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Raising Power Quality and Improving Reliability by Distribution Network Reconfiguration in the Presence of Renewable Energy Sources

.Mohamad Taghi Babajani BaghmisheZad[1], Hosein NasirAghdam[2]
[1,2]Department of Electrical Engineering, Ahar Branch, Islamic Azad University, Ahar, Iran
[1]Babajani.mohamad@yahoo.com

Abstract

In this paper, reconfiguration problem of distribution network has been investigated to improve reliability and reduce power loss by placement of renewable energy sources; i.e. solar cell and wind turbine. For this, four reliability indices are considered in objective function; which are as follows: System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), Cost of Energy Not Supplied (CENS), and Momentary Average Interruption Frequency Index (MAIFI). B*y using a novel technique, the target function was normalized. Simulation has been performed on IEEE 69-bus test system. A genetic algorithm could solve this nonlinear problem.*

Keywords: Reconfiguration, Solar cell, Wind turbine, Genetic algorithm, power loss reduction, reliability improvement

1-Introduction

In the radially distribution system, the configuration may be varied to obtain a new network structure to reduce power loss, increase system security and enhance power quality. In these systems, there are many switches that are divided into two types: sectionalizing-switch (normal closed) and tie-switch (normal open). The change (reconfiguration) in distribution system is performed by opening sectionalizing and closing tie switches so that the radial feature of the network is maintained and all of the loads are energized. The discrete nature of the switch values and radial feature constraint prevent the use of classical optimization techniques to solve the distribution feeder reconfiguration (DFR) problem. Therefore, most of the algorithms in the literature are based on heuristic search techniques [1].Ref. [2] has presented a full algorithm to target functions paid and solved an efficient algorithm for multi-objective distribution feeder reconfiguration based on Modified Honey Bee Mating Optimization (MHBMO) approach. In [3], a methodology has been proposed for the reconfiguration of radial electrical distribution systems based on the bio-inspired meta-heuristic Artificial Immune System to minimize energy losses approach that can handle this combinatorial mixed integer problem of nonlinear programming. A step-by-step heuristic algorithm has been suggested in [4] for the reconfiguration of radial electrical distribution systems, aiming at power loss minimization. The proposed methodology is based on a dynamic switches set approach, which is updated due to topological changes in the electrical network to avoid the premature convergence of the algorithm in suboptimal solutions. The proposed methodology of Ref. [5] is called the Interval Multi-objective Evolutionary Algorithm for Distribution Feeder Reconfiguration (IMOEA-DFR) which uses interval analysis to perform configuration assessment by considering the uncertainties in the power demanded by the customers.

Su *et al.* in [6] have introduced an ant Colony Search Algorithm (ACSA) to solve the optimal network reconfiguration problem for power loss reduction. The ACSA was applied using the state transition rule, local pheromone updating rule, and global pheromone-updating rule to facilitate the computation. In [7], a new multi objective called improved shuffled frog leaping algorithm (ISFLA), is proposed to investigate the distribution feeder reconfiguration (DFR) problem from the reliability enhancement point of view. Nevertheless, since the total cost of MW loss is an important and attractive subject to the electric power utilities, the total active power losses were also considered as an objective function in the investigations. Ref. [8] presents Variable Scaling Hybrid Differential Evolution (VSHDE) for solving the network reconfiguration for power loss reduction and voltage profit enhancement of distribution systems. One three-feeder distribution system from the literature and one practical distribution network of Taiwan Power Company (TPC) were used to compare the performance of the proposed method with HDE, genetic algorithms (GAs), and simulated annealing (SA). In [9], a novel method has been proposed to improve the adaptability and efficiency of genetic algorithms (GAs) when applied to the minimal loss reconfiguration problem. This research reduces the searching space (population) when a new codification strategy and novel genetic operator, called accentuated crossover and directed mutation, is used. In [10], a reconfiguration methodology based on a novel improved adaptive imperialist competitive algorithm (IAICA), is proposed for the sake of minimizing real power losses and enhancing the voltage profile. Unlike ICA, an inherently continuous algorithm reconfiguration is a discrete nonlinear optimization problem. Therefore, the mapping strategy is used to adapt ICA to the reconfiguration problem.

