TÜBİTAK

Research Article

The parallel resonance impedance detection method for parameter estimation of power line and transformer by using CSA, GA, and PSO

Bahadır AKBAL∗**, Abdullah ÜRKMEZ**
Department of Electrical and Electronics Engineering, Faculty of Engineering, Selçuk University, Konya, Turkey

Abstract: Power line parameters are an important factor in relay applications and power quality studies. In the literature, the phasor measurement unit method and measuring of current and voltage at two ends of the power line were usually used to estimate the power line parameters. In this study, the parallel resonance impedance detection method was used to estimate the power line parameter to obtain input data. The real measurement values are used to obtain parallel resonance impedance in this method. The real measurement values include the measurement errors of the current and voltage transformer. Thus, the estimated parameter values are realistic. The electrical network with has 27 busbars that belongs to an organized industrial zone in Turkey was used for the application. Harmonic measurement of the power line of the electrical network was made to obtain parallel resonance impedance. The obtained parallel resonance impedance was used in the maximization problem. The maximization problem was defined as the estimated accuracy rate and was solved by using the clonal selection algorithm, genetic algorithm, and particle swarm optimization to make the most realistic parameter estimation. These methods can be defined as parameter estimators and are selected because they are all used widely in electrical engineering problem solutions. The results of these methods were compared with real parameter values, and accuracy of the estimate was determined for each method.

Key words: Clonal selection algorithm, electric network, genetic algorithm, particle swarm optimization, parallel resonance impedance, parameter estimation, power line

1. Introduction

Power line estimation studies were usually made by using the data obtained by measuring current and voltage at two ends of the power line. The obtained data were evaluated by using some estimation algorithms, and power line parameter estimation was made with these methods. The phasor measurement unit (PMU) was widely used to estimate long transmission line parameters [1]. Primarily, the equivalent π circuit was used to model long transmission lines. Use of an equivalent π circuit is a good approach because an equivalent π circuit gives the exact result for a long transmission line. Data of the PMU were obtained by using the ElectroMagnetic Transient Program, and measurement errors of the current transformer and voltage transformer were neglected because the results of the simulation program were used. Current, voltage, and phasor angle were measured at two ends of the line. A line parameter estimation algorithm was combined with PMU configuration. The accuracy of estimation of the algorithm is 99% approximately. This value is very good result, but neglect of measurement errors is wrong. Estimation errors with low values may be due to neglect of measurement errors. If measurement errors of current and voltage transformers increase, the estimation errors of the algorithm

∗Correspondence: bakbal@selcuk.edu.tr

increase. In another study related to parameter estimation [2], an equivalent π circuit was used to model long transmission lines. Measurement error was determined with a formula and it was tried to minimize it. However, no simulation or applications were done. Thus, the accuracy rate of estimation of the algorithm is not known. An equivalent π circuit was applied by using a simulation program to model a transmission line of 220 kV, 300 km in length, and 60 Hz [3]. The obtained data, which were obtained by measuring current and voltage at two ends of the transmission line, were used in the Newton–Raphson method, and estimate error was found to be less than 1%. This result cannot reflect reality because the measurement errors were neglected. Namely, the simulation result was used instead of the real measurement result. PMU-based line and transformer parameter estimations were made in [4]. To obtain data of current and voltage it is necessary to measure at two ends of the line. The obtained data, which are signals of current and voltage, were evaluated by weighted least square estimation method to estimate power line and transformer parameters. The measurement error, which was defined as noise, was added to the signals of current and voltage. It was seen that the estimate error was less than 4% at the end of simulation, but this value may increase when real measurement values are used. Estimations of long transmission line parameters were made for relay application [5]. The equivalent π circuit in the simulation program was used to obtain data of long transmission line parameters. Required data for estimation were obtained from the simulation program. Thus, measurement error was determined by using estimated values (for example, 20%), and estimation error was determined according to this error. It was seen that methods of power line parameter estimates are similar, and a simulation program was usually used to obtain data.

In this paper, usage of parallel resonance impedance of the power line is suggested to obtain data [6–8]. The real measurement values are used to obtain parallel resonance impedance of the power line, and measurement errors are included for estimated results. Therefore, realistic results are obtained. The obtained data are used in the maximization problem. The maximization problem is defined as the estimated accuracy rate and is solved by using the clonal selection algorithm (CSA), genetic algorithm (GA), and particle swarm optimization (PSO). These methods can be defined as parameter estimators and are selected because they are all widely used in electrical engineering problem solutions.

In parameter estimation studies, current and voltage measurement is required at the two ends of the power line to obtain data. This measurement is easy for transmission lines, but it can be difficult for distribution lines because the electrical network of distribution lines can be very complex due to unplanned urbanization. In this case, two ends of the power line cannot be found to measure current and voltage. Although measurements from two ends of the line are needed to obtain data in the literature, harmonic measurement from a single point is enough to obtain parallel resonance impedance in this paper. Although application of the other methods is difficult for distribution lines of complex electrical networks, both transmission lines and distribution lines are compatible with the suggested method. Materials and methods of this paper are explained in detail in Section 2.

2. Materials and methods

The power line of the electrical network was used to obtain real measurement values. The electrical network belongs to organized industrial region in Turkey. A schema of the electrical network is shown in Figure 1. The electrical network includes 27 busbar units. A 28th busbar, which belongs to the factory, will take electrical energy from the electrical line (line 2) that belongs to the 27th busbar of the electrical network. Namely, connection of the factory to line 2 will be made with the 28th busbar from point A. Thus, electrical line parameters of the 27th busbar, power and parameters of the TRB transformer, and electrical line parameters of the 28th busbar must be determined. These parameters are shown in Figure 2. The power line parameters are

defined as the sum of electrical line parameters of the 27th busbar with electrical line parameters of the 28th busbar. Namely, resistance of the power line is R, and $R = R_1 + R_2$. Inductance of the power line is L, and $L = L_1 + L_2$. The power line is shown as the dashed line in Figure 1. Harmonic measurement was made first from A point of line 2 when electricity consumption was highest. The harmonic measurement schema is seen in Figure 3. The results of harmonic measurements made from point A (connection) of line 2 are seen in Figure 4. According to Figure 4, the 7th and 5th harmonics are dominant in the power line. The curve of parallel resonance impedance of the power line was calculated approximately according to Figure 4. This curve is shown in Figure 5. The maximum value of parallel resonance impedance is approximately between 1 and 0.087 ohm. In Figure 5 it is seen that the value of parallel resonance impedance is highest near 350 Hz. It is understood that the 7th harmonic is dominant in the power line. Thus, parallel resonance frequency may be accepted as 350 Hz [6].
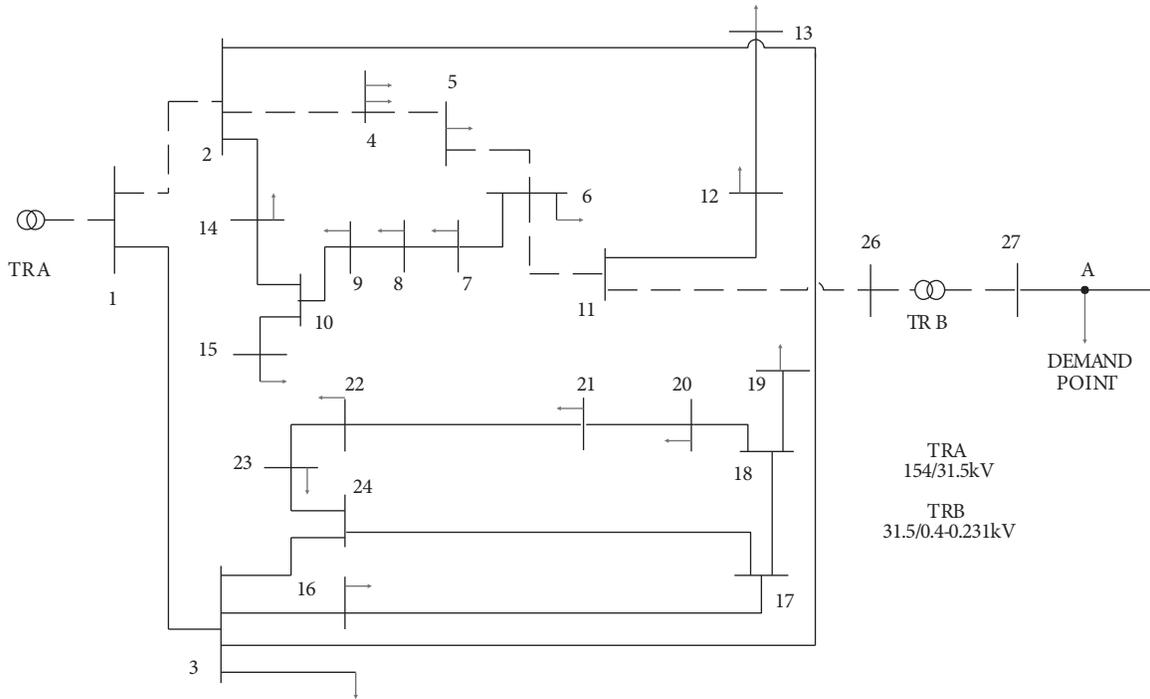
Figure 1. The bus system of the electrical network.
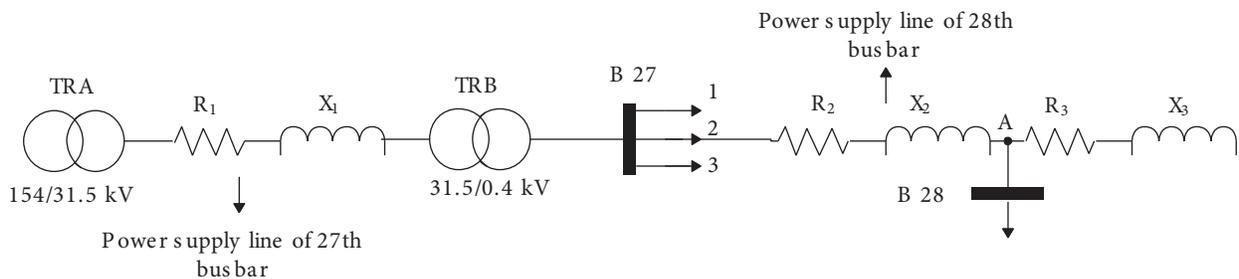
Figure 2. Single-line diagram of the power line.
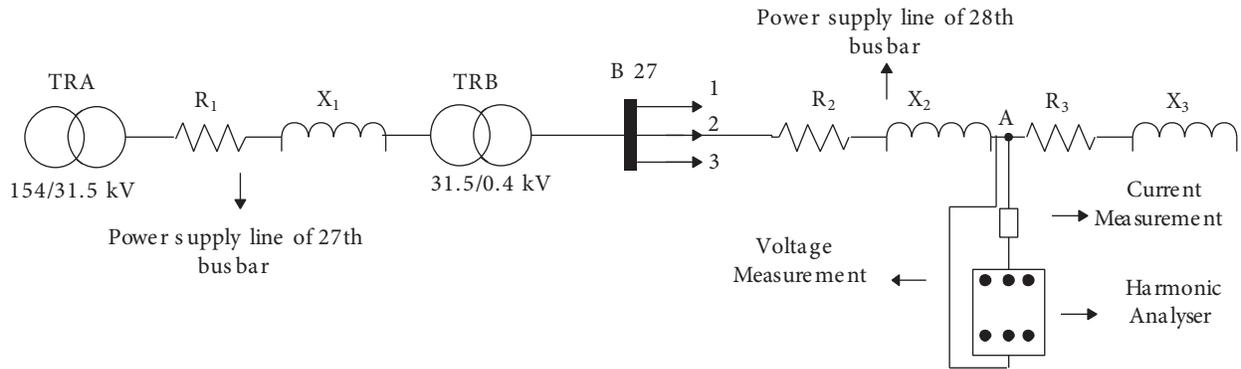
Figure 3. Harmonic measurement from point A.
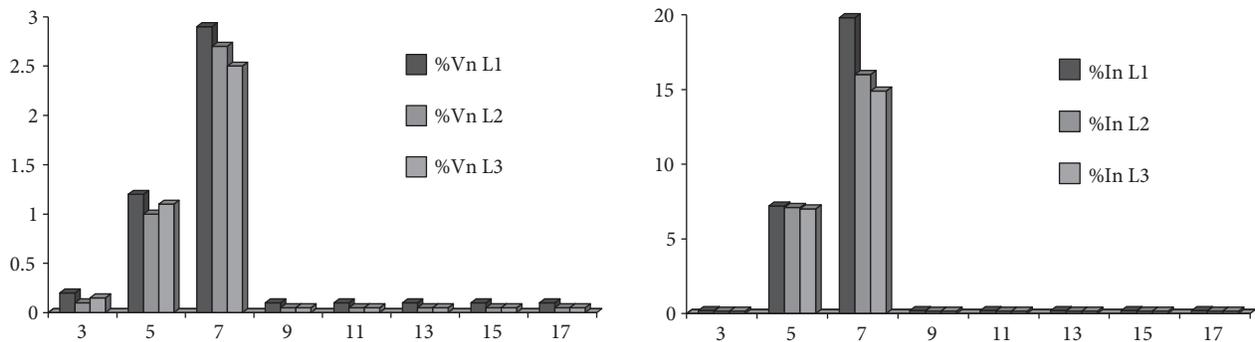
Figure 4. The result of harmonic measurement.
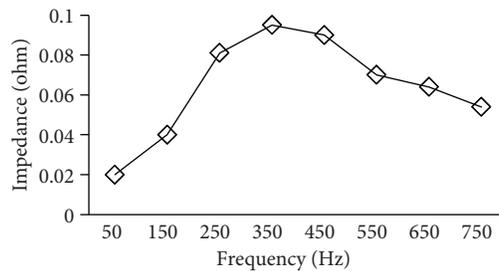
Figure 5. Curve of parallel resonance.

