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Parameter optimization of quick artificial bee colony algorithm for dynamic deployment problem of wireless sensor networks using Taguchi method

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Abstract

Finding a good parameter setting is a crucial issue in implementation of evolutionary computation based algorithms since it is generally a difficult and time consuming process while it effects the success of the implementation. So, it is one of the popular research fields. In this paper, an experimental design study is presented for parameter optimization of quick artificial bee colony algorithm in dynamic deployment problem of wireless sensor networks using Taguchi method. Colony size, limit and neighborhood radius are considered as design factors. Ratio of uncovered area to total area of the interest is adopted as the performance characteristic. A robust experimental design with an inner orthogonal array is conducted by computer simulation, and the optimal parameter setting is presented. Effects of the factors are examined, and analysis of variance study is performed. A comparison is hold between the predicted and actual signal to noise ratios and reliability of the prediction is confirmed with a small error.

Keywords: *Quick artificial bee colony algorithm, dynamic deployment problem, wireless sensor network, design of experiment, Taguchi method.*

Taguchi yöntemi kullanılarak kablosuz algılayıcı ağların dinamik dağıtım problemi için hızlı yapay arı kolonisi algoritmasının parametre optimizasyonu

Öz

Uygulamanın başarısını etkilerken genellikle zor ve zaman alıcı bir işlem olduğu için iyi bir parametre ayarı bulmak evrimsel hesaplama tabanlı algoritmaların uygulanmasında çok önemli bir konudur. Bu nedenle popüler araştırma alanlarından biridir. Bu

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çalışmada, kablosuz algılayıcı ağların dinamik dağıtım probleminde hızlı yapay arı kolonisi algoritmasının parametre optimizasyonu için Taguchi yöntemi kullanılarak bir deneysel tasarım çalışması sunulmuştur. Koloni büyüklüğü, limit ve komşuluk yarıçapı tasarım faktörleri olarak dikkate alınmıştır. Kapsanmayan alanın toplam ilgilenilen alana oranı performans karakteristiği olarak kabul edilmiştir. Bilgisayar simülasyonu ile iç ortogonal dizili bir gürbüz deneysel tasarım gerçekleştirilmiş ve optimum parametre ayarı sunulmuştur. Faktörlerin etkileri incelenmiş ve varyans analizi çalışması yapılmıştır. Tahmin edilen ve gerçek sinyal-gürültü oranları arasında bir karşılaştırma yapılmış ve tahminin güvenilirliği küçük bir hata ile doğrulanmıştır.

Anahtar kelimeler: *Hızlı yapay arı kolonisi algoritması, dinamik dağıtım problemi, kablosuz algılayıcı ağ, deney tasarımı, Taguchi yöntemi.*

1. Introduction

Wireless sensor networks (WSNs) have several important applications like military, environmental, home and medical applications in many fields. Use of the network of cheap, small and smart sensors allows to collect various kinds of information easily. So, deployment of these sensor nodes in a WSN is an important issue that effects the performance and outputs of the network directly. In some cases, the sensors are located with an engineering study while in some cases they positioned randomly. For example, for the areas like inaccessible terrains, the second type of the cases where the randomness is used can be preferred with some algorithms and protocols having self-organizing capabilities [1]. In dynamic deployment problem of WSNs, initial random deployment is tried to be improved by using the position changeability of mobile sensor nodes to optimize some profits like total coverage of the network. Evolutionary computation based optimization algorithms have been widely used for this problem [2-18].

Artificial bee colony (ABC) algorithm is an evolutionary computation based optimization algorithm which uses swarm intelligence [19-21]. ABC and its different versions have been used to solve the dynamic deployment problem, successfully [2-3, 7, 22-27]. A recent study given in [27] applies quick ABC (qABC) algorithm to the dynamic deployment problem of WSNs considering different scenarios. In qABC [28], only the onlooker bee phase of the ABC is modified. In standard ABC, onlooker bees select their food source by evaluating the food source information which is given by employed bees and then exploit that food source. However, in qABC algorithm, onlookers do not exploit the selected source directly. They go to the region centered with the selected food source and they search the best food source to exploit in that region. In order to determine the size of the region a new control parameter called neighborhood radius is used in qABC algorithm.

Evolutionary computation based optimization algorithms need appropriate settings for their control parameter values and parameter tuning studies that show the effects of control parameters' values to the performance of the algorithm. In this study, a robust experimental design is provided for the setting of the control parameters of the qABC algorithm in dynamic deployment problem of WSNs using Taguchi method. Signal to noise (SN) ratio is considered as the response characteristic. Effects of the design factors and their statistical significance are examined. Optimal levels of the parameters are proposed, and a comparative study is provided between the predicted value and the calculated value from the observations. For the network, binary detection model is used, and the following assumptions are considered:

- A WSN includes only mobile sensors which are able to change their positions,
- Each sensor has its location information,
- All sensors have the ability to communicate with other sensors,
- A two-dimensional (2D) grid is used to represent the sensor field,
- All sensors' detection radius is the same.

The remainder of the paper is organized as follows. In the first section, some details about the binary detection model are given. In the second section, the qABC algorithm is presented. Experimental studies and some basics of the Taguchi method are explained in section 3. Finally, section 4 concludes the paper.

2. Binary detection model

In many studies on the dynamic deployment problem of WSNs, binary model is used for determining whether a point is detected by the sensors or not [2, 6, 24-25, 27]. According to this model there is no associated unreliability in readings of a sensor and if a point is inside of a sensor's detection range, it is detected by the network. Detection range of a sensor can be expressed by using a radius as a circular shape in 2D environments. Binary detection model can be explained basically by Equation 1.

$$c_{xy}(s) = \begin{cases} 1, & \text{if } d(P_s(x_s, y_s), P(x,y)) \leq r_d \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where $c_{xy}(s)$ gives the coverage information of point $P(x,y)$ considering sensor s. $P(x,y)$ represents any point in the area of the interest while $P_s(x_s, y_s)$ is the position of sensor s. $d(P_s(x_s, y_s), P(x,y))$ denotes to the Euclidean distance between $P(x,y)$ and $P_s(x_s, y_s)$. r_d is the detection radius of the sensors.

Total coverage rate of the network, CR, can be found by using Equation 2.

$$CR = \frac{\bigcup_{s \in S} cov_s}{A} \tag{2}$$

where cov_s denotes the coverage of sensor s and S is the set that includes all sensors in the network. A represents the total size of the area of the interest.

In this study, uncovered area is minimized by using Equation 3 as the objective function in qABC algorithm.

$$f(x_i) = 1 - CR \tag{3}$$

where x_i is the ith solution in the population.

3. qABC algorithm

qABC algorithm provides a more detailed model for the phase of onlookers in ABC algorithm [28]. Except this phase, rest of the qABC is the same as ABC. In these algorithms, each food source and quality of this food source refer to a solution and fitness of this solution, respectively. In order to search new food sources or exploit the existing ones, honeybees work in three different bee groups according to division of labor. The first bee group is scouts which randomly search new food sources. In the initialization phase, food sources are randomly found by scouts. So, in the optimization process initial solutions are produced using Equation 4.

$$x_{i,j} = lb_j + \text{rand}(0,1) \times \left(ub_j - lb_j\right) \tag{4}$$

where $x_{i,j}$ is the jth dimension value of the ith solution in the population. ub_j and lb_j represent the upper and lower bounds for the jth dimension, respectively.

After finding the sources, these scouts become employed bees which is the second bee group. An employed bee has a food source in her mind and works on this source: it tries to improve the source by finding a better one around it or exploits it. In the algorithm, Equation 5 is used to find a new candidate v_i around the current solution x_i.

$$v_{i,j} = x_{i,j} + \phi_{i,j} \times \left(x_{i,j} - x_{k,j}\right) \tag{5}$$

where x_k is a randomly selected solution from the population ($k \neq i$) and j is a randomly chosen dimension. $\phi_{i,j}$ is a random number from the range $[-1,1]$.

Fitness of the solution x_i, $fit(x_i)$, is calculated from its objective function value $f(x_i)$ using Equation 6.

$$fit(x_i) = \begin{cases} 1/\left(1 + f(x_i)\right), & if\ f(x_i) \geq 0 \\ 1 + |f(x_i)|, & if\ f(x_i) < 0 \end{cases} \tag{6}$$

If the bee finds a better source (if $fit(v_i) > fit(x_i)$), then it leaves the current source and starts to exploit the new one. It means a greedy selection is applied between the current and candidate solutions. Every solution has a trial counter that shows the number of unsuccessful improvement attempts by the bees. So, whenever the candidate solution is not selected in a greedy selection process, trial counter value of the related solution is increased by one since the current source is exploited, otherwise value of this counter is set to zero again. At the end of each cycle, the solution having the maximum trial counter value is found and if its counter value is greater than the value of the control parameter *limit*, then it is changed with a new solution produced by Equation 4. Actually, in here, if there is an exhausted food source the related employed bee becomes a scout and randomly finds a new source instead of the old one. Only one scout bee can occur in a cycle.

The last bee group includes onlooker bees. In qABC algorithm, an onlooker bee takes the information of food sources from the employed bees and selects one of the food sources considering their qualities with a probability p_i calculated by Equation 7.

$$p_i = \frac{fit(x_i)}{\sum_{i=1}^{SN} fit(x_i)} \tag{7}$$

where SN is the total number of food sources in the population. It should be stated that, the number of employed bees, onlooker bees and food sources are equal in this algorithm. So, colony size $CS = 2 \times SN$.

The selected food source x_i points a region N_i of which it is in the center. The onlooker examines all food sources in that region and find the best one ($x_{N_i}^{best}$), then works on that local best solution in a similar way with employed bees. So, in qABC algorithm Equation 8 is used to produce the candidate solution.

$$v_{N_i,j}^{best} = x_{N_i,j}^{best} + \phi_{i,j}\left(x_{N_i,j}^{best} - x_{k,j}\right) \tag{8}$$

To determine the bounds of N_i, mean Euclidean distance md_i is calculated between x_i and the rest of the solutions in the population by Equation 9.

$$md_i = \frac{\sum_{t=1}^{SN} d(i,t)}{SN-1} \tag{9}$$

where $d(i,t)$ represents the Euclidean distance between x_i and x_t.

The solutions in N_i can be found using Equation 10 similar to the study given in [28].

$$x_t = \begin{cases} a\ neighbor\ of\ x_i, & \text{if d(i, t)} \le \text{r} \times md_i \\ not\ a\ neighbor\ of\ x_i, & else \end{cases} \tag{10}$$

r represents a radius which adjusts the bounds of N_i and has to be used as $r \geq 0$. If the parameter r is set as 0, qABC algorithm works as ABC algorithm.

Basic steps of the qABC algorithm are presented in Figure 1.

4. Experimental design and analysis

Taguchi method is one of the robust experimental designs and it can be used to set the parameters of evolutionary computation based algorithms by using a small number of experiments [29-34]. This method uses two main concepts in an integrated way. One of these concepts is the orthogonal array which is a well-balanced small portion of full factorial design. In the orthogonal array, design factors are placed to columns and the combinations of levels are placed to rows. Design factors include the controllable factors. In our study, control parameters of the qABC algorithm namely colony size, limit and neighborhood radius are used as design factors. Considering the previous studies in this field like [27-28], four levels are chosen for each design factor. Therefore, $L_{16}(4^3)$ orthogonal array is used to determine optimal values. Design factors and their levels are presented in Table 1 while the orthogonal array is given in Table 2. The other concept used in Taguchi method is signal to noise (SN) ratio which is utilized as the objective function that will be maximized. It is also used for analysis of the data and optimum result prediction. SN ratio is obtained by using the mean and the variation of the responses at each raw in orthogonal array. Since the response (performance characteristic) is taken as the ratio of uncovered area to total area of the interest, "smaller is better" approach is used to calculate the SN ratio. The related formulation is given by Equation 11.

$$\text{SN ratio} = -10 \times log_{10}\left(\left(\sum_{i=1}^{n} {y_i}^2\right)/n\right) \tag{11}$$

where n shows the number of observations for each design factor level combination and y_i refers to the response of ith observation. In this study, 30 independent runs of qABC algorithm were taken for each parameter setting. Therefore, $n = 30$.

- Determine problem settings (detection radius r_d, size of the interest area A, number of mobile sensors ms).
- Set the control parameters of qABC (colony size CS, limit l for the scout, neighborhood radius r, maximum number of cycles $MaxNum$).
- For each solution, randomly generate initial deployment of ms mobile sensors using Equation 4.
- Evaluate the solutions by using Equation 3 and Equation 6 and memorize the best one.
- $cycle = 0$
- **REPEAT**
  - **For each employed bee**
    - Using Equation 5, generate a candidate solution v_i from the current solution x_i.
    - Evaluate v_i using Equation 3 and Equation 6.
    - If v_i is better than x_i, update the ith solution of the population as v_i and set the trial counter of this solution as 0, otherwise increase the value of this counter.
  - Using Equation 7, determine the selection probabilities of the solutions for onlooker bees.
  - **For each onlooker bee**
    - Considering the selection probabilities, select a solution x_i.
    - Specify N_i of x_i using Equation 9 and Equation 10.
    - Find the best solution $x_{N_i}^{best}$ in N_i and return its index as b in the population.
    - Using Equation 8, generate a candidate solution $v_{N_i}^{best}$ from the current solution $x_{N_i}^{best}$.
    - Evaluate $v_{N_i}^{best}$ using Equation 3 and Equation 6.
    - If $v_{N_i}^{best}$ is better than $x_{N_i}^{best}$, update the bth solution of the population as $v_{N_i}^{best}$ and set the trial counter of this solution as 0, otherwise increase the value of this counter.
  - Memorize the best solution achieved so far.
  - If there is an exhausted solution, replace it with a new one which is generated by Equation 4 and set its trial counter value as 0. Evaluate it by using Equation 3 and Equation 6.
  - $cycle = cycle + 1$
- **UNTIL (**$cycle = MaxNum$**)**

Figure 1. Basic steps of the qABC algorithm for dynamic deployment problem of WSNs.

In our simulation studies, there are 100 mobile sensors and $r_d = 7$ m. $A = 10000$ m^2 with a length of 100 m and width of 100 m. In order to determine the covered regions, totally 10000 (100 × 100) points that are picked horizontally and vertically with an interval of 1 m are considered beginning from $P(0,0)$ in the area of the interest. Solution string of the algorithm includes 200 items having continuous numerical values from $[0, 100]$. Each of these items provides x or y coordinate of a sensor. The maximum number of function evaluations is 20000 in a run. Design of experiment study is carried out using Minitab® 20.3 software. Average responses and SN ratios are given in Table 3.

Table 1. Design factors and their levels.

Design Factors	**Levels**			
	1	**2**	**3**	**4**
Colony Size (A)	20	40	80	160
Limit (B)	1000	2000	4000	8000
Neighborhood radius (C)	0	1	3	infinite

Table 2. $L_{16}(4^3)$ orthogonal array.

Experiment no	**A**	**B**	**C**
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	2	1	2
6	2	2	1
7	2	3	4
8	2	4	3
9	3	1	3
10	3	2	4
11	3	3	1
12	3	4	2
13	4	1	4
14	4	2	3
15	4	3	2
16	4	4	1

Using the SN ratios, effectiveness of the factors is examined. Taguchi response table is presented as Table 4. From the response table, it can be seen that neighborhood radius has the largest effect on the response characteristic. Then, colony size and limit come, orderly. According to delta values that give the magnitude of the effects, there is a big difference between the sizes of the effect of the neighborhood radius and the effect of the colony size. However, difference for the colony size and the limit is not so high. The best level for the neighborhood radius is 3, colony size is 20 and limit is 1000 since the maximum SN ratios are obtained with these levels. Main effects plot given in Figure 2 also demonstrates that the neighborhood radius has the largest effect on the SN ratio comparing to the colony size and limit. In Figure 2, increase on the mean of SN ratios with the change through the levels becomes higher for the neighborhood radius than the ones for the other two design factors.

Table 3. Average response and SN ratio values.

Experiment no	**A**	**B**	**C**	**Average Response**	**SN Ratio**
1	1	1	1	0.013627	37.2325
2	1	2	2	0.003843	47.7255
3	1	3	3	0.002720	50.7164
4	1	4	4	0.002470	50.9642
5	2	1	2	0.004567	46.4054
6	2	2	1	0.026443	31.5157
7	2	3	4	0.002723	50.5438
8	2	4	3	0.002633	50.9539
9	3	1	3	0.002517	51.1236
10	3	2	4	0.002843	50.0432
11	3	3	1	0.046720	26.5775
12	3	4	2	0.005960	44.1105
13	4	1	4	0.002610	50.6247
14	4	2	3	0.002757	50.0391
15	4	3	2	0.005897	44.1131
16	4	4	1	0.073093	22.7042

Table 4. Response table for SN ratios.

Level	**A**	**B**	**C**
1	46.66	46.35	29.51
2	44.85	44.83	45.59
3	42.96	42.99	50.71
4	41.87	42.18	50.54
Delta	4.79	4.16	21.20
Rank	2	3	1

Table 5 shows the result of analysis of variance. Design factor that significantly contributes to the response characteristic with a confidence level of 95% is the neighborhood radius. Since the related p-values are greater than 0.05, it can be stated that the effects of the colony size and limit are not statistically significant.

Table 5. Analysis of variance for SN ratios.

Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**
A	3	53.53	53.53	17.845	3.17	0.107
B	3	41.97	41.97	13.989	2.48	0.158
C	3	1201.41	1201.41	400.469	71.12	0.000
Residual Error	6	33.79	33.79	5.631		
Total	15	1330.69				

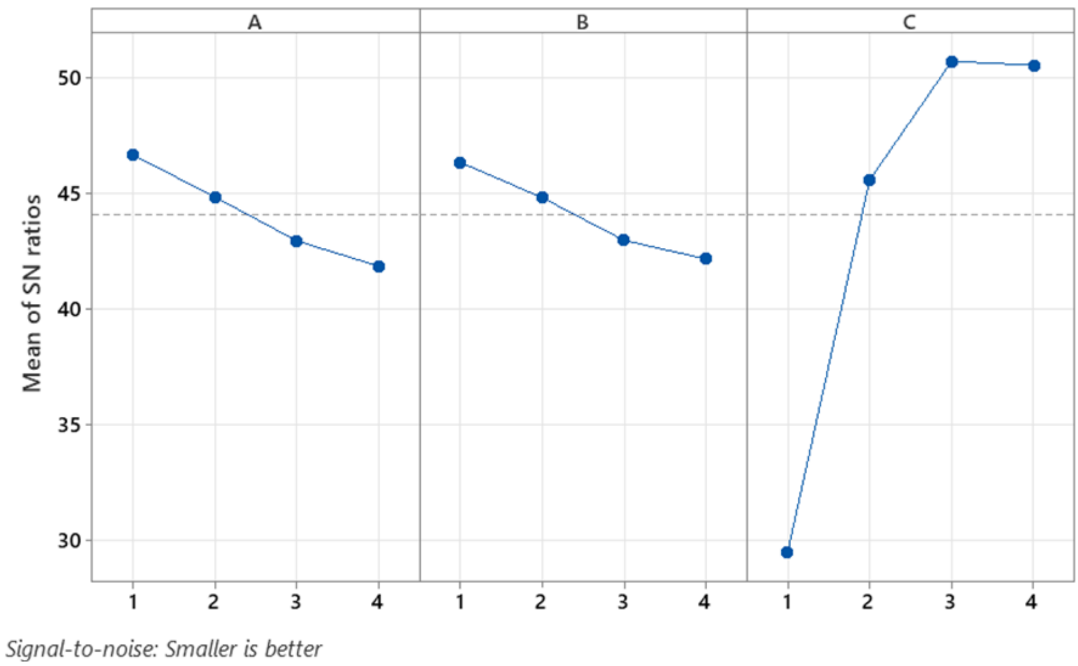

Figure 2. Main effects plot for SN ratios.

In order to see if the model meets the analysis assumptions, residual plots are presented in Figure 3-6. Figure 3 gives the normal probability plot which supports the assumption that the residuals are normally distributed since it has a pattern in the form of a straight line. In the analysis, it is also assumed that the residuals are randomly distributed having a constant variance. Considering the residuals versus fits plot in Figure 4, it can be said there is not a significant violation to this assumption. In Figure 5, there are not any outliers or skewness in histogram of the residuals. Independency of the residuals are verified with the residuals versus order plot given in Figure 6. In this plot, residuals are randomly scattered around the line lying at the center. So, the collection time or order is not seemed to affect the residuals.

When predicting the SN ratio, Equation 12 is utilized since only the neighborhood radius is found as a significant factor in the Taguchi analysis.

$$\eta_{predicted} = \eta_{mean} + (\eta_{C3} - \eta_{mean}) \tag{12}$$

where η_{mean} is the mean of all SN ratios provided in Table 3 and η_{C3} is the average of the SN ratios for neighborhood radius at level 3. In order to confirm the reliability of the prediction, qABC algorithm is independently executed 30 times for the dynamic deployment problem of WSNs using the best factor levels (neighborhood radius is 3, colony size is 20 and limit is 1000). A comparative analysis is carried out between the predicted and actual SN ratios. These values are presented in Table 6. According to the table, percentage error of the prediction is 1.4265%. Therefore, the prediction is verified with the observations.

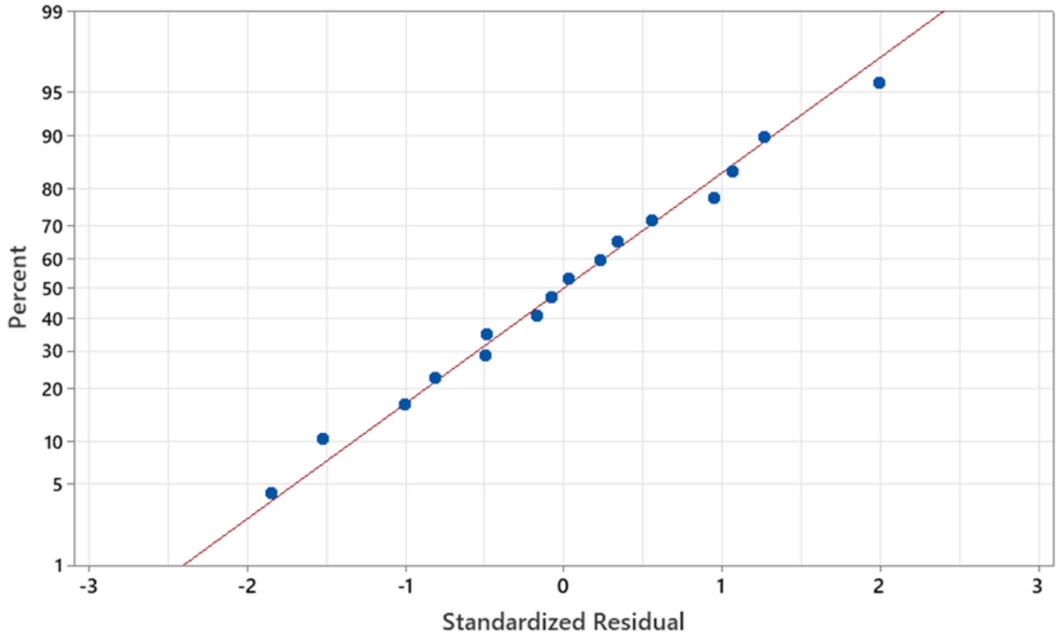

Figure 3. Normal probability plot (response is SN ratios).

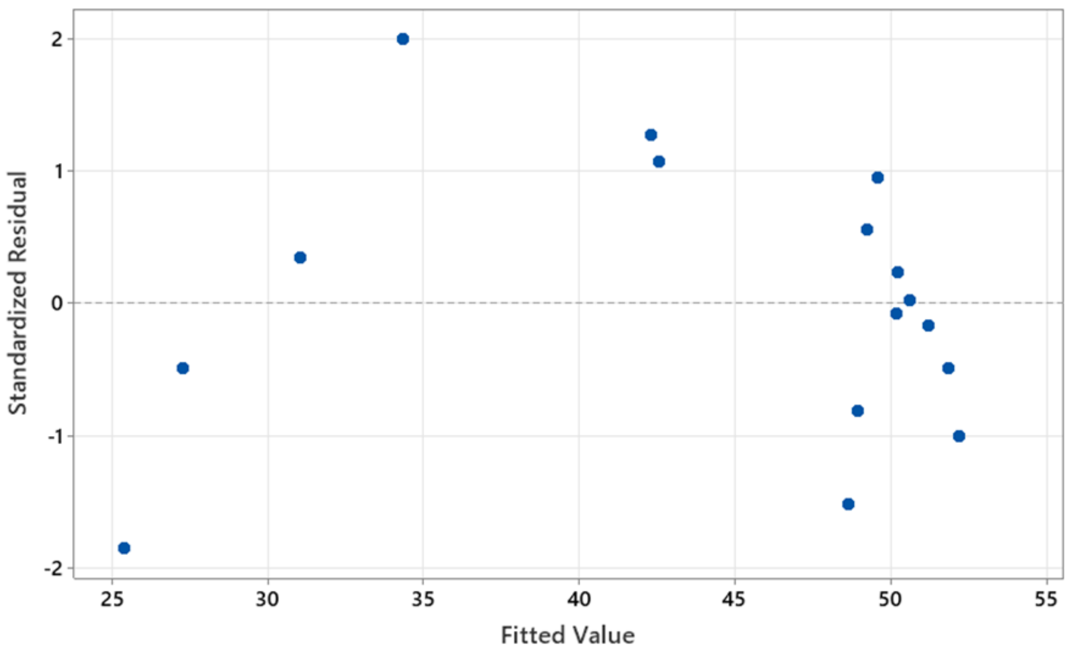

Figure 4. Residuals versus fits (response is SN ratios).

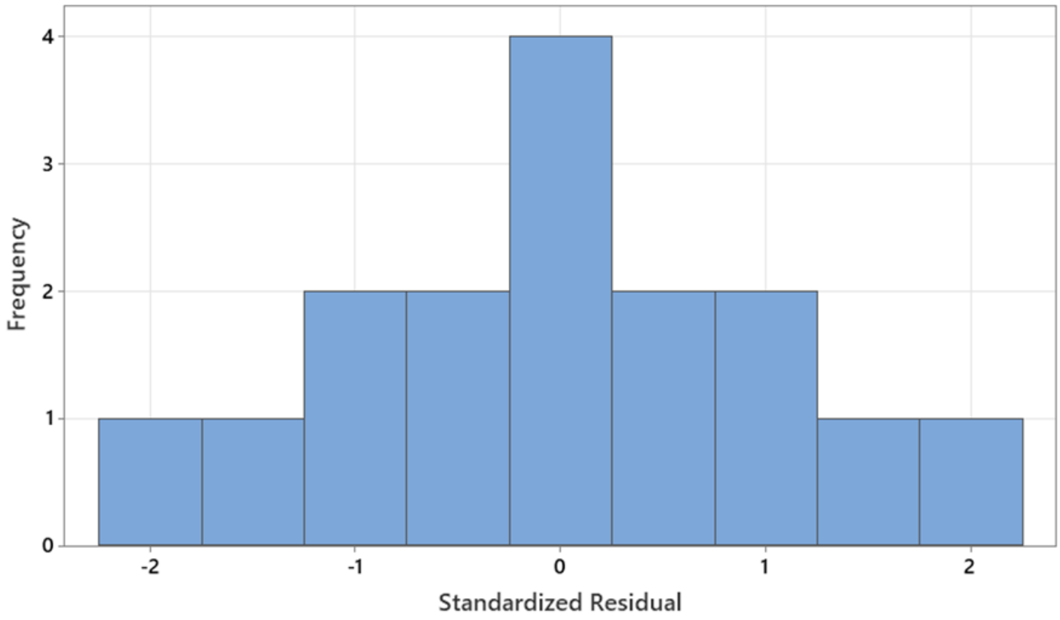

Figure 5. Histogram (response is SN ratios).

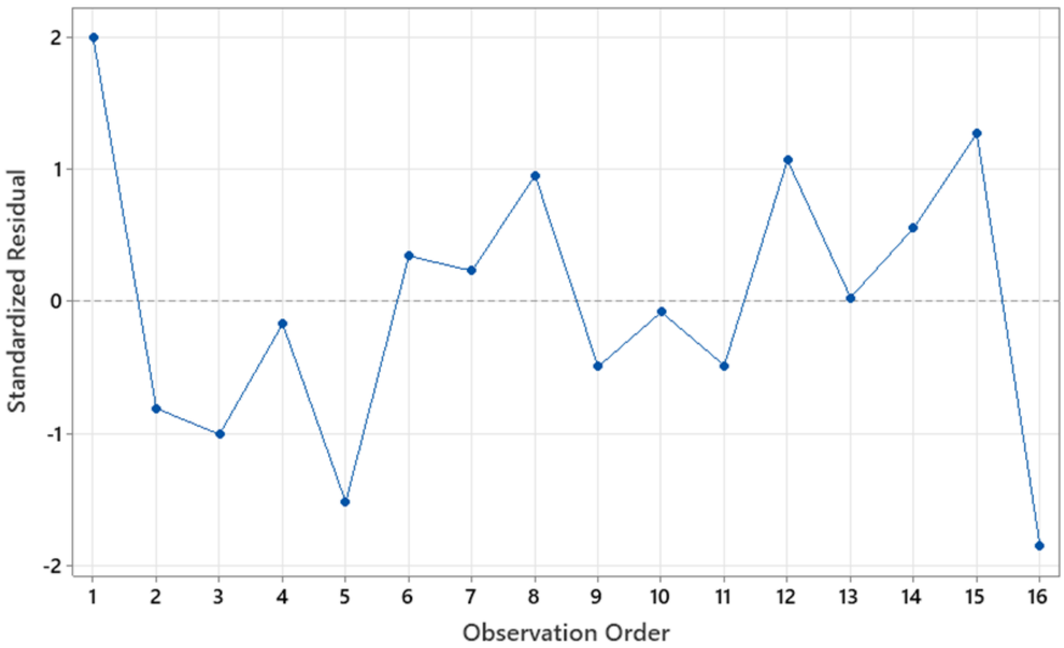

Figure 6. Residuals versus order (response is SN ratios).

Table 6. Predicted and experimentally obtained SN ratio values.

Prediction	**Confirmation**
50.7083	49.9951

5. Conclusions

In this paper, a design of experiment study is presented to set the control parameters of qABC for dynamic deployment problem of WSNs using Taguchi method. In this way, a robust design is aimed while performing a low number of experiments. Analysis results show that the neighborhood radius, colony size and limit effects the response characteristic namely SN ratio, orderly. The optimal levels for these factors are determined as level 1 (20) for colony size, level 1 (1000) for limit and level 3 (3) for neighborhood radius. However, analysis of variance points out that only the effect of the neighborhood radius is statistically significant. Then a comparative study is conducted between the predicted SN ratio of the Taguchi model and the calculated one from the actual observations for the proposed values of the control parameters. Result indicates that these values are very close, and the model reliably predicts the SN ratio.

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