In [11], a probabilistic approach is proposed to perform an optimal reconfiguration in order to reduce the total cost of operation, including the cost of switching and benefit of loss reduction. Considering time-varying loads, the proposed method can obtain an optimal balance. Ref. [12] proposes an evolutionary approach for optimal time interval determination. In the mentioned paper, basic reconfiguration models are discussed to form an optimal time interval model gradually. Authors of Ref. [13] have formulated reconfiguration as a single objective one, where, as main criterion, active power losses have been chosen. There is no unique acceptance regarding the most proper approach (based on heuristics, meta-heuristics, genetic algorithms, etc.) to use in order to solve this problem. The main purpose of Ref. [14] is to assess the Reconfiguration strategy as a costless technique to enhance the reliability of the distribution systems. The target functions to be investigated are: SAIFI, AENS, total active power losses and the total network cost. In this context, reconfiguration of distribution system and renewable sources placement have been performed in simultaneous mode. The paper has been organized in five sections. Problem formulation and the concept of genetic algorithm have been presented in Sections 2 and 3, respectively. Simulation results are visible is Section 4. This work has been concluded in Section 5.

2-Objective function

The proposed target function consists of three reliability indices considered in target function. Indices of System Average Interruption Duration Index (SAIFI) and System Average Interruption Frequency Index (SAIFI) are improvement indices from the viewpoint of costumers and Cost of Energy Not Supplied (CENS) is due to viewpoint of Distribution Company. Thus OF is formulated as:

$$OF=\sum_{k=1}^{ny}\left\{\frac{SAIFI_k}{SAIFI_0}+\frac{SAIDI_k}{SAIDI_0}+\frac{CENS_k}{CENS_0}+\frac{MAIFI_k}{MAIFI_0}+\frac{Loss_k}{Loss_0}\right. \quad (1)$$

Where, *ny* is system lifetime. $SAIFI_0$, $SAIDI_0$, $MAIFI_0$ and $CENS_0$ are indices' values before DG and reclose placement. By using this technique, values of four indices are normalized. To calculate reliability indices, SAIDI, SAIFI and CENS, analytical methods based on error modes and their effects (FMEA) are used [15]. Accordingly, the mentioned parameters are calculated using Eqs. (2-7).

$$SAIDI_i=\left(\lambda_{sys}\frac{l_i}{l_t}\right)\left[\left(r_{loc}\frac{l_{loc,i}}{l_t}\right)\left(\frac{N_{loc,i}}{N_t}\right)+r_{rep}\frac{N_{rep,i}}{N_t}\right] \quad (2)$$

$$CENS_i=\left(\lambda_{sys}\frac{l_i}{l_t}\right)\left[\left(r_{loc}\frac{l_{loc,i}}{l_t}\right)\left(P_{loc,i}\right)+r_{rep}P_{rep,i}\right] \quad (3)$$

$$SAIFI_i=\left(\lambda_{sys}\frac{l_i}{l_t}\right)\left[\left(\frac{l_{loc,i}}{l_t}\right)\left(\frac{N_{loc,i}}{N_t}\right)+\frac{N_{rep,i}}{N_t}\right] \quad (4)$$

$$SAIDI_{sys}=\sum_{i=1}^{k}SAIDI_i \quad (5)$$

$$CENS_{sys}=\sum_{I=1}^{K}CENS_i \quad (6)$$

$$SAIFI_{sys}=\sum_{i=1}^{k}SAIFI_i \quad (7)$$

Where,

$Cens_i$: Energy Not Supplied due to an error in the *i*th region
$Saidi_i$: System Average Interruption Duration Index due to an error in the *i*th region
λsys: Annual failure rate of system
λins: Instant failure rate of system
l_i: Length of the *i*th region
l_t: Total length of feeder

r_{loc}: Average time for locating the fault
$l_{loc,\ i}$: The length of region which is de-energized for locating the fault due to an error in the *i*th region
$N_{loc,i}$: Total number of customers who are de-energized for locating the fault due to an error in the *i*th region
N_t: Total number of system customers
r_{rep}: Average time to repair a fault
$N_{rep,\ i}$: The number of customers who are de-energized for repairing the fault due to an error in the *i*th region.
C_{ns}: The average cost of a 1 *kWh* outage
$P_{loc,\ i}$: The average outage active power for repairing the fault due to an error in the *i*th region
$P_{rep,\ i}$: The average outage reactive power for repairing the fault due to an error in the *i*th region.

