Available online www.jsaer.com

***Journal of Scientific and Engineering Research*, 2018, 5(12):147-157**

Research Article

ISSN: 2394-2630
CODEN(USA): JSERBR

A novel multilevel threshold-optimization method to detect ice load of overhead lines in real ambient conditions

Bahadır AKBAL

Department of Electrical & Electronics Engineering, Faculty of Engineering, Selçuk University, Konya, Turkey

Abstract Ice load faults cause destructive effect on overhead lines. Ice load occurs cold and heavy fog ambient conditions, and these conditions generally occur in the night. Ice load detection studies are made to prevent ice load faults, and image processing methods are used in ice load detection studies. If image processing is used for ice load detection, dark and heavy fog ambient conditions must be considered because ice load generally occur in the night and under heavy fog ambient conditions. In literature, multilevel threshold methods are used with optimization methods to detect ice load under dark and heavy fog ambient conditions, and 20 level CSA-Otsu method is specified as the best method, but local optimum falling problems occur because of high threshold levels. Hence image processing faults occur due to local optimum falling problems. In this study, ice load detection studies are made for overhead lines under dark and heavy fog ambient condition, and three different multilevel threshold methods are used with three different optimization methods to prevent local optimum falling problems. The local optimum problems are solved by using 5 level GA-Ramesh Method, and its accuracy rate is 99.6%.

Keywords Clonal Selection Algorithm (CSA), Genetic Algorithm (GA), local optimum falling, multilevel threshold, ice load detection, image processing, optimization methods.

1. Introduction

Transmission and distribution of electrical energy are generally made by overhead lines. For example, overhead distribution line length is 969.237,4 km according to TEDAŞ (Turkish Electricity Distribution Company) data, and overhead transmission line length is 53.709,3 km according to TEİAŞ (Turkish Electricity Transmission Company) data in Turkey. Therefore overhead line faults arean important issue for continuity of electrical energy. Causes of overhead line faults generally originate from environmental factors, and ice load is one of the most important factors among these environmental factors. For example, In 2012 year, 122 unit electric poles of distribution line overturned because of ice load in Turkey/Adıyaman. Alsovarious ice load faults are encountered every year in Turkey and world.In Figure 1, an ice load fault which occurred in 2014 in Turkey/Kırşehir is shown. This ice load fault belongs to a overhead distribution line. This distribution line voltage is 31.5 kV, and its conductor is 1/0 AWG (Raven). In literature, there are many ice load detection studies. Image processing, capacitive sensor, meteorological sensors, load sensors and meteorological data of the past years were used for ice load detection studies. In load sensor application, load sensor was mounted on insulator of transmission line, and ice load weight was measured, so ice load was estimated. However, application of this method is very difficult for the current overhead lines. Also accuracy rate of this method was not explained [1]. Meteorological data of the past years were used with BP Neural Network to estimate ice load. Resulting error of this method was found as 200 kg [2]. This error cannot be accepted for ice load detection studies. Meteorological data which are obtained from meteorological sensors were send to an expert software by using GSM, Zigbee and SMS, but the accumulated ice load was not explained [3]. Capacitive sensor was used to measure ice load thickness, but the accuracy rate of this method was not explained [4]. In Canada and China, the major ice load faults occur every year. For example, the major ice load faults occurred in Zhaotong area, Yunnan Province, South China, and Modified hidden semi-Markov model (HSMM) was used to estimate ice load [5]. Also mechanical calculation model was used to detect ice load [6]. Image processing is an easy and inexpensive method for all overhead lines. If image processing is used to detect ice load, ambient conditions are considered because ice load generally occurs at night and under heavy fog ambient conditions [7]. Image segmentation and edge detection methods are basic functions of image processing. Sobel Algorithm and Hough transform were used as edge detection in ice load studies, but dark and heavy fog ambient conditions were not conditions [8]. Classification methods are used in image processing studies. Support Vector Machine (SVM) is a classification method. SVM and mathematic morphology were used to detect the iced conductor image. However, this study was not made under dark and heavy fog ambient conditions [9]. Line search algorithm was used for ice load detection studies. The estimation error of this method was found only 2 pixels. Namely, accuracy rate of this method is very well, but this study was not made under dark and heavy fog ambient conditions [10]. Multilevel threshold methods were used with artificial intelligence methods in ice load detection studies for transmission line. Otsu and Kapur methods were generally used as multilevel threshold method. Clonal Selection Algorithm (CSA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) were generally used as artificial intelligence methods. In [11,12,13], dark and heavy fog ambient conditions were not considered. In [14,15,16], dark and heavy fog ambient conditions were considered, but accuracy rate of these methods were not indicated. In [17], ice load detection studies were made under dark and heavy fog ambient conditions to detect ice load of transmission lines, also accuracy rate of these methods were indicated. 20 level CSA-Otsu Method is suggested for ice load detection studies in [17] because the result of 20 level CSA-Otsu Method is better than the results of other methods, and its accuracy rate is 99.1%. This accuracy rate is very well. However local optimum falling problems occurred in [17] because of 20 level threshold. Hence image processing faults occurred, and ice load detection program was interrupted by local optimum falling problems.

Figure 1: Pole of overturned distribution line in Turkey

It is seen that dark and heavy fog ambient conditions, accuracy rate of the proposed method and local optimum fallings are important problems for ice load detection studies. In this study, Ramesh method was improved and used as a new multilevel threshold method, and it was used with optimization methods to solve these problems. Also Ramesh method results were compared with the results of Otsu and Kapur method. So far, Ramesh method was used for bi-level threshold studies in literature. In this study, Ramesh method was improved to use in multilevel threshold method studies. Clonal Selection Algorithm (CSA), Genetic Algorithm (GA), Particle Swarm Optimization (PSO) were used as optimization methods.

The remainder of the paper is organised as follows. In materials and methods section, ice load detection methods are explained. In ice load detection methods, multilevel threshold methods are formulated, and algorithms of optimization methods are introduced shortly. In the In results and discussion section, the results of CSA-Otsu, CSA-Kapur, CSA-Ramesh, PSO-Otsu, PSO-Kapur, PSO-Ramesh, GA-Otsu, GA-Kapur, GA-Ramesh methods are shown in Table 2, Table 3 and Table 4 for ice load detection studies, and the results of these methods are compared.

2. Materials and methods

In this study, primarily ice load faults were examined in Turkey, and ambient conditions of these faults were taken in Turkish State Meteorological Service Archive. These ambient conditions were created in an artificial climate cabinet (ACC) to create ice load on 1/0 AWG (Raven) overhead distribution line conductor in laboratory. ACC was designed especially for ice load studies in this study. In ACC, temperature can be adjusted between 50 ˚C and -10 ˚C, humidity can be adjusted between 0% and 99.9% and wind speed can be adjusted between 0 m/s and 10 m/s. Also dark and heavy fog ambient conditions were created in ACC. ACC is shown in Figure 2, and a sample iced 1/0 AWG (Raven) overhead distribution line conductors in ACC are shown in Figure 3. Where, diameter of Raven conductor is 1 cm.

In this study, image processing was used to detect the iced conductor thickness. Causes of usage of image processing for ice load detection studies is sorted as follows:

- Application of image processing is an easy, inexpensive and compatible application for all overhead lines.
- Accuracy rate of image processing is better than the other method in literature.
- The results of image processing are confidential, rapid and stable.

A night vision outdoor camera was used to take the iced conductor image. This camera was placed inside of ACC, and the iced conductor image was taken under dark and heavy fog ambient conditions. The taken iced conductor image is shown in Figure 4. The ice load occurred under -2°C, 99% humidity in 23 hours. It is seen in Figure 4 that dark and heavy fog conditions reduce the iced conductor image contrast. Hence multilevel threshold methodsare used as image processing method. In this study three different multilevel threshold method are used. These methods are Otsu, Kapur and Ramesh methods. Otsu method is based on gray level clustering, Kapur method is based on histogram entropy, and Ramesh method is based on histogram shape. Gray level histogram of the iced conductor image must be obtained before multilevel threshold are used. Gray level histogram of the iced raven conductor is shown in Figure 5.

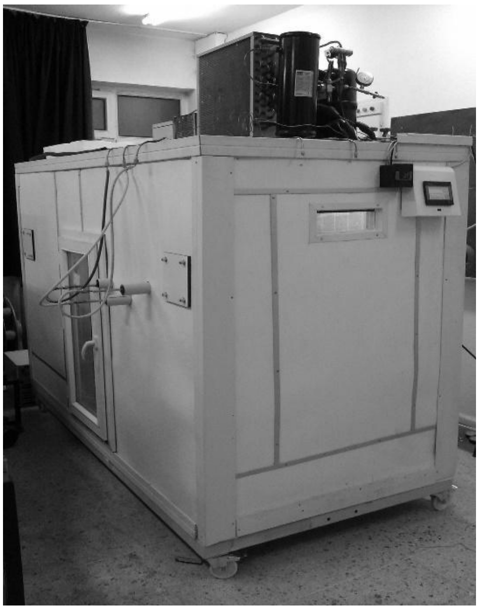

Figure 2: The artificial climate cabinet

Figure 3: The iced conductor in ACC

Figure 4: The iced conductor in ACC under dark and heavy fog ambient conditions

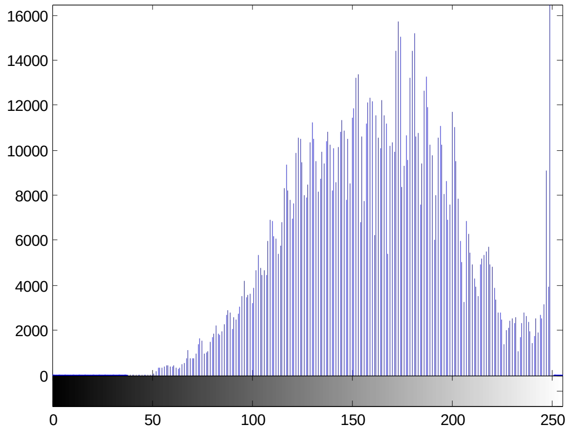

Figure 5: Gray level histogram of the iced conductor

2.1. Otsu Method

Otsu indicated variance of between classes for image segmentation. In this method, variance of different classes must be a maximum value. If an image is divided as two classes, these classes can be defined as C_0 and C_1. If threshold level of C_0 and C_1 is determined as t, C_0 includes the gray level from 0 to t-1, and C_1 includes the Gray level from t to L. Gray level probabilities are defined as w_0 and w_1, and distribution of Gray level probability of classes as follows [18] ;

$$C_0 = \frac{P_0}{w_0}, ..., \frac{P_{t-1}}{w_{t-1}} \text{ and } C_1 = \frac{P_t}{w_t}, ..., \frac{P_L}{w_L} \tag{1}$$

$$w_0 = \sum_{i=0}^{t-1} P_i \text{ and } w_1 = \sum_{i=t}^{L} P_i \tag{2}$$

The mean levels of classes are defined as μ_i. The mean level of image is defined as μ_T.

$$\mu_0 = \sum_{i=0}^{t-1} \frac{i.P_i}{w_0} \text{ and } \mu_1 = \sum_{i=t}^{L} \frac{i.P_i}{w_1} \tag{3}$$

$$\mu_0.w_0 + \mu_1.w_1 = \mu_T \text{ and } w_0 + w_1 = 1 \tag{4}$$

Otsu's method is described as follows;

$$f(t) = \sigma_0 + \sigma_1 \tag{5}$$

$$\sigma_0 = w_0.(\mu_0 - \mu_T)^2 \text{ and } \sigma_1 = w_1.(\mu_1 - \mu_T)^2 \tag{6}$$

In bi-level threshold studies, optimal threshold level (t) is determined by Otsu method as follows;

$$t = \arg\max\{f(t)\} \tag{7}$$

Multilevel thresholding of an image can be extended to determine the variance between classes function.

$$f(t) = \sum_{i=0}^{m} \sigma_i \tag{8}$$

The number of threshold is m ($t_0, t_1, t_2, \ldots, t_m$), and the number of classes in the original image is m ($C_0, C_1, C_2, \ldots C_m$).

Where $$f(t) = \sigma_0 + \sigma_1 + \sigma_2 + \ldots + \sigma_m \tag{9}$$

$$\begin{aligned} \sigma_0 &= w_0.(\mu_0 - \mu_T)^2 \\ \sigma_1 &= w_1.(\mu_1 - \mu_T)^2 \\ \sigma_2 &= w_2.(\mu_2 - \mu_T)^2 \ldots \\ \sigma_m &= w_m.(\mu_m - \mu_T)^2 \end{aligned} \tag{10}$$

The optimum threshold levels ($t_0, t_1, t_2, \ldots, t_3$) are determined as follows ;

$$(t_0, t_1, t_2, \ldots, t_m) = \arg\max\{f(t)\} \tag{11}$$

2.2. Kapur Method

Kapur indicated maximum entropy method for image segmentation. After Gray level histogram of image is obtained, the optimal threshold value can be obtained. Images are indicated with L gray levels (0, 1,...,L-1). i-th probability is defined as p(i) as indicated in [19,20];

$$p(i) = \frac{h(i)}{\sum_{i=0}^{L-1} h(i)} \tag{12}$$

h(i) is defined as the number of pixels of gray-level i. Kapur entropy can be described for bi-level threshold as follows:

$$H(0) = -\sum_{i=0}^{t-1} \frac{p(i)}{\omega_0} \ln \frac{p(i)}{\omega_0}, \quad \omega_0 = \sum_{i=0}^{t-1} p(i) \tag{13}$$

$$H(1) = -\sum_{i=t}^{t-1} \frac{p(i)}{\omega_1} \ln \frac{p(i)}{\omega_1}, \quad \omega_1 = \sum_{i=t}^{L-1} p(i) \tag{14}$$

If the sum of the class entropies is maximum, the threshold level is optimum. This case is shown in Equation (15):

$$t = \arg\max(H_0 + H_1) \tag{15}$$

Multilevel threshold can be made with Kapur entropy when Equation (16) is used.

$$H(0) = -\sum_{i=0}^{t_1-1} \frac{p(i)}{\omega_0} \ln \frac{p(i)}{\omega_0}, \omega_0 = \sum_{i=0}^{t_1-1} p(i)$$
$$H(1) = -\sum_{i=t_1}^{t_2-1} \frac{p(i)}{\omega_1} \ln \frac{p(i)}{\omega_1}, \omega_1 = \sum_{i=t_1}^{t_2-1} p(i)$$
$$H(2) = -\sum_{i=t_2}^{t_3-1} \frac{p(i)}{\omega_2} \ln \frac{p(i)}{\omega_2}, \omega_2 = \sum_{i=t_2}^{t_3-1} p(i) \quad (16)$$
$$H(j) = -\sum_{i=t_j}^{t_{j+1}-1} \frac{p(i)}{\omega_j} \ln \frac{p(i)}{\omega_j}, \omega_j = \sum_{i=tj}^{t_{j+1}-1} p(i)$$
$$H(m) = -\sum_{i=t_m}^{L-1} \frac{p(i)}{\omega_m} \ln \frac{p(i)}{\omega_m}, \omega_m = \sum_{i=t_m}^{L-1} p(i)$$

Sum of entropies must be made maximum to obtain the optimal threshold levels values. This is shown in Equation (17):

$$(t_0, t_1, t_{2,.......,} t_m) = \arg\max(\sum H(i)) \quad (17)$$

2.3. Ramesh method

Image gray level is presented L (0,1,2,…L-1). ith gray level probability of image is p(g), and p(g) is calculated with Equation 18.

$$p(g) = h(g)/(NxM) \text{ (g=0,1,2….L-1)} \quad (18)$$

h(g) is an string which indicates image histogram. In bi level threshold method, minimization of the sum of square errors is made by using Equation (19) and Equation (20). Where T is threshold value. The sum of square errors is shown in Equation (21) [21].

$$b_0(T) = \frac{\sum_{g=0}^{T} gp(g)}{\sum_{g=0}^{T} p(g)} \quad (19)$$

$$b_1(T) = \frac{\sum_{g=T+1}^{L-1} gp(g)}{\sum_{g=T+1}^{L-1} p(g)} \quad (20)$$

$$T_{opt} = \arg\min \left\{ \sum_{g=0}^{T} (b_0(T) - g)^2 + \sum_{g=T+1}^{L-1} (b_1(T) - g)^2 \right\} \quad (21)$$

In this study, bi-level Ramesh threshold method isimproved by using Equation (22) and Equation (23) for multilevel threshold method studies.

$$b_0(t_0)=\frac{\sum_{g=0}^{t_0} gp(g)}{\sum_{g=0}^{t_0} p(g)},b_1(t_1)=\frac{\sum_{g=t_0+1}^{t_1} gp(g)}{\sum_{g=t_0+1}^{t_1} p(g)},...,b_m(t_m)=\frac{\sum_{g=t_{m-1}+1}^{L-1} gp(g)}{\sum_{g=t_{m-1}+1}^{L-1} p(g)} \quad (22)$$

$$T_{opt}=\arg\min\left\{\sum_{g=0}^{t_0}(b_0(t_0)-g)^2+\sum_{g=t_0+1}^{t_1}(b_1(t_1)-g)^2+...+\sum_{g=t_{m-1}+1}^{t_{m-1}}(b_m(t_m)-g)^2\right\} \quad (23)$$

It is seen that Otsu and Kapur methods are a maximization problem, and Ramesh method is a minimization problem, and threshold levels of these methods should be increased to obtain sensitive results. However, if threshold level of multilevel threshold method increases, computational time of multilevel threshold method increases. Hence, optimization methods are used with these methods to reduce computational time and to find optimum threshold level. Namely, maximization and minimization problems are solved by optimization methods in this study.

In this study, CSA, PSO and GA are used as artificial intelligence method. Equation (11) is objective function of these algorithms for Otsu method. Equation (17) is objective function of these algorithms for Kapur method, and Equation (23) is objective function of these algorithms for Ramesh method. A block diagram summarizing the proposed approach for ice load detection studies is shown in Figure 6.

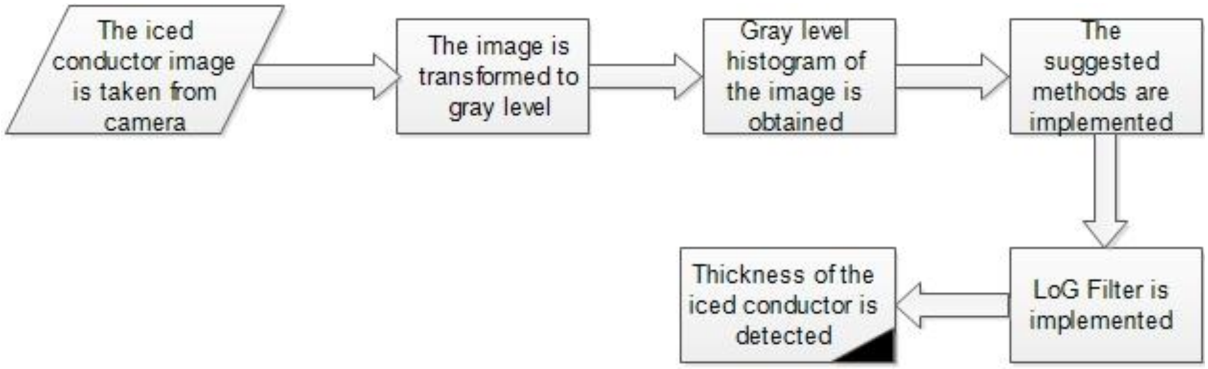

Figure 6: A block diagram summarizing the proposed approach

In genetic algorithms, the variables of optimization problem are defined with chromosomes and gene, and genes of the i[th] chromosome are defined as $Cr_i=(g_{i1},g_{i2},g_{i3},...,g_{iD})$. The optimum solution is found by using interactions between chromosomes. The interactions of chromosomes are made by crossover operator, and the radical change of chromosomes is made by mutation operator. The optimum solution is searched randomly inside the chromosome population [22]. CSA is used for optimization and classification in electrical engineering. CSA occurs from two important operators. These operators are Cloning and Mutation. The variables of optimization problem are defined antibody in CSA, and i[th] antibody is defined as $Ab_i=(ab_{i1},ab_{i2},ab_{i3},...,ab_{iD})$ [22]. The variables of optimization problem are defined as particle in Particle Swarm Optimization (PSO). Particles have a position and velocity. i[th] particle position is defined as $X_i=(x_{i1},x_{i2},x_{i3},...,x_{iD})$, and velocity is defined as $V_i=(v_{i1},v_{i2},v_{i3},...,v_{iD})$. Particles have a memory, and the memory is defined as $p_{best}=(p_{best1},p_{best2},p_{best3},...,p_{best.i})$. The best previous position of particle is saved in the memory. The best position is selected inside of P_{best} at the end of each iteration, and the best position is defined as $g_{best_i}=(g_{i1},g_{i2},g_{i3},...,g_{iD})$. Velocity and position of particles are updated as follows [23]:

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \quad (24)$$

$$v_{id}(t+1)=v_{id}(t)+c_1\times r_1(pbest_{id}-x_{id})+c_2\times r_2(gbest_{id}-x_{id}) \quad (25)$$

Where r_1 and r_2 are random numbers between 0 and 1, c_1 and c_2 are learning coefficients, and c_1 and c_2 are usually selected as $c_1+c_2> 4$.

3. Results and Discussion

3.1. The results of ice load detection studies

Image processing is very practical method for ice load determination studies, but dark and heavy fog ambient conditions, local optimum falling and accuracy rate are very important problems. In literature, multilevel threshold methods were used with optimization method to detect ice load of transmission line under dark and heavy fog ambient conditions. In these studies, the good results were obtained at high threshold levels, but local optimum falling problems were occurred because of high threshold level, and image processing faults occurred because of local optimum falling. It is seen at the end of experimental studies that if threshold level of multilevel-optimization method is reduced, local optimum falling problems do not occur. Namely, threshold level must be reduce to prevent local optimum falling problems, and ice load detection studies should be made at low threshold level. In this study, overhead distribution line conductor was used to detect ice load. Diameter of distribution line conductor is less than transmission line conductor diameter. Hence ice load detection of distribution line is more difficult than transmission line, and threshold level for distribution line is more than transmission line. Namely, if local optimum falling problem is solved for distribution line, this problem is solved for transmission line. In Table 1, algorithm parameter values of CSA, PSO and GA are shown. The results of CSA-Ramesh, PSO-Ramesh and GA-Ramesh are shown in Table 2. The results of CSA-Otsu, PSO-Otsu and GA-Otsu methods are shown in Table 3. The results of CSA-Kapur, PSO-Kapur and GA-Kapur methods are shown in Table 4. In Table 2, Table 3 and Table 4 threshold level is indicated as m, the detected iced conductor thickness is indicated as D (cm). Also thresholds and accuracy rate of these methods are indicated. In literature, maximum threshold level was determined as 20, and the best method was determined as CSA-Otsu method for ice load detection studies under dark and heavy ambient conditions. In CSA-Otsu method, the maximum accuracy rate was obtained at high threshold level (20 level), so local optimum falling occurred. In this study, threshold level was reduced, and maximum threshold level was determined as 5 to prevent local optimum falling problems. It is seen in Table 2, Table 3 and Table 4 that accuracy rate of Ramesh method is generally better than Otsu and Kapur method at low threshold level. The result of 4 level CSA-Ramesh is better than the results of 4 level PSO-Ramesh and 4 level GA-Ramesh methods. However, local optimum falling occurred in 4 level CSA-Ramesh method although threshold level was reduced. Accuracy rate of 5 level GA-Ramesh method is very well. Also local optimum falling did not occur during ice load detection studies. Namely GA-Ramesh method is better than CSA-Otsu method. Therefore GA-Ramesh method is more confidential than other methods. Threshold results of 5 level GA-Ramesh is shown in Figure 7, and vertical border of the detected iced conductor thicknessesof5 level GA-Ramesh is shown in Figure 8.

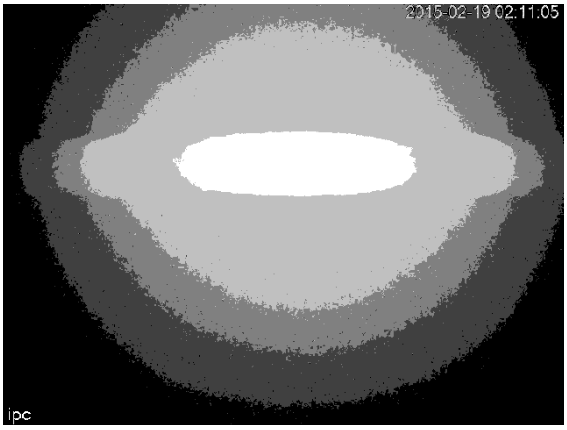

Figure 7: Threshold results of 5 level GA-Ramesh

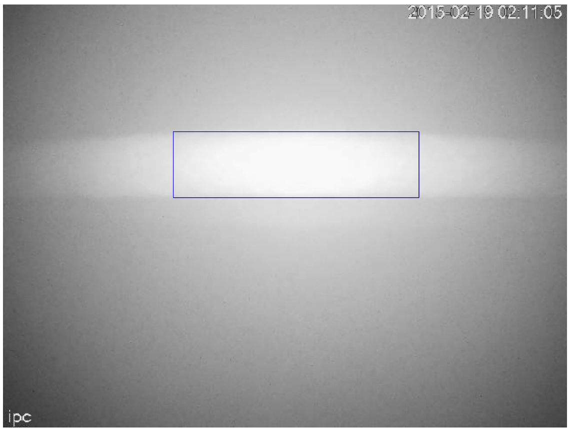

Figure 8: The detected iced conductor thicknesses of 5 level GA-Ramesh

Table 1: Parameter values for different algorithms

CSA		**GA**		**PSO**	
Population size	25	Population size	25	Population size	25
Iteration number	25	Iteration number	25	Iteration number	25
Multiplying coefficient	3	Crossover rate	0.7	C_1 coefficient	2
		Mutation rate	0.001	C_2 coefficient	2

Table 2: The results of CSA-Ramesh, PSO-Ramesh, and GA-Ramesh Methods

	m	**D (cm)**	**Thresholds**	**Accuracy Rate**
CSA-Ramesh	2	4,19	168 214	33.06%
	3	3,64	170 207 218	54.98%
	4	2,48	168 180 190 231	98.80%
	5	2,42	144 148 169 227 235	96.01
PSO-Ramesh	2	4,83	138 209	7.56%
	3	3,62	145 191 218	55.77%
	4	2,7	101 133 182 224	92.43
	5	2,46	39 112 143 186 234	98.00%
GA-Ramesh	2	3,74	21 217	50.99%
	3	3,6	24 119 219	56.57%
	4	2,7	18 73 162 223	92.43
	5	2,52	20 131 159 179 230	99.60%

Table 3: The results of CSA-Otsu, PSO-Otsu, and GA-Otsu Methods

	m	**D (cm)**	**Thresholds**	**Accuracy Rate**
CSA-Otsu	2	8,64	142 192	very low
	3	4,78	135 173 210	9.5%
	4	4,41	117 151 182 213	24.30%
	5	3,08	96 134 164 192 220	77.29%
PSO-Otsu	2	8,62	142 191	very low
	3	4,83	124 167 209	7.56%
	4	3,07	112 146 178 220	77.68%
	5	2,66	106 132 161 192 225	94.02%
GA-Otsu	2	8,32	144 193	very low
	3	4,9	134 176 209	4.78%
	4	3,67	104 141 177 218	53.78%
	5	3,1	85 124 155 190 220	76.49%

Table 4: The results of CSA-Kapur, PSO-Kapur, and GA-Kapur Methods

	m	**D (cm)**	**Thresholds**	**Accuracy Rate**
CSA-Kapur	2	10.56	109 182	very low
	3	5.67	103 151 204	very low
	4	5.2	93 130 165 208	very low
	5	4.04	95 124 160 191 215	39.04%

PSO-Kapur	2	10.56	108 182	very low
	3	5.82	101 151 203	very low
	4	5.67	80 116 159 204	very low
	5	4.75	79 109 141 173 211	10.75%
GA-Kapur	2	10.35	109 183	very low
	3	4.78	103 157 210	10.75%
	4	4.04	106 148 185 215	39.04%
	5	3.08	91 128 161 191 220	77.29%

References

[1]. Guo-ming M, Cheng-rong L, Jian J, Jiang-tao Q, Yang-chun C. Design of Fiber Bragg Grating Load Sensor used in Ice Monitoring on Overhead Transmission Lines. In: International Conference on High Voltage Engineering and Application 2010; 11-14 October 2010; New Orleans, LA, USA: pp. 232-235.
[2]. Peng L, Qimao L, Min C, Shangfei G, Haiyan H. Time Series Prediction for Icing Process of Overhead Power Transmission Line Based on BP Neural Networks. In: Chinese Control Conference; 22-24 July 2011; Yantai, China: pp. 5315–5318.
[3]. Xinbo H, Qindong S, Jianguo D. An On-line Monitoring System of Transmission Line Conductor De-icing. In: Conference on Industrial Electronics and Applications; 3-5 June 2008; Singapore: IEEE. pp. 891-896.
[4]. Michael JM, Thomas B, Hubert Z, Georg B. Capacitive Icing Measurement in a 220 kV Overhead Power Line Environment. In: Sensors Conference; 1-4 November2010; Kona, HI, USA: IEEE. pp. 1754-1758.
[5]. Wu X, Li L, Rui X. Icing load accretion prognosis for power transmission line with modified hidden semi-Markov model. IET GenerTransm Dis 2014; 8: 480-485.
[6]. Jiang X, Xiang Z, Zhang Z, Hu J, Hu Q, Shu L. Predictive Model for Equivalent Ice Thickness Load on Overhead Transmission Lines Based on Measured Insulator String Deviations. IEEE T Power Deliver 2014; 29: 1659-1665.
[7]. Akbal B. System Design And Implementation To Melt The Ice Occurring In High Voltage Aerial Transmission Lines. Ph.D, Selçuk University Directorate of Graduate School of Natural and Applied Sciences Institute of Science, Konya, Turkey, 2015.
[8]. Xie W. Monitoring System of Power Line Icing Based on GPRS. In: International Conference on Medical Physics and Biomedical Engineering; 26-31May 2012; Beijing, China: pp.705-711.
[9]. Runhai J, Bin L, Yuancheng L. Detection of Cladding Ice on Transmission Line Based on SVM and Mathematical Morphology. In: International Congress on Image and Signal Processing; 16-18 October 2010; Yantai, China: pp.1624-1628.
[10]. Jiazheng L, Jing L, Hongxian Z, Bo L. An Image Recognition Algorithm Based on Thickness of Ice Cover of Transmission Line. In: International Conference on Image Analysis and Signal Processing; 21-23 October 2011; Hubei, China: pp. 210-213.
[11]. Akbal B, Aydın M. Usage of GA with Multilevel Thresholding to Detect Ice Thickness of Iced Conductor. American Academic & Scholarly Research Journal 2014; 6: 276-282.
[12]. Akbal B, Aydın M. Multilevel Threshold and PSO for Ice Load Detection on Aerial Lines. J Appl Environ Biol Sci 2014; 4: 50-55.
[13]. Akbal B, Aydın M. DE-Otsu Method to Eliminate Ice Load Effect. J Appl Environ Biol Sci 2014; 4: 423-427.
[14]. Akbal B, Aydın M. Comparison of PSO-Kapur and DE-Kapur Methods to Determine Ice Load on Aerial Lines. In: International Conference 6th Edition Electronics, Computers and Artificial Intelligence; 23-25 October 2014; Bucharest, Romania: IEEE. pp. 23-27.

[15]. Akbal B, Aydın M. CSA-Kapur Method to Determine Ice Load Amount on Electric Transmission Line Conductors. In: International Conference 6th Edition Electronics, Computers and Artificial Intelligence; 23-25 October 2014; Bucharest, Romania: IEEE. pp. 19-22.

[16]. Akbal B, Aydın M. Determining of Iced Conductor Thickness using CSA-Kapur and GA- Kapur Methods. In: 2014 International Conference on Trends in Computer Science, IT and Civil Engineering; 9-10 October 2014; Antalya, Turkey: pp. 1-5.

[17]. Akbal B, Aydın M. Multilevel thresholding and artificial intelligence methods to detect the thickness of iced conductor in ambient conditions. Turk J Elec Eng & Comp Sci2015; DOI: 10.3906/elk-1410-96.

[18]. Otsu A. A threshold selection method from gray-level histograms. IEEE T Syst1979; 9: 62–66.

[19]. Sahoo PK, Kapur JN, Wong AKC. A new method for gray-level picture thresholding using the entropy of the histogram. ComputVisionGraph1985; 29: 273–285

[20]. Horng MH. Multilevel thresholding selection based on the artificial bee colony algorithm for image segmentation. ExpertSystAppl2011; 38: 13785–13791.

[21]. Sezgin M. Quantitative Evaluation of Image Thresholding Methods and Application to Nondestructive Testing. Ph.D, İstanbul Technical University Graduate School of Science Engineering and Technology, İstanbul, Turkey, 2002.

[22]. Akbal B, Ürkmez A. The parallel resonance impedance detection method for parameter estimation of power line and transformer by using CSA, GA and PSO. Turk J Elec Eng & Comp Sci 2013; DOI: 10.3906/elk-1305-114.

[23]. Akbal B, Ürkmez A. PSO and Inertia Weight to Determine Parallel Resonance Power in Electrical Networks. In: the 5th edition of the International Conference Electronics, Computers and Artificial Intelligence; 27-29 June 2013; Pitesti, Romania: IEEE. pp. 13-18.