It is known that parallel resonance occurs between the power capacitor and system impedance, so total capacitive power of system must be determined. Capacitive power of the power line was detected by a harmonic analyzer as 250 kVAR at 50 Hz, so the value of the power capacitor in the power line was accepted as 250 kVAR [6].

By using the obtained data, parameters of the power line and TRB were estimated with the CSA, GA, and PSO. The results of these three algorithms were evaluated separately, and an accuracy rate was obtained for each parameter. Primarily, an objective function should be composed to use artificial intelligence techniques. In Section 3, an objective function is composed and an affinity value is calculated.

3. Problem formulation

An objective function is a mathematical model used to solve engineering problems. Figure 6, which shows a single-line diagram of the power line and TRB during parallel resonance, was used to obtain the objective

function, where R is the power line resistance, X_L is inductive reactance of the power line, X_{Tr} is power transformer inductive reactance, X_C is compensation capacitor reactance, and Z_Y is load resistance. Eq. (1) and Eq. (2) are determined with Figure 6. Eq. (1) and Eq. (2) are used to determine the objective function as follows [6]:
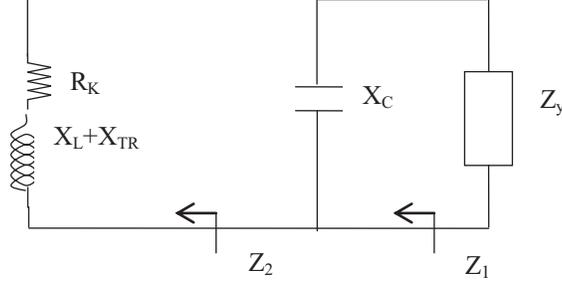
Figure 6. Single-line diagram during parallel resonance.

$$Z_1 = \frac{Z_y x(-jX_C(i))}{Z_y + (-jX_C(i))}(ohm),$$ (1)

$$Z_2(i) = \frac{[R(i) + j(X_L(i) + X_{Tr}(i))] \, x Z_1(i)}{[R(i) + j(X_L(i) + X_{Tr}(i))] + Z_1(i)}(ohm),$$ (2)

$$\begin{aligned} X_L &= 2 \times \pi \times f \times L_h(ohm) \\ X_{Tr} &= 2 \times \pi \times f \times L_{Tr}(ohm) \quad , \\ X_C &= {}^1\!/{(2 \times \pi \times f \times C)}(ohm) \end{aligned}$$ (3)

where L_h is the power line inductance and L_{Tr} is the transformer inductance. C is the capacitance of the power line capacitors. When electrical energy consumption time is high, the power line capacitance is determined with a harmonic analyzer as 0.004975 μF (250 kVAR) at 50 Hz. Parameter borders are L_h: [0–0.0133] H, L_{Tr}: [0–0.006] mH, and R: [0.0025–1.883] ohm. In the CSA and GA, a binary code system was used. L_h is defined with 14-bit binary code, L_{Tr} is defined with 6-bit binary code, and R is defined with 15-bit binary code. Real values were used in PSO. Calculating the sensitivity of the algorithm is called the affinity value. The affinity value is determined with Eq. (4) as follows:

$$Aff.Val. = |Z_{Resonance} - Z(i)|,$$ (4)

where $Z_{Resonance}$ is the calculated resonance impedance after harmonic measurement at the load connection (A) point of the power line is made, and Z(i) is the estimated resonance impedance. The rate of convergence that is the similarity between the estimated value and the real value is defined as the estimation accuracy rate of algorithm. If the estimation accuracy rate is high, the results of the algorithm are close to the real value of the power line parameter. Namely, this process solves the maximization problem. The accuracy rates of the algorithms are calculated with Eq. (12), Eq. (13), and Eq. (14) as follows:

$$Acc_1(i) = \begin{cases} R_r > R(i), \frac{R(i)}{R_r} \\ R_r < R(i), \frac{|2xR_r - R(i)|}{R_r} \end{cases} \quad ,$$

$$Acc_2(i) = \begin{cases} L_h > L_h(i), \frac{L_h(i)}{L_h} \\ L_h < L_h(i), \frac{|2xL_h - L_h(i)|}{L_h} \end{cases},$$

$$Acc_3(i) = \begin{cases} L_{tr} > L_{tr}(i), \frac{L_{tr}(i)}{L_{tr}} \\ L_{tr} < L_{tr}(i), \frac{|2xL_{tr} - L_{tr}(i)|}{L_{tr}} \end{cases},$$

where R_r is the real value of the power line resistance, and R(i) is the estimated power line resistance. L_h is the real value of the power line inductance, and $L_h(i)$ is the value of the estimated power line inductance. L_{Tr} is the real value of TRB inductance, and $L_{Tr}(i)$ is the value of the estimated TRB inductance. Resistance of TRB was neglected. Acc_1 is defined for the power line resistance estimation accuracy rate, Acc_2 is defined for the power line inductance estimation accuracy rate, and Acc_3 is defined for the TRB inductance estimation accuracy rate. Acc_1, Acc_2, and Acc_3 will be determined separately for each algorithm.

Total accuracy rate is defined only to compare the results of the algorithms. Namely, the total accuracy is not defined as the accuracy rate of algorithm. Total accuracy is calculated via Eq. (5) for this study.

$$Acc(i) = \frac{Acc_1(i) + Acc_2(i) + Acc_3(i)}{3} \qquad (5)$$

In other studies related to parameter estimation with parallel resonance impedance, Acc_1, Acc_2, and Acc_3 were not indicated [7,8], and only the total accuracy rate of the algorithm was determined. Therefore, these studies' results cannot be compared with other literature, and in this case, the algorithm sensitivity cannot be determined exactly.

4. Artificial intelligence methods

4.1. Clonal selection algorithm

The CSA is based on relationships between an antibody and antigen. The optimum value of the function is defined as the antigen, and to find the optimum value of the function the antibody is used. The ith antibody can be defined as $Ab_i = (ab_{i1}, ab_{i2}, ab_{i3}, ..., ab_{iD})$, and the antigen can be defined as $Ag_i = (ag_{i1}, ag_{i2}, ag_{i3}, ..., ag_{iD})$.

Cloning and mutation operators are important in the CSA. In the cloning process, antibodies are multiplied by multiplying coefficients. Multiplying coefficients are determined according to affinity of the antibody. The mutation process is done by mutation coefficient. The mutation coefficient is inversely proportional to the affinity of the antibody.

The CSA flow chart is shown in Figure 7 [9,10].

1. The antibody population occurs randomly. Bits of antibody occur from bits of R, L_h, and L_{tr}.

2. The fitness value is calculated by objective function for each antibody in the antibody population (P). Namely, parallel resonance impedance is calculated. The fitness value of the antibody determines the affinity value.

3. The selection process of the best antibodies is made according to affinity value, and population P_n is created.

4. The cloning operation is applied to antibodies that are selected in the selection process and the C population is created.

5. The mutation operation is implemented for the C population to provide a variety of antibodies, and a mutated antibody pool (C_1) is created.

6. The antibody's fitness value is calculated by objective function for each antibody in the antibody population (C_1).

7. If the affinity value of the antibody is not good, this antibody is eliminated in the mutated antibody population (C_1).

8. The antibody selection process is applied to C_1, and the antibody population is updated according to new antibodies.
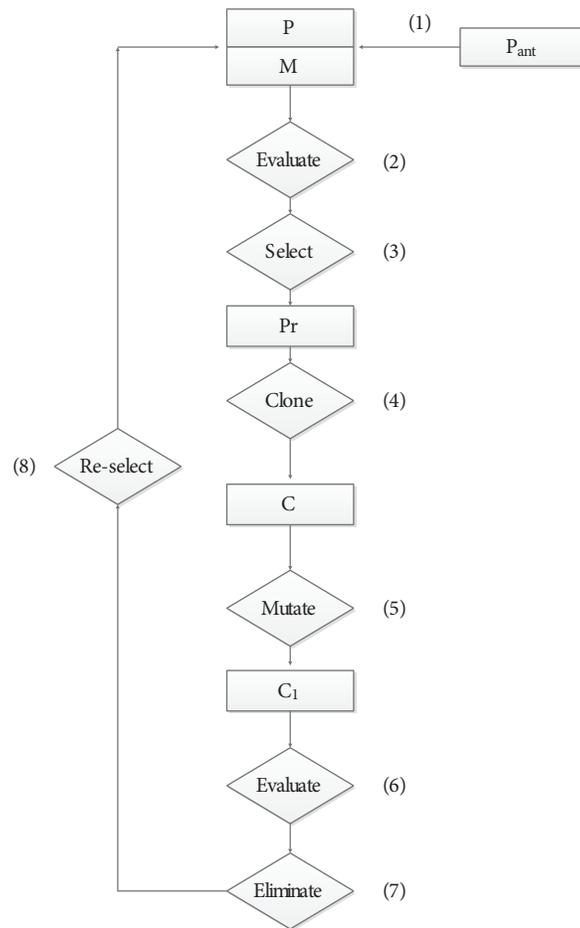
Figure 7. Flow chart of the CSA.

A new antibody population is created after this process finishes. This process continues until we find the best result, or the maximum iteration number.

4.2. Genetic algorithm

The GA is based on relationships between chromosomes and genes. Primarily, a chromosome population occurs randomly. An optimum solution is sought in the chromosome population. The most important operators of

the GA are crossover and mutation. Crossover and mutation are used to ensure diversity in the chromosome population. Chromosomes that will be selected for crossover operation are determined by the crossover ratio. The crossover ratio is determined between 0 and 1. Genes that will be selected for mutation operation are determined by the mutation ratio. The mutation ratio is determined between 0 and 1. These two operators work randomly.

In Figure 8 the working principle of the GA is shown, as follows [11]:
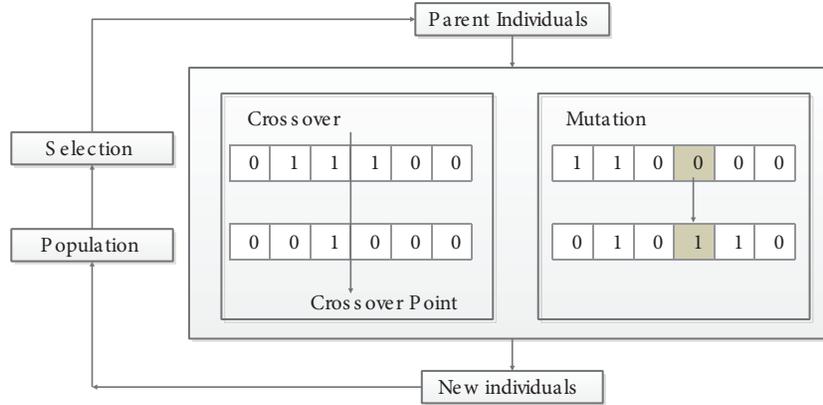
Figure 8. Flow chart of the GA.