3-Genetic Algorithm

Genetic algorithms perform a heuristic global optimization search using a form of guided random search. The search is performed using a population of individuals. Each individual represents a point in the search space. For the traffic signal timing problem, each individual represents a particular network signal timing plan. The set of decision variables is encoded into a form of genetic material. Associated with each individual is the computed objective function value. For delay minimization in traffic networks, the associated target function value will be the delay produced by the particular signal timings. Optimization is performed by manipulating the population of individuals [17]. Figure 1 shows optimization by a genetic algorithm. Optimization is performed by manipulating the population of individuals using the following steps:

Initialization: The individuals in the initial population are assigned to points in the search domain. Typically, each individual is assigned to a random point in the search domain (i.e. each point in the search domain has the same probability of being chosen).

Selection: Individuals in the population are selected for reproduction. The selection probability for each individual is usually a function of the target function value. For maximization problems, individuals with a larger objective function value have a larger selection probability. For minimization problems, individuals with a smaller target function value are favored for selection.

Recombination/Crossover: Once individuals have been selected for reproduction, these “parents” are paired and one or more “children" are created using a crossover operator. Crossover creates children by combining or blending the genetic material of the two parents, (i.e. the decision variable sets of the two parents are combined to form a new set for each child).

Mutation: The mutation operator performs random alterations to the genetic material of an individual. Mutation will alter one or more of the individual’s decision variables with small probability. Mutation is typically applied to the children created by recombination.

4-Case Study

Concepts of reconfiguration, target function and genetic algorithm have been introduced in prior sections. Simulation results have been illustrated in this section to confirm capability of the proposed technique. To do this, IEEE 69-bus distribution system has been used as a test system. Figure 2 shows single line diagram of the system. In figures and tables, 35 cases have been introduced, based on the number of sources. First and second numbers show the number of wind turbine and solar cell, respectively.

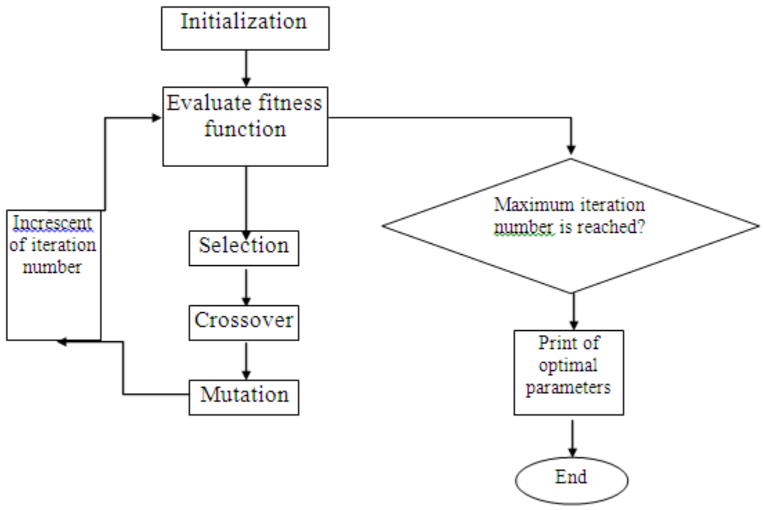

Fig.1. Flowchart of optimization by genetic algorithm

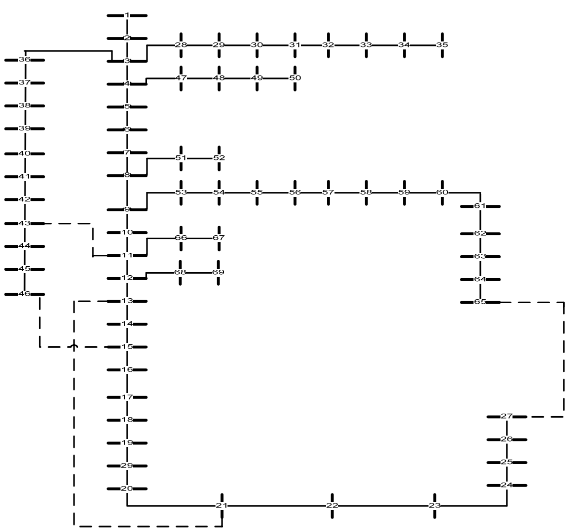

Fig. 2. Single line diagram of IEEE 69-bus test system

4-1- SAIFI Parameter

Figure 3 shows optimal values of SAIFI cases. Based on Figures 3, the minimum value for SAIFI obtains in C.01 (placement of one solar cell) with value 41.5459 which is considereable less than C.01 (placement of one wind turbine and two solar cells). From the best solution view, four cases (i.e. 15, 32, 35 and 44) are less than 38 and have the minor differences. Among these cases, C.35 (placement of three wind turbine and five solar cells) present the best solution.

4-2- CENS Parameter

CENS parameter is the second parameter which has been studied and its results have been illustrated in Figure 4

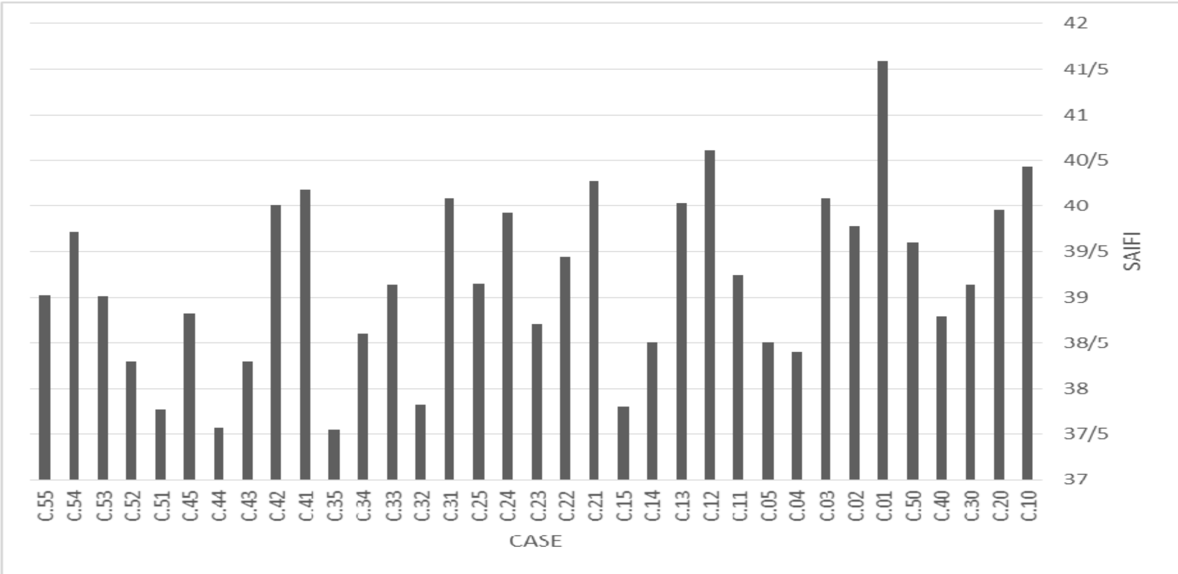

Fig.3. Values of SAIFI pararmeter

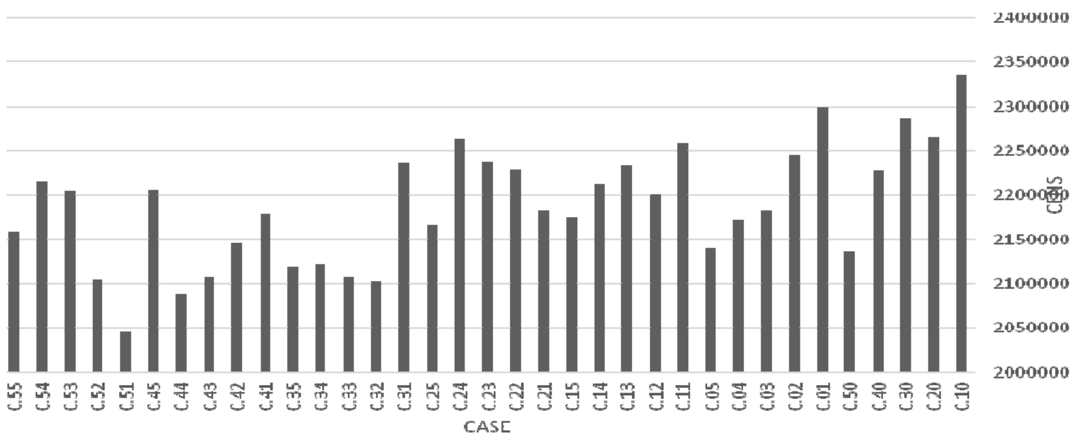

Fig.4. CENS of SAIFI pararmeter

By considering results of Figure 4, generally range of CENS difference becomes less. The maximum value of CENS happens in one solar cell placement. After that, placement of one wind turbine has the worst solution for CENS. C.51 (placement of five wind turbines and one solar cell) has reducted CENS parameters considerably.

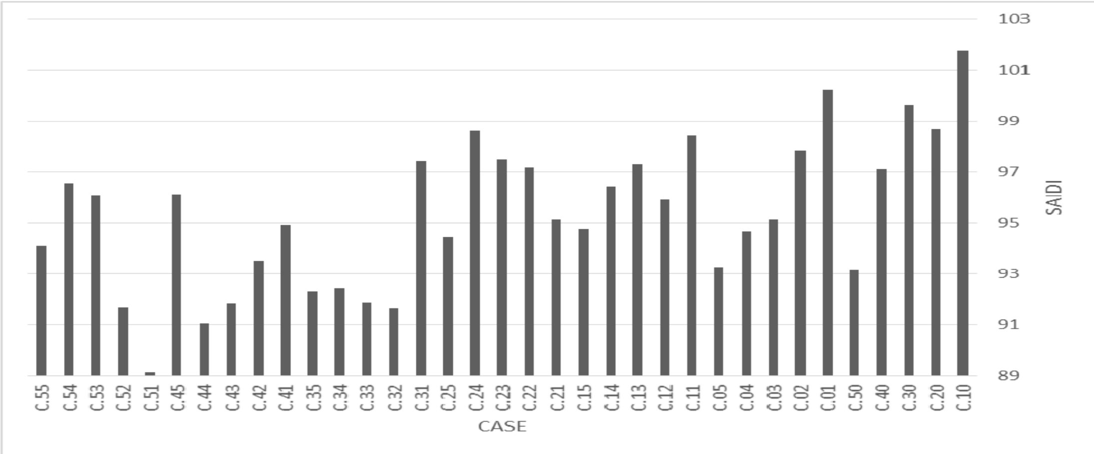

Fig.5. Values of SAIFI pararmeter

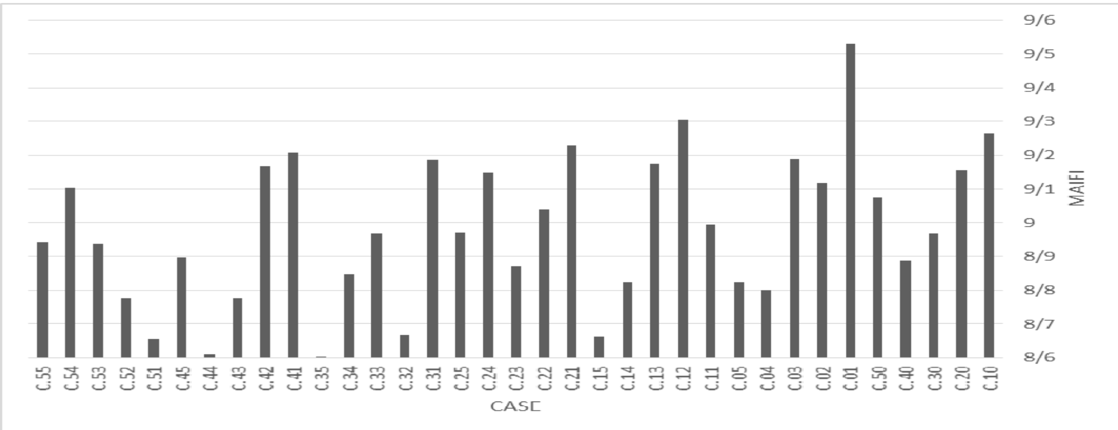

Fig.6. Values of MAIFI pararmeter

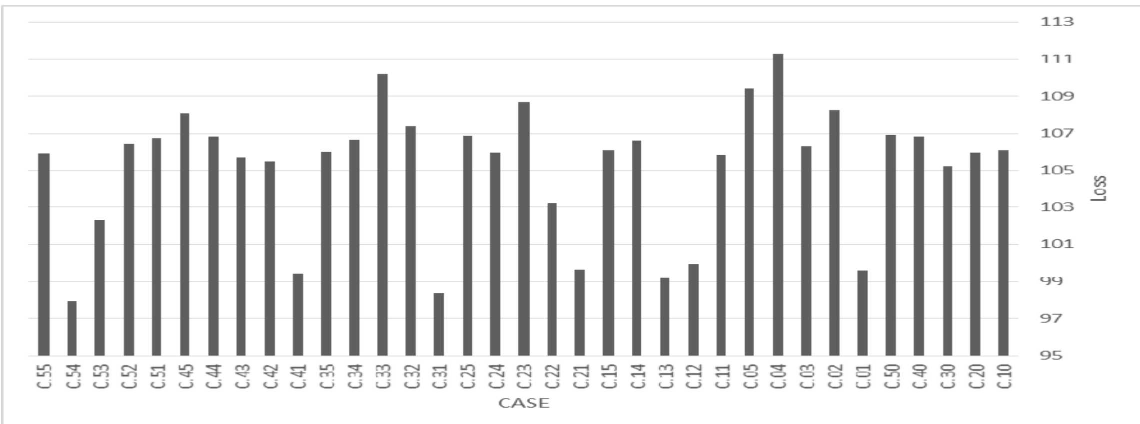

Fig.7. Values of power loss

Then allocation of four units for solar cell and wind turbine (i.e. C.44) has a better solution.

4-3- SAIDI parameter

Let us visit Figure 5, to view the corresponding values SAIDI for 35 proposed states. By focusing on results of Figure 5, we can claim that behaviors of SAIDI and CENS are similar. Case 10 (placement of one wind turbine) presents the worst solution. Except this case, only placement of one solar cell generates more than 100 for SAIDI. Placement of five units (i.e. five solar cells and five wind turbines) are the only cases is that the SAIDI of 90 occurs. Note that the placement of five units of each of the resources (i.e. case 50 and 05) with responses are very close to each other.

4-4- MAIFI parameter.

The fourth and latest reliability indices are MAIFI parameters. The optimal values of MAIFI are visible in Figure 6. By considering results of Figure 6, case 44 (placement of four wind turbines and four solar cells) and case 35 (placemen of three wind turbine and five solar cells) have the responses very close to the best possible answers. Although case 35 in particular presents better solution, the worst solution obtains in placement of one solar cell. Interestingly, C.12 (placement of one wind turbine and two solar cells) after C.01 has the worst solution.

4-5-Power loss

Figure 7 shows power loss of test. By considering results of Figure (7), it can be argued that cases 04 (placement of only four wind turbines) and the 33 (placement of three wind turbines and three solar cell) over the rest of the losses will be offered. The power of numbers of cases have less than 100 kW among which these case placements of five wind units and four solar units (i.e. C.54) present the best solutions.

4-6- Target function

The last curve is target function values which is visible in Figure 8.

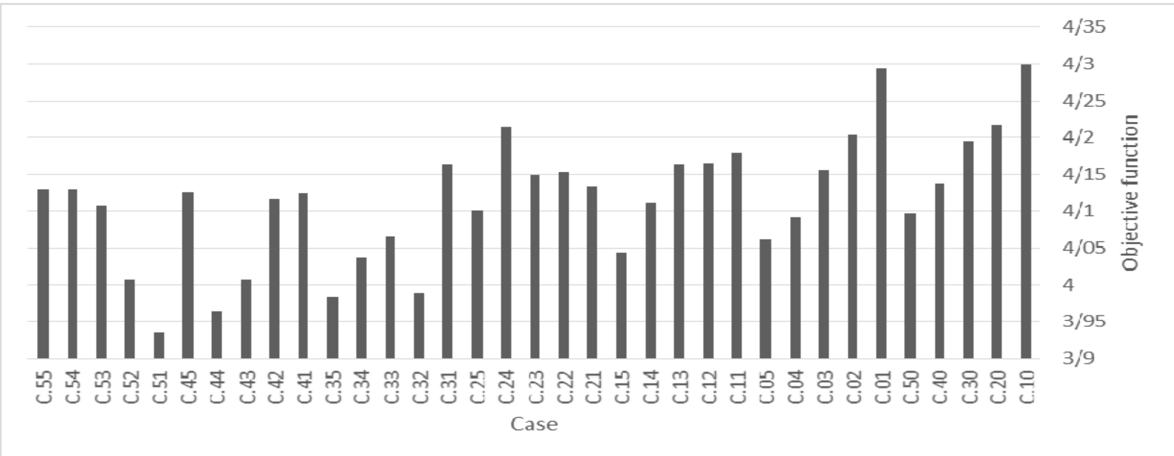

Fig.8. Values of target function