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Adaptive Cuckoo Search Algorithm based Method for Economic Load Dispatch with Multiple Fuel Options and Valve Point Effect

Ly Huu Pham[1], Thang Trung Nguyen[1], Dieu Ngoc Vo[2] and Cuong Dinh Tran[1*]

[1]Faculty of Electrical and Electronics Engineering, Ton Duc Thang University, No. 19 Nguyen Huu Tho Street, Tan Phong Ward, