A new genetic algorithm to optimize mobile data offloading in smart grids

Milad Riyahi[a], Marjan Kuchaki Rafsanjani[a], Rouzbeh Motevalli[b], Ahmad Hashemi[b]

[a]*Department of Computer Science, Faculty of Mathematics and Computer, Shahid Bahonar University of Kerman, Kerman, Iran*

kuchaki@uk.ac.ir

[b]*Department of Computer Science, Sari branch, Islamic Azad university, Sari, Iran*

Abstract

The smart grid is an electric grid that can deliver electricity in a controlled and two-way smart connection from points of generation to active consumers. A communication infrastructure is an essential part to the success of the emerging smart grid. A scalable and pervasive communication infrastructure is crucial in both construction and operation of a smart grid. To deal with the communication problem of smart grids, specifically increasing the speed of data flow, mobile data offloading technique can be used. Performance of mobile data offloading depends on the sites of deployed access points. In this paper, a novel genetic algorithm with ability to deal with premature convergence to increase the performance of data offloading is presented.

Keywords: Smart grids, Communication infrastructure, Mobile data offloading, Genetic algorithm (GA)

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1. Introduction

New facilities like monitoring devices and communication equipment introduce a new generation of distributing systems entitled smart grids. This is an evolution that allows the application of intelligent methods for new functions such as primary feeder reconfiguration, system self-healing, management of different power sources, real-time pricing monitoring, demand-side management, power quality improvement (Brown, 2008). Research on smart grid spans a wide spectrum: from technology (Bose, 2010) to economy, marketing, policy and legal issues (Tabors et al., 2010); from power generation, transmission, distribution (Saint, 2009), to load management, failure diagnosis and recovery (Russell et al., 2010), and also to the smart meter implementation and communications (Prasanna et al., 2009).

Due to the importance of data flow in smart grids, communication infrastructure can be considered as an important part of the smart grid. In fact, a smart grid is characterized by the bidirectional connection of electricity and information flows to create an automated and widely distributed delivery network. In this communication, electricity should be transmitted from suppliers to final consumers and data of consumer's consumption has to be gathered and being sent to control unit. It incorporates the legacy of electricity grid benefits of modern communications to deliver real-time information and enable the near-instantaneous balance of supply and demand management (U.S. Department of energy, 2007). Communication in smart grids can be done by wired technology such as power line communication (PLC) systems or by wireless technologies such as cellular networks (Yan et al., 2013).

With the development of smart grids, the PLC on the power transmission and distribution networks has become one of the most important technologies to exchange the information between the end users and the authorities. Practical result showed that the main reason influencing the reliable communication of high-speed data on the power line is the attenuation of the high-frequency signal, which exhibits more obviously in the branch of power line (Zhai, 2011). It is almost impossible to use the frequency range from 10 to 20 MHz for the reliable communications from the distribution transformer to the end user, so it must be solved with the aid of means such as the repeater and the modulation schemes. However, it seems that PLC is a suitable communication for centralized, low speed, and high latency applications, such as data gathering, monitor and control of the household power consumption (Siano, 2014).

Another option for communication that has been brought by new technologies is cellular networks like GSM and GPRS. The performance of cellular networks is far better than PLC in smart grid communication. In spite of the better performance, the main drawback with cellular networks is the hardware infrastructure of smart meters. In the other words, the lack of IP based smart meters increases the communication cost, astonishingly. Therefore, most common approaches split communication into two parts and use a combination of PLC technology and cellular networks (Siano, 2014). Figure 1 shows a scheme of communication infrastructure in smart grids. As it is shown in figure 1, data collectors gather data from smart meters by PLC and then send gathered data to a central unit via cellular network.

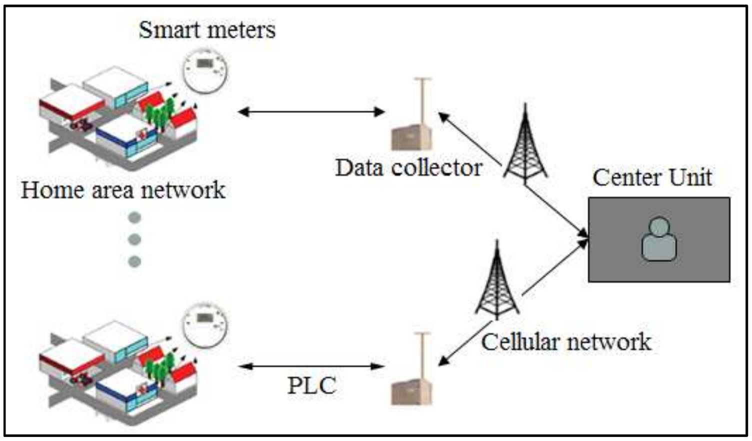


Fig.1. Communication infrastructure in smart grids

Even though, the lack of IP based smart meters is solved by this scheme, high mobile data traffic on cellular networks is another important weak point that has to be handled. Obviously, high mobile traffic diminishes the performance of the data flow in smart grids. It happens because the traffic on cellular networks reduces the speed of data transmission and consequently the performance of smart grids, because of the low speed of data transmission will be reduced. In this paper, we try to find a solution for this problem and increase performance of smart grids.

The remainder of this paper is organized as follows. In section 2, we highlight our main motivations and discuss some main mobile data offloading approaches. Description of problem and proposed method (MRGA) is discussed in section 3. The experimental results are provided in Section 4 and the discussion on the results can be found in Section 5. Finally, we conclude the paper in Section 6.

2. Motivations and data offloading

We were motivated into improving data transmission between data collectors and center unit in smart grid communication by the attraction of this untapped area. Using the cellular network for data transmission in smart grids does not have adequate performance due to the fact that mobile data traffic on cellular network continues its tremendous growth path, with an increasing number of smart phones, and tablets requiring ubiquitous Internet access. As a side effect of this mobile data explosion, nowadays, we face the challenge of managing traffic overloads in cellular networks. Based on the technical report (Cisco. 2013), mobile data traffic will grow at a compound annual growth rate of 66% from 2012 to 2017, reaching 11.2 Exabyte per month by 2017.

Many different approaches have been proposed to reduce mobile data traffic on the cellular networks. Mobile data offloading can be considered as one of the most efficient approaches in this area. Mobile data offloading, also referred to as mobile cellular traffic offloading, is the use of complementary network communication technologies to deliver mobile data traffic originally planned for transmission over cellular networks. Two main types of mobile data offloading are named WiFi and Femtocell offloading (Han et al., 2011). Utilizing WiFi networks for mobile data offloading on cellular network seems more efficient because of easier accessibility, simpler use for users, and no interference with cellular networks (Bulut et al., 2012). Figure 2 shows the scheme of mobile data offloading via WiFi networks.

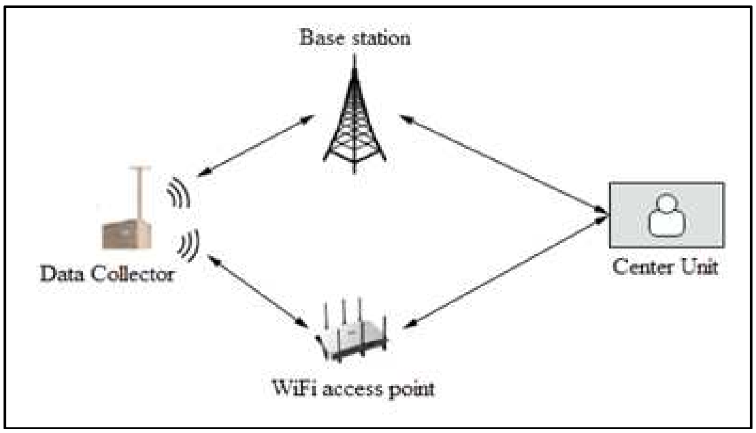


Fig.2. WiFi offloading scheme in smart grids

As it can be clearly seen in figure 2, data offloading by WiFi technology is done via access points. In fact, access points make additional networks to reduce data on cellular networks. The key point of utilizing mobile data offloading of WiFi is finding the best places to deploy access points to have the most cover because access points have to be accessible by users. Many approaches have been proposed to find better places for deploying access points. The best places can be found among candidate places by the threshold level technique as it was done in (Dimatteoet al., 2011). In this research, if one byte of desired information could be downloaded about 10 seconds, the point was considered as a happy point, otherwise it was unhappy. When a node was unhappy, one unhappy request was added to the list of unhappy requests at that point. After finding the number of requests at each candidate point, access points were placed in some of candidate points based on considered threshold level. Bulut et al. (2012) introduced a greedy algorithm to find appropriate places for access point's deployment. They divided workplace into some grids and placed access points in grids with highest requests from users. Moreover, they solved a sub-problem like the main one at each grid to find the best place in each grid for deploying an access point. They selected some candidate points at each grid and evaluated which point is the best one to deploy the access point. Kim et al. (2013) focused on finding the minimum number of needed access points in overlay networks. To achieve their aim, firstly, they set the target average per-user throughput and then they found minimum number of access points based on a mathematical model.

3. Description of the problem and the proposed method

Section 3.1 describes the main problem of this paper and a novel genetic algorithm (MRGA) is proposed in section 3.2 to solve the problem.

3.1. Problem definition

The problem which we are concerned can be described as follows: there is a workplace with a predefined number of data collectors and some potential places for deploying access points which are distributed throughout the workplace. Also, there are different types of access points with different coverage ranges and costs. Different access points can be deployed to each potential place without any restriction. Finding the best places for deploying access points is the main goal of this paper. Deploying access points to the best places will lead to highest possible coverage rate along with the lowest possible cost. So to evaluate the answers, two factors should be considered; Cost and Cover.

■ Cost: different types of access point (AP) with different cover ranges are used in this research. Obviously, the access points with higher coverage ranges are more expensive than access points with lower coverage ranges. The factor determines the total costs of all hired access points in the workplace.

■ Cover: this factor calculates the number of data collectors that are in range of at least one access point. The value of the factor would be the ideal if we be able to cover all data collectors.

There are two important restrictions on this problem. Firstly, it has to be considered that at most one access point can be deployed at each potential place. It means, we can deploy one access point in a potential place or leave it empty. Secondly, overlap has to be removed in Cover calculation. It means that, data collectors which are covered by different access points have to be counted only one time.

3.2. Proposed genetic algorithm

Even though, genetic algorithm can be used to solve the problem, this algorithm needs to be modified for the better performance due to classic drawbacks of the algorithm. Designed genetic algorithm tries to improve the performance of the classic algorithm by new operators. Moreover, the classical process of genetic algorithm is changed in the proposed algorithm based on different conditions.

3.2.1. Encoding and population creation

We use linear chromosomes in the proposed method. The number of genes is defined as many as the number of potential places for deploying access points. Each gene in chromosome can have a value between 0 and types of access points. Value 0 shows that there is no access point at the corresponding potential place and the other values show the deployment of different types of access points in corresponding potential place. Figure 3 illustrates designed chromosomes of the population with 29 genes, 29 potential places, and three types of access points. As it is shown in the figure, there are N chromosomes at each population.

	Gene 1				Gene 29
CH 1	2	3	3	…	1
CH 2	1	0	0	…	2
.			.		.
.			.		.
.			.		.
CH N	2	1	3	…	0

Fig.3. Chromosomes of a population

3.2.2. Fitness function

The fitness function is defined to determine the quality of chromosomes, and it is usually relevant to the objective function to be optimized. Covered area by each chromosome and cost of using access points are factors that we consider in the fitness function. Equation (1) shows the fitness function.

$$Fitness(CH_i) = \frac{Cost(CH_i)}{Max(1, Cover(CH_i))} \tag{1}$$

It is plainly visible that we want to reduce the value of the fitness function by diminishing Cost and increasing Cover. The factors, namely Cover and Cost would be zero for a chromosome with zero values in all genes. This is an exceptional case because the fitness function will receive a vague value. To this end, $Max(1,Cover(CH_i))$ is used in the denominator of the fitness function.

3.2.3. Selection

Selection operator is responsible to choose chromosomes for reproduction. In most of selection strategies, operator completely depends on fitness value. Premature convergence can be cited as the main drawback of selection operators based on fitness value. In this case, population will be filled by similar chromosomes, because these chromosomes have more chance to be selected (Qing-dao-er-ji et al., 2012). To avoid this problem, we use the variance value of fitness of chromosomes. Variance gives us an overview of diversity in population and differences between fitness of chromosomes. Based on the variance value of population and a predefined threshold, selection operator is divided into two sections. Algorithm 1 shows the proposed selection operator.

■ Selection 1: if the variance value of population is less than predefined parameter α and also iteration number is less than 75% of total iterations, the population has a great chance to trap in convergence because the diversity of the population is low and the population is filled by similar chromosomes. In this case, we do not run selection because using selection strategies based on fitness values can easily lead to premature convergence. So, selected population is current population.

■ Selection 2: when the variance of the population is not less than α or iteration number is more than 75% of all iterations, we use Roulette wheel selection strategy. In Roulette wheel strategy, a value as the selection probability is given to each chromosome according to equation (2) and chromosomes will be selected based on selection probability.

$$Selection\ probability(CH_i) = \frac{Fitness(CH_i)}{\sum_{j=1}^{N} CH_j} \tag{2}$$

Algorithm 1: Selection

Begin

α=predefined threshold
M = total iteration number
Compute variance of chromosomes fitness
if (variance<α) and (iteration number<$\frac{3}{4}$M) **then**
Do not change population;
else
Compute selection probability;
Use roulette wheel strategy;
end if

End

3.2.4. Crossover

The goal of the crossover is to obtain better offspring by making use of the parental information. We use two-point crossover strategy in the proposed method. In this strategy, two points of the parents will be selected in a random way and then the values of genes between these two points will be substituted in two parents and two children will be made. Crossover operation will be done on two parents by considering the probability P_c.

3.2.5. Mutation

The mutation operator further carries out some adjustments for a parent's individual and gets an offspring. It can increase the diversity of the population and is helpful to jump out local optimal solutions. To increase the performance of mutation, we define mutation distance (MD) as a new criterion in mutation operator. The definition of mutation distance for chromosome CH_i is presented in equation (3).

$$MD_i = |fitt(muted\_CH_i) - average| \tag{3}$$

Where $muted\_CH_i$ is the result of the new mutation strategy on CH_i. Moreover, the fitness value of new chromosome is calculated by $fitt(muted\_CH_i)$. Also, the average parameter is the average of fitness of all chromosomes in the population, which is calculated by equation (4).

$$average = \frac{\sum_i^N fitt(CH_i)}{N} \tag{4}$$

In this research, we create a new mutation strategy based on swap mutation and MD. Figure 4 illustrates the process of the new mutation strategy. As it can be clearly seen in the figure, at the first step, µ candidates will be produced by swapping strategy. Then, MD will be calculated for each candidate and the best one, candidate with highest MD value, will be selected as the result of the new mutation strategy. The result will be replaced with the parent in population at the end of the process.

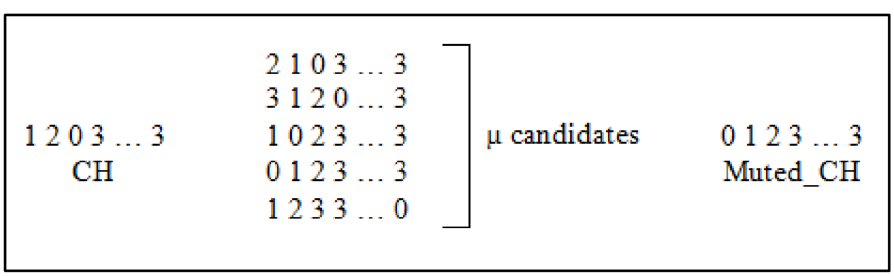


Fig.4. The process of the new mutation strategy

To deal with the lack of diversity in the population, the new mutation strategy is used in two different ways depends on different conditions. Mutation probability is the difference between these usages. The ways are described as follows:

■ Mutation 1: When the diversity of the population is adequate, the new mutation strategy operates on a chromosome based on probability P_m. In this way of usage, a random number will be produced for each chromosome in the population. If the number is less than P_m, The chromosome undergoes the new mutation strategy otherwise the chromosome goes to the next generation without any change.

■ Mutation 2: In the event of lack of diversity in the population, the mutation strategy will be ignored. In this case, we certainly need to increase the diversity of the current population. Therefore, we select β chromosomes of the current population and run the new mutation strategy on these chromosomes.

3.2.6. Replacement

In this paper, the chromosomes of the next generation will be selected based on fitness values. Actually, chromosomes with better fitness values among parents and children have permission to build the next generation.

3.2.7. Stopping criterion

Stopping criterion indicates when genetic algorithm has to be ended. We continue our proposed genetic algorithm for some specific iterations and our final answer is the best chromosome in the last generation.

3.2.8. Framework of MRGA

We proposed our new genetic algorithm based on defined operators. The process of the proposed genetic algorithm, MRGA, is shown in algorithm 2. According to the problem complexity, occurrence of the cited conditions in selection 1 is one of the most possible cases. If it happens, we need more diversity in the population. So, in MRGA, we use mutation 2 without considering selection, crossover, and P_m. We expect that omitting P_m brings us an improvement in diversity of population.

Algorithm 2: MRGA

Begin
  M = total iteration number
  P_c = Crossover probability
  P_m = Mutation probability
  μ = Number of candidates in mutation
  α =predefined threshold
  Generate initial population randomly;
  j=1;
  while j<M **do**
    Evaluate fitness value of chromosomes;
    Compute variance of fitness values;
    if(variance<α) and ($j<\frac{3}{4}M$) **then**
      Use selection 1;
      Use mutation 2 based on μ;
      j=j+1;
    else
      Use selection 2;
      Use crossover based on P_c;
      Use mutation 1 based on P_m and μ;
      Use replacement strategy;

j=j+1;
end if
end while
End

Premature convergence is an abnormal state that can happen for genetic algorithm during iterations. We suggest a practical way to tackle this problem. However, in the normal conditions, the proposed genetic algorithm works based on the classic version with new designed mutation strategy.

4. Experimental results

In this paper, a new genetic algorithm to increase quality of data flow in smart grids is designed. To evaluate the performance of the proposed approach, this method is implemented in Matlab on a computer with 2.00 GHz Intel core *i7* CPU. Two groups of parameters, namely public and genetic have to be defined for implementation.

■ Public parameters: this group includes parameters like dimensions of workplace, number of data collectors, etc. we consider an area with dimensions 10 km by 10 km as the work area. We distribute 500 data collectors throughout the work area, randomly. Moreover, we consider 29 potential locations for deploying access points. The distance between each pair of adjacent locations is considered about 1660 meters; however, the distance is a little bit more in the four corners. Figure 5 illustrates the designed work area where the red circles are potential places.

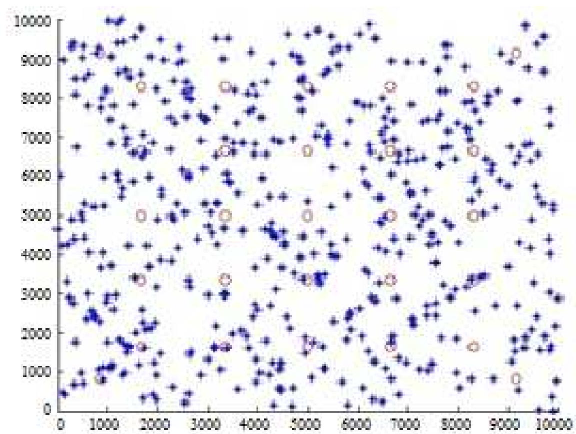


Fig.5. Designed work area

Another factor that has to be indicated for implementation is access point's types. We use three types of access point with different ranges and different costs. Table 1 stands for information of considered AP’s ranges and corresponding costs.

Table 1
Access points ranges and costs

AP types	Range	Cost
Type 1	1 km	1000 $
Type 2	1.5 km	1500 $
Type 3	2 km	2000 $

■ Genetic parameters: because of 29 potential places in work area, designed chromosomes have 29 genes and each gene can accept a number among 0, 1, 2, and 3. The size of population at each generation is selected 100 (*N=100*). Moreover, the probability of crossover is set to 0.8 ($P_c=0.8$), the probability of mutation is considered 0.008 ($P_m=0.008$), and the threshold level for variance of the population is considered 28 ($\alpha=28$). In addition, the number of candidates for mutation is 3 ($\mu=3$) and also mutation 2 is done on 3 chromosomes ($\beta=3$). Finally, the genetic algorithm with defined parameters and random first generation is run for 200 iterations (*M=200*).

We ran the proposed genetic algorithm 10 times, independently. It has to be considered that public parameters were constant as well as genetic parameters at each implementation. The best chromosome of the last generation is pointed as final answer at each round. Table 2 shows different implementation results of running MRGA.

Table 2
Implementation results

Run	Fitness	Cover (%)	Cost ($)
1	55.02	83.6	23000
2	66.12	72.6	24000
3	55.69	82.6	23000
4	51.02	78.4	20000
5	63.67	84.8	27000
6	54.08	83.2	22500
7	54.54	77.0	21000
8	58.68	85.2	25000
9	63.10	82.4	26000
10	54.45	80.8	22000

Our aim is to make a trade-off between Cost and Cover. According to this trade-off and also based on used fitness function, less fitness value means better performance. Based on table 2, Runs 4 and 6 had better performances. Figure 6 shows deployed APs at runs 4 and 6. In this figure, APs type 1, 2, and 3 are shown by circles red, yellow, and green, respectively.

