which are also candidate sites for concentrators.

Network characteristics are synthesized in table 2:

| \( f_j \) | 18 | 15 | 20 | 24 | 22 | 25 | 14 | 35 | 17 | 18 | 30 | 16 | 20 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| \( d_t^j + a_t + c_t \) | site 1 | site 2 | site 3 | site 4 | site 5 | site 6 | site 7 | site 8 | site 9 | site 10 | site 11 | site 12 | site 13 | site 14 | site 15 |
| \( T_1 \) | 3 | 18 | 30 | 32 | 28 | 38 | 34 | 44 | 56 | 58 | 76 | 30 | 52 | 64 | 1 |
| \( T_2 \) | 36 | 1 | 24 | 28 | 20 | 40 | 56 | 32 | 52 | 76 | 80 | 116 | 24 | 68 | 92 |
| \( T_3 \) | 15 | 6 | 2 | 4 | 11 | 4 | 16 | 14 | 7 | 18 | 14 | 23 | 12 | 11 | 22 |
| \( T_4 \) | 48 | 21 | 12 | 1 | 36 | 24 | 60 | 45 | 33 | 66 | 54 | 81 | 39 | 45 | 78 |
| \( T_5 \) | 28 | 10 | 22 | 24 | 1 | 14 | 18 | 6 | 20 | 28 | 34 | 52 | 22 | 28 | 36 |
| \( T_6 \) | 38 | 20 | 8 | 16 | 14 | 1 | 24 | 20 | 6 | 28 | 20 | 38 | 32 | 34 | 36 |
| \( T_7 \) | 23 | 14 | 16 | 20 | 9 | 12 | 2 | 6 | 9 | 5 | 9 | 18 | 20 | 13 | 9 |
| \( T_8 \) | 34 | 16 | 28 | 30 | 6 | 20 | 12 | 1 | 26 | 22 | 30 | 48 | 28 | 34 | 30 |
| \( T_9 \) | 88 | 52 | 28 | 44 | 40 | 12 | 36 | 52 | 1 | 44 | 28 | 64 | 76 | 16 | 60 |
| \( T_{10} \) | 84 | 57 | 54 | 66 | 42 | 42 | 15 | 33 | 33 | 1 | 12 | 39 | 75 | 45 | 12 |
| \( T_{11} \) | 116 | 80 | 56 | 72 | 68 | 40 | 36 | 60 | 28 | 16 | 2 | 36 | 104 | 44 | 92 |
| \( T_{12} \) | 76 | 58 | 46 | 54 | 52 | 38 | 36 | 48 | 32 | 26 | 18 | 4 | 70 | 40 | 34 |
| \( T_{13} \) | 15 | 6 | 12 | 13 | 11 | 16 | 20 | 14 | 19 | 25 | 26 | 35 | 3 | 23 | 29 |
| \( T_{14} \) | 26 | 17 | 11 | 15 | 14 | 17 | 13 | 17 | 4 | 15 | 11 | 20 | 23 | 3 | 19 |
| \( T_{15} \) | 32 | 23 | 22 | 26 | 18 | 18 | 9 | 15 | 15 | 4 | 8 | 17 | 29 | 19 | 2 |

\( R_t \) was set at 7 and \( P_c \) was set at 40 megabits per second (Mbps).

The solution offered by the algorithm is to locate 3 concentrators at sites 2,9,10 with a total cost of 191, according to the following allocation scheme:

- terminal nodes \( T_1, T_2, T_3, T_4, T_5, T_8, T_{13} \) are allocated to the concentrator located at site 2;
- terminal nodes \( T_6, T_9, T_{14} \) are allocated to the concentrator located at site 9;
- terminal nodes \( T_7, T_{10}, T_{11}, T_{12}, T_{15} \) are allocated to the concentrator located at site 10;

Further, the algorithm was applied to 50 networks with different structures and sizes, which have been randomly generated.

The dimension of the problems underwent a progressive growth starting from \( n=20, m=20 \) till \( n=100, m=50 \). The locations of the terminal nodes and those of the potential sites for the location of the concentrators have been chosen randomly, in a 100x100 square grid. The network's characteristics have been generated according to a distribution scheme described in [10] and [11]:

\[
c_j = d_j \cdot rand([5,10])
\]

\[
d_j = rand([5,10])
\]

\[
a_j = 40 \cdot rand([0,1])
\]

\[
f_j = w \cdot (40 + \frac{rand([0,1])}{4})
\]
where \( d_{ij} \) is the Euclidean distance between the terminal node \( T_i \), \( i \in I \) and a concentrator located at site \( j, j \in J \).

The processing limit of a concentrator was set at 400, which lead to an average of 20 terminal nodes, allocated to a concentrator.