1. The chromosome population occurs randomly. Genes are bits of R, L_h, and L_{Tr}.

2. The fitness value of the chromosome is calculated by objective function, and the affinity value is calculated. The chromosome selection process for crossover operation is done according to the affinity value. In this study, a tournament selection method was used as the selection process, and the selection population occurred for crossover.

3. Crossover is made after the selection process. Crossover is the mutual exchange of genes between two selected chromosomes and is made according to the crossover rate (P_c). The number is produced randomly between 0 and 1 for any chromosome that will be selected for crossover. If the number is less than P_c, this chromosome is selected for crossover.

4. Mutation is made when radical change is needed in genes. Mutation provides variation in the population and is made according to the mutation rate. The number is produced randomly between 0 and 1 for any bit that will be selected for mutation. If the number is less than the mutation rate, this bit is selected for the mutation process. If the value of the bit is 1, the value of the bit is changed to 0. If the value of the bit is 0, the value of the bit is changed to 1.

4.3. Particle swarm optimization

PSO is an algorithm based on swarm intelligence. Each individual in PSO is defined as a particle. Each particle has position and velocity. There are not cloning, crossover, or mutation operators in PSO. To find the optimum result, the swarm moves through the search space according to the position of particles. If thr swarm consist of i unit particles in D dimensional space, the ith particle position is defined as $X_i = (x_{i1}, x_{i2}, x_{i3}, ..., x_{iD})$, and velocity is defined as $V_i = (v_{i1}, v_{i2}, v_{i3}, ..., v_{iD})$. Each particle has a memory. Memory is defined as $p_{best} = (p_{best1}, p_{best2}, p_{best3}, ..., p_{best.i})$. The best previous position of the particle is saved in the memory at the

end of iteration. The best position is selected in the swarm at the end of the iteration. This position is defined as $g_{best_i} = (g_{i1}, g_{i2}, g_{i3}, ..., g_{iD})$. The optimum result is sought according to g_{best} and p_{best}. Velocity of each particle is updated with Eq. (6) and the position of each particle is updated with Eq. (7) as follows [12]:

$$v_{id}(t+1) = v_{id}(t) + c_1 \times r_1(pbest_{id} - x_{id}) + c_2 \times r_2(gbest_{id} - x_{id}), \tag{6}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1), \tag{7}$$

where r_1 and r_2 are random numbers between 0 and 1, and c_1 and c_2 are learning coefficients and are usually selected as $c_1 + c_2 > 4$. Particles are directed with these coefficients towards p_{best} and g_{best}.

In this study, the algorithm works as follows [13]:

1. In the first iteration, positions of particles are determined randomly, and the value of the velocity is zero. Each particle occurs from real values of R, L_h, and L_{Tr}.

2. The fitness value of the position of a particle is calculated with an objective function. Quality of particle position is determined with the affinity value after the fitness value of each particle is calculated. The best position is determined according to the affinity value of particles. The best position of a particle is stored in p_{best}. Current affinity value of a particle is compared with the best previous affinity value of the particle in p_{best} at the end of the iteration. If the current affinity value of the particle is better than the best previous affinity value of the particle, $p_{best}(i,d) = x(i,d)$. Otherwise, $p_{best}(i,d)$ does not change. Also, in the first iteration, $p_{best}(i,1) = x(i,1)$.

3. The best particle in p_{best} is called g_{best}.

4. If an optimum solution is found, the program is stopped and g_{best} is saved. Otherwise, a new position and new velocity is calculated for each particle according to g_{best}. Namely, particles are updated according to g_{best}, and we go to the 2nd step. This process continues until the maximum iteration number or optimum value.

5. The application and the results

The 28th busbar, which belongs to the electric supply of the factory, will be connected to line 2 of the 27th busbar of the electrical network. Parameters of the power line and TRB transformer are known. However, it was assumed that these parameters were not known, and these parameters were estimated using artificial intelligence methods. In this section, parameter estimation is made using the CSA, GA, and PSO. Population size, iteration number, and required coefficient values are shown in Table 1 for each algorithm. The results of the CSA, GA, and PSO are shown in Table 2. The estimated values of parameters and values of Acc_1, Acc_2, and Acc_3 are also shown in Table 2. Total accuracy rate of the CSA, GA, and PSO were determined and were used to compare these algorithm results.

Table 1. Algorithms parameters values.

Parameter value					
CSA		GA		PSO	
Parameter	value	Parameter	value	Parameter	value
Population size	100	Population size	100	Population size	100
Iteration number	100	Iteration number	100	Iteration number	100
Multiplying coefficient	100	Crossover rate	0.7	C_1 coefficient	3
		Mutation rate	0.001	C_2 coefficient	1

Table 2. The estimation results of the algorithms.

The estimated results			
Parameter	CSA	GA	PSO
Line resistance (ohm)	1.85	1.66	0.88
Acc_1 (%)	97.8	92.2	48.9
Transformer inductance (H)	2.44e-5	2.5e-5	2.43e-5
Acc_2 (%)	99.6	98	99
Line inductance (H)	0.0132	0.0113	0.0130
Acc_3 (%)	99.2	85	97.7
Power transformer (kVA)	1250	1250	1250
Total accuracy rate (%)	98.68	91.63	81.86

5.1. The results of the CSA

Input data for the algorithm were obtained from real measurement values. Real measurement values contain the measurement errors of the current transformer and voltage transformer. Low error rate results were obtained with the CSA. The results of the CSA are shown in Table 2. When Acc_1, Acc_2, and Acc_3 are evaluated, estimation errors can be seen as less than 1%. The results are realistic according to the results of the literature because real measurement values were used as input data. Total accuracy rate was found as 98.68%, and change of total accuracy rate according to iteration number is shown for the CSA in Figure 9.

5.2. The results of the GA

Real measurement values were used as input data to obtain GA results. Values of the estimated parameters and accuracy rate are shown in Table 2. When Acc_1, Acc_2, and Acc_3 are evaluated, the estimation errors are high compared to CSA results. Total accuracy rate is 91.63%, and change of total accuracy rate according to iteration number is shown for the GA in Figure 10. The estimation errors are slightly high, but it is realistic.
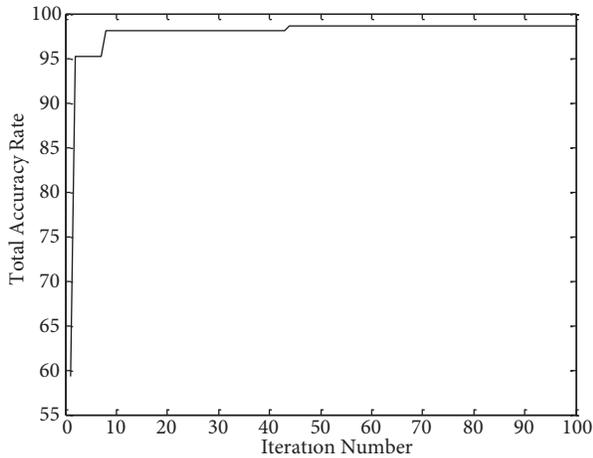
Figure 9. Total accuracy rate of the CSA.
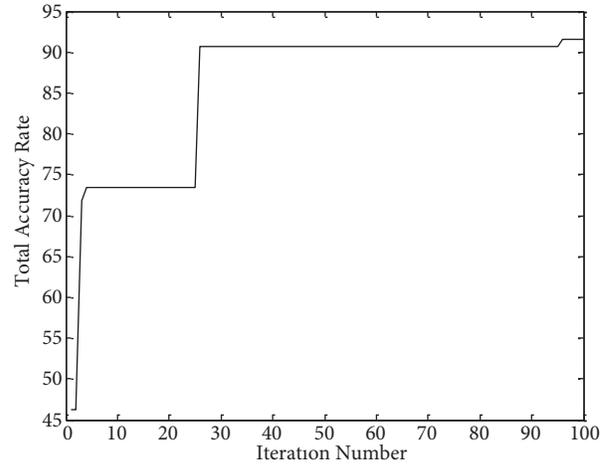
Figure 10. Total accuracy rate of the GA.

5.3. The results of PSO

Parameter estimation was made by using the PSO algorithm. Real measurement values were used as input data for PSO. Parameter estimation results are shown in Table 2. The PSO algorithm's speed is very good compared

to the other algorithms. When Acc_1, Acc_2, and Acc_3 are evaluated, estimation errors are high compared to the other algorithms. Total accuracy rate is 89.76%, and change of total accuracy rate according to iteration number is shown for PSO in Figure 11. The results of the GA and CSA are better than the results of PSO.
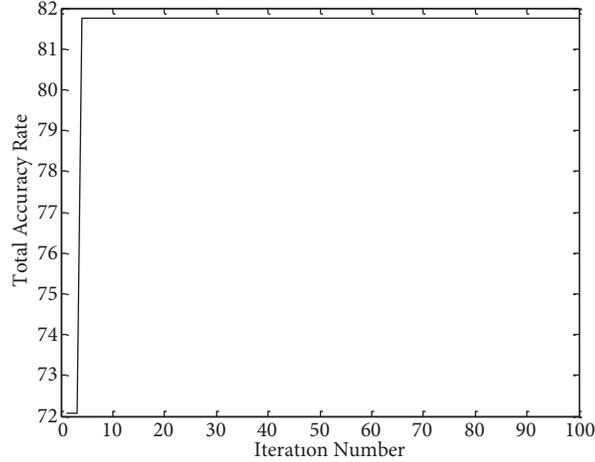
Figure 11. Total accuracy rate of PSO.

6. Conclusion

In this paper, usage of parallel resonance impedance was proposed as an input parameter for parameter estimation of the power line and supply transformer. Primarily, harmonic measurement must be made to obtain parallel resonance impedance. Harmonic measurement from a single point, which is the factory (new load) connection point, is enough to obtain data. This method provides convenience for complex electrical networks. Namely, this method is suitable for applications of transmission lines and distribution lines.