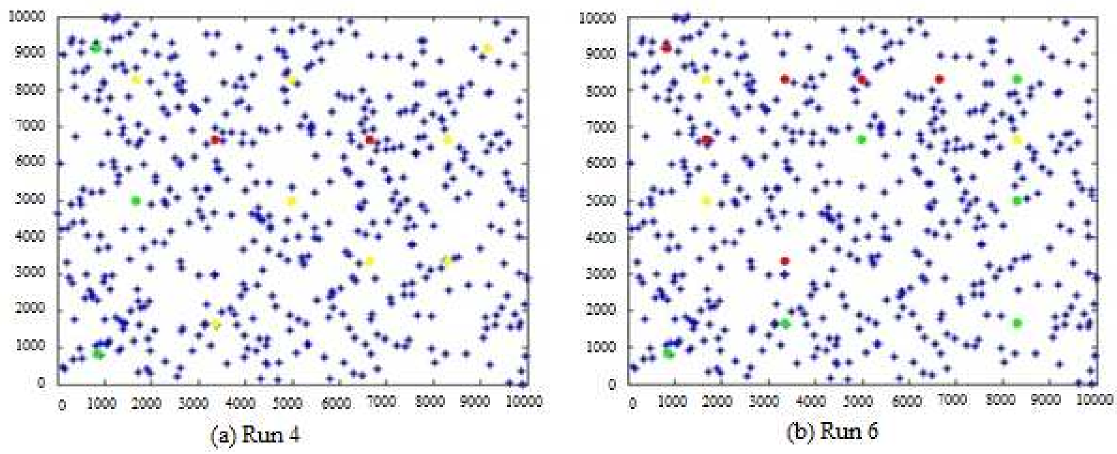


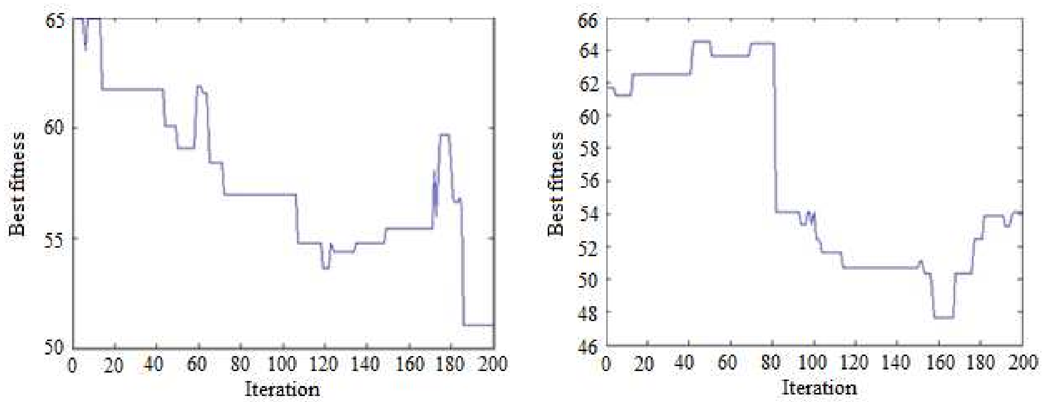
Fig.6. Deployed access points

As it is shown in figure 6, at run 4, we used 2 access points of type 1, 8 access points of type 2, and 3 access points of type 3. According to table 1, Cost of this solution is 20000 dollars. Also, run 6 used 6 access points of type 1, 3 access points of type 2, and 6 access points of type 3. Total cost of this run, according to considered costs is 22500. Even though, these runs do not have highest coverage rate, based on the trade-off between Cost and Cover, these runs have better performances.

5. Discussion

After implementing the proposed method, we evaluate MRGA in this section. Three criteria are selected for evaluation proposed genetic algorithm. Best fitness, Variance of the population, and Median of fitness can evaluate the performance of MRGA. Due to the fact that runs 4 and 6 had the best performance among 10 implementations, we evaluate these two runs by introduced criteria.

■ Best fitness: considering the proposed fitness function, a decreasing trend is expected in the plot of the best fitness. Figure 7 illustrates the best fitness of each generation in runs 4 and 6. As it can be clearly seen, in spite of some increasing points in the plot of run 4, total trend of the plot is diminishing. Likely, the trend of the best fitness in each generation is decreasing in run 6.



(a) Run 4 (b) Run 6

Fig.7. Plots of the best fitness

■ Variance of population: variance is used to point premature convergence trap. We try to increase diversity of the population when the population is going to get stuck in premature trap. Figure 8 shows the variance of the population in runs 4 and 6. As it can be observed, the plot of variance in run 4 has eye-catching decreasing trend before 20th iteration. It shows that the chromosomes of the population are similar and this population is going to converge very soon. At this point, we increase the diversity of the population by mutation 2 which is visible between 20th and 60th iterations. This process is continued till the 150th iteration when 75% of iterations are just passed. After 150th iteration, the proposed genetic algorithm will be done in the classic way. The trend of the plot is diminishing that shows population is going to reach the convergence point. Likewise, run 4, the plot of variance at run 6 shows different premature trap points.

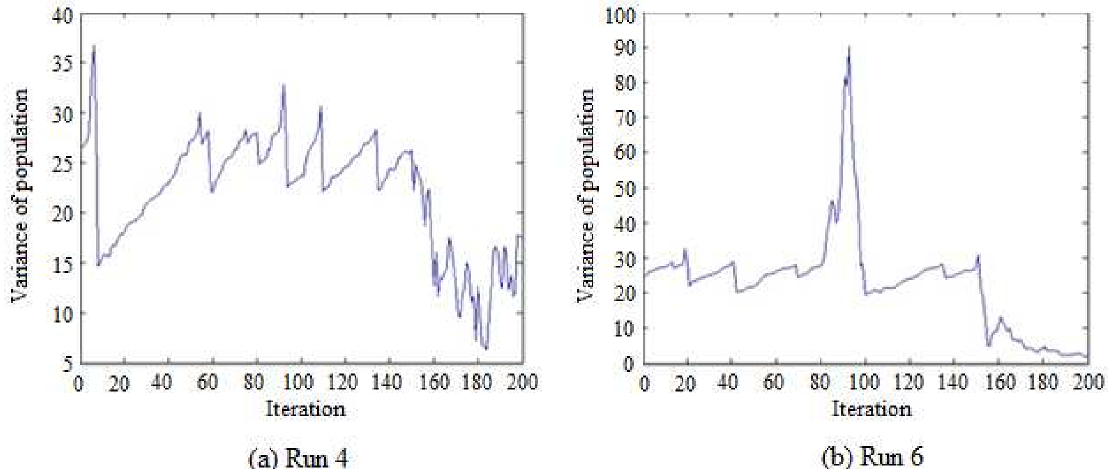


Fig.8. Plots of variance

■ Median of fitness: we expect the median value of fitness in final population be close to the best fitness in the last population. Figure 9 shows this factor for runs 4 and 6. As it can be clearly seen in both runs, the trend is decreasing. Moreover, the median of fitness in the last population at 200^{th} iteration is close to the best fitness at this iteration. These close values indicate that the population is converged to the optimum point.

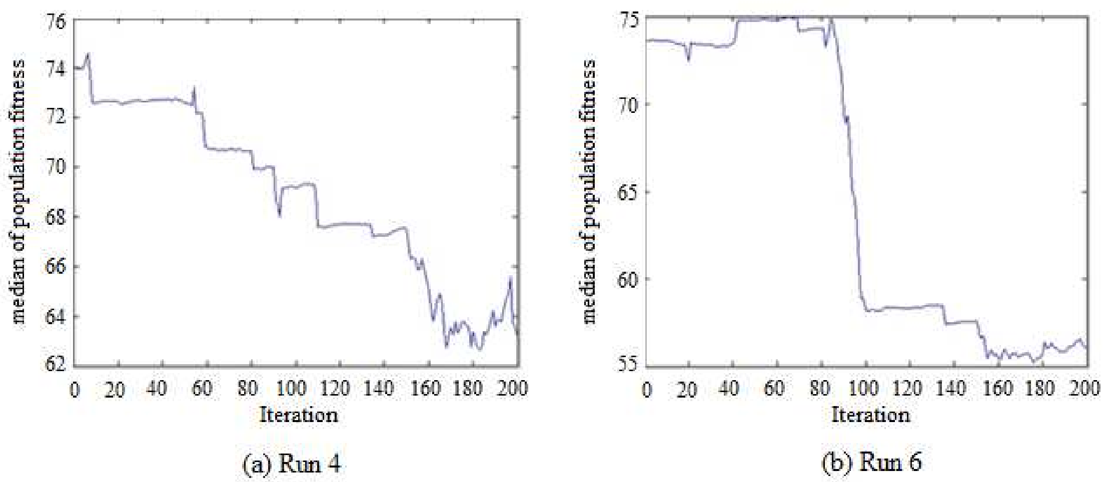


Fig.9. Plots of median

To compare the performance of MRGA, we solve the problem with the classic genetic algorithm. We run the classic genetic algorithm with Roulette wheel strategy for selection, Two-point crossover, and finally Swap mutation. Classic genetic algorithm (GA) is done on the same work place with same genetic parameters, except α, β, and μ, which are exclusive for MRGA. We run the classic genetic algorithm 10 times, independently, and analyze the best answer among them.

Best fitness happened at first run and it was 59.16 when the others were larger than 65. Figure 10 shows the best answer of solving the problem by classic genetic algorithm. In this run, 4 access points of type 1, 5 access points of type 2, and 7 access points of type 3 are deployed.

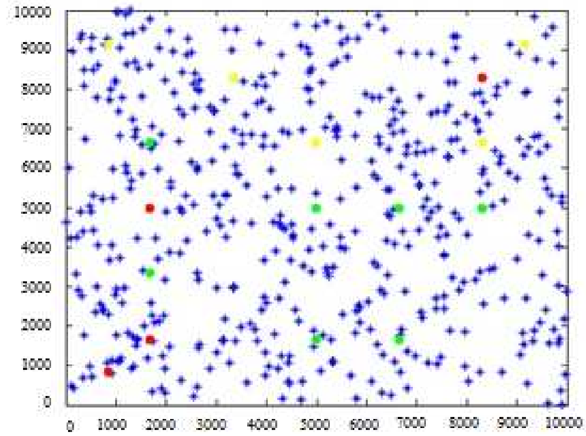


Fig.10. The best answer of running classic GA

Figure 11 shows the plot of best chromosome at each generation when the classic genetic algorithm is utilized to solve the problem. The fluctuating trend in this plot is plainly visible. It indicates that the classic genetic algorithm is unable to find better answers, appropriately.

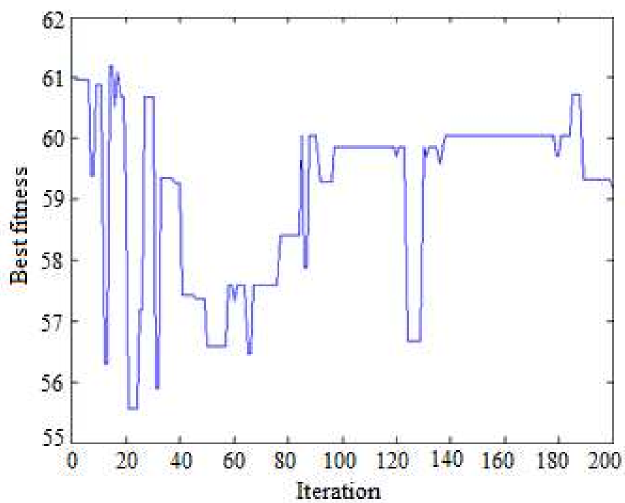


Fig.11. The best fitness of running classic GA

Figure 12 shows the plot of variance in each generation when the classic genetic algorithm is used to solve the problem. Decreasing trend in the plot of variance is plainly visible. The value of variance is almost zero even before 80th iteration, which describes the weak performance of the classic genetic algorithm. It happens because the classic genetic algorithm is in premature convergence and can't search new answers spaces.

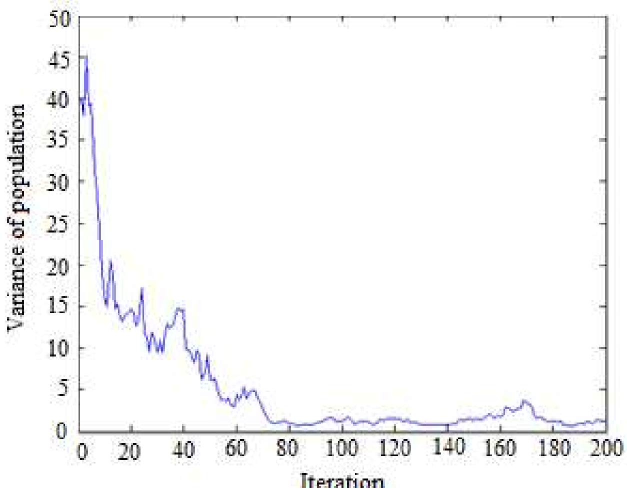


Fig.12. The **v**ariance of running classic GA

6. Conclusion

In this paper, a new genetic algorithm (MRGA) to solve WiFi mobile data offloading in smart grids is introduced. Three types of access points with different cover range and cost are used in the work area to achieve the best coverage with the most logic cost. In MRGA, we used variance of fitness values at each population in selection operator. Moreover, we introduced a new mutation strategy based on mutation distance. We could solve premature convergence problem by these new strategies.

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