For the problems with the same dimension, the fix costs for the installation have been modified within the network’s structure, which have progressively grown, from twice to 10 times as large (through the corresponding modification of the \( w \) parameter). The obtained results have shown that the bigger the installation costs, the smaller the number of sites selected for the location, thus less concentrators have been installed within the network.

Another conclusion is the fact that if the ratio between the installation costs and the communication costs increases, the number of iterations necessary for obtaining the optimal solution grows accordingly, at the same time with the growth of the execution time, as displayed in table 3.

Standard deviation and the percentage of the best solutions out of 100 runs are also displayed in table 3. Figure 2 displays the average computing time (s) for the first and last instance of all the classes of problems took in consideration, starting with the first configuration (\( m=20, n=20, w=2 \)) till (\( m=50, n=100, w=10 \)).

![Figure 2. The average computing time (s).](image)

| Table 3. Computational results. |
|---|---|---|---|---|---|---|
| m  | n  | w  | PS | Iterations | St.Dev(100 runs) | % best sol. |
| 20  | 20 | 2  | 50 | 500        | 0.00              | 100         |
| 20  | 20 | 10 | 50 | 500        | 0.00              | 100         |
| 20  | 30 | 2  | 100| 1000       | 0.04              | 98          |
| 20  | 30 | 10 | 100| 1000       | 0.05              | 96          |
| 30  | 50 | 2  | 100| 1500       | 0.09              | 92          |
| 30  | 50 | 10 | 100| 1500       | 0.38              | 90          |
| 50  | 70 | 2  | 150| 1500       | 0.47              | 87          |
| 50  | 70 | 10 | 150| 1500       | 1.76              | 85          |
| 50  | 100| 2  | 200| 2000       | 2.35              | 80          |
| 50  | 100| 10 | 200| 2000       | 3.12              | 76          |

5. Conclusions
This paper addresses an enhanced Genetic Algorithm method for solving the capacitated concentrator location-allocation problem. Results obtained from experiments indicate good performances of the algorithm regarding quality of solutions and computing time.
The mathematic model of this problem can be considered as a prototype for a whole range of location-allocation problems from the field of telecommunication network-design, for example transportation hub location problem, but also from the field of transportation, for example vehicle routing problems or inventory-routing problems. The designed algorithm can be applied (with only minimal changes) for the locational models from the logistics domain, starting with the classic location-allocation problems, to more complex extensions and versions: multi-product flow models, hierarchical models, dynamic or stochastic models, multi-objective approaches, etc.

References
[1] Yu G and Dugan S 1998 *Industrial Applications of Combinatorial Optimization* (Springer Science+Business Media)
[2] Chardaire P, Lutton J L and Sutter A 1999 Upper and lower bounds for the two-level simple plant location problem *Annals of Operations Research* 86 117-140
[3] Kapov D S 1993 On a cost allocation problem arising from a capacitated concentrator covering problem *Operations Research Letters* 13 315-323
[4] Shetty B Sarathy R and Sen A 1992 The K-coverage concentrator location problem *Applied Mathematical Modelling* 16 pp 94-100
[5] Marin A Canovas L and Landete M 2006 New formulations for the uncapacitated multiple allocation hub location problem *European Journal of Operational Research* 172 274–292
[6] Gouveia L and Saldanha-da-Gama F 2006 On the capacitated concentrator location problem: a reformulation by discretization *Computers & Operations Research* 33 pp 1242–1258
[7] Labbe M 2005 *Concentrator Location in Telecommunications Networks* (Boston: Springer Science + Business Media)
[8] Laporte G, Nickel S and DaGama F S 2015 *Location Science* (Switzerland: Springer)
[9] Gourdin E, Labbe M and Yaman H 2002 Telecommunication and Location In Facility Location: Applications and Theory, ed Z Drezner and H W Hamacher (Springer)
[10] Raja V T and Han B T 2003 An Efficient Heuristic for Solving an Extended Concentrator Location Problem *Telecommunication Systems* 23 171-199
[11] Pirkul H 1987 Efficient algorithms for the capacitated concentrator location problem *Computers and Operations Research* 14 197-208
[12] Yaman H 2005 *Concentrator Location in Telecommunications Networks* (Springer Science + Business Media)
[13] Dinu S 2015 Multi-objective Assembly Line Balancing Using Fuzzy Inertia-adaptive Particle Swarm Algorithm *Studies in Informatics and Control* 24 283-292
[14] Dinu S and Pomazan C 2013 *A New Hybrid Fuzzy Genetic Algorithm Optimization Method For Dynamic Economic Dispatch with Valve-Point Loading Effects*, Proc. 6th Int. Conf. MEQAPS ’13 (Brasov) (WSEAS Press) pp 217-223
[15] Lee M A and Takagi H 1993 *Dynamic Control of Genetic Algorithms Using Fuzzy Logic Techniques: Proc. Fifth Conf. on Genetic Algorithms* (San Mateo: Morgan Kaufmann) pp 76-83