The parameter estimation problem was defined as the maximization problem in this study, and the CSA, GA, and PSO were used to solve the maximization problem. The CSA, GA, and PSO can also be defined as parameter estimators. The maximization problem was defined as the maximization of Acc_1, Acc_2, and Acc_3. The total accuracy rate was defined to compare the results of the algorithms. When total accuracy rates of the algorithms were compared, the accuracy rate of the CSA was higher than the other algorithms, but the algorithm speed of the CSA was lower than the other algorithms. Although the total accuracy rate of PSO was lower than the other algorithms, its algorithm speed was higher than the other algorithms. When Acc_1, Acc_2, and Acc_3 of the CSA were evaluated, it was seen that the results of the CSA are good and realistic according to the literature.

Short-circuit current, voltage drop, and power loss must be compared according to the estimated parameters. The real short-circuit current was found as 3.04 kA. When the estimated parameters of the CSA were used to calculate short-circuit current, it was found as 3.03 kA. This result is closest to the real value. When the results of the GA and PSO were used, short-circuit current was found as 3.5 kA and 3.61 kA, respectively. These results are larger than the real value. If the results of the GA and PSO are used, cost of protection elements can increase. This is unnecessary. In the relay applications, if GA short-circuit current or PSO short-circuit current is used as the relay set current, the relay cannot properly work because the real value is lower than the value of the GA and PSO. Thus, the relay does not feel the short-circuit current, and the circuit breaker does not cut the short-circuit current during short circuit.

When the result of the CSA was used to calculate voltage drop and power loss, the results were closest to

the real value. When the results of the GA and PSO were used, voltage drop and power loss were found lower than the real value. GA and PSO results are misleading, and if these results are used, extreme voltage drop and power loss may occur in the real application. Thus, power quality of the power line would be reduced.

The estimated parameter values of the CSA are realistic because the real measurement values that include measurement error were used. Transformer power was detected as well, so the amount of loads that will be connected to the electric line can be adjusted according to the power capacity of transformer.

References

[1] Jiang J, Yang J, Lin Y, Liu C, Too T. An adaptive PMU based fault detection/location technique for transmission lines—Part II: PMU ımplementation and performance evaluation. IEEE T Power Deliver 2000; 15: 1136–1146.

[2] Liao Y. Algorithms for power system fault location and line parameter estimation. In: 39th Southeastern Symposium on System Theory; 4–6 March 2007; Macon, GA, USA. New York, NY, USA: IEEE. pp. 189–193.

[3] Indulkar CS, Ramalingam K. Estimation of transmission line parameters from measurements. Int J Elec Power 2008; 30: 337–342.

[4] Borda C, Olarte A, Diaz H. PMU-based line and transformer parameter estimation. In: PSCE '09 IEEE/PES Power Systems Conference and Exposition; 15–18 March 2009; Seattle, WA, USA. New York, NY, USA: IEEE. pp. 1–8.

[5] Liao Y, Kezunovic M. Online optimal transmission line parameter estimation for relaying applications. IEEE T Power Deliver 2009; 24: 96–102.

[6] Akbal B. The measurement of harmonic in factory supply and design of harmonic filters. MSc, Selçuk University, Konya, Turkey, 2011.

[7] Akbal B, Ürkmez A. Detection of the most suitable method to estimate short-circuit parameter's values of the electric facility. In: International Conference on Electronics Computer and Computation; 1–3 November 2012; Ankara, Turkey. pp. 202–206.

[8] Akbal B, Ürkmez A. PSO and CSA to estimate of parameter in power line. In: 5th International Conference on Electronics, Computers and Artificial Intelligence (ECAI 2013); 27–29 June 2013; Pitesti, Romania. New York, NY, USA: IEEE. pp. 1–6.

[9] Wang X. Clonal selection algorithm in power filter optimization. In: IEEE Mid-Summer Workshop on Soft Computing in Industrial Applications; 28–30 June 2005; Espoo, Finland. New York, NY, USA: IEEE. pp. 1–6.

[10] Akbal B, Ürkmez A. Clonal selection algorithm to reduce parallel resonance effect in electrical networks. In: International Symposium on Innovations in Intelligent Systems and Applications; 2–4 July 2012; Trabzon, Turkey. New York, NY, USA: IEEE. pp. 1–5.

[11] Aydın İ, Karaköse M, Akın E. The fault diagnosis model based on artificial immune system using genetic algorithm. Dokuz Eylül University Journal of Engineering Sciences 2009; 11: 58–72.

[12] Valle Y, Venayagamoorthy GK, Mohagheghi S, Hernandez JC, Harley RG. Particle swarm optimization: basic concepts, variants and applications in power systems. IEEE T Power Deliver 2008; 12: 171–194.

[13] Akbal B, Ürkmez A. PSO and inertia weight to determine parallel resonance power in electrical networks. In: 5th International Conference on Electronics, Computers and Artificial Intelligence (ECAI 2013); 27–29 June 2013; Pitesti, Romania. New York, NY, USA: IEEE. pp. 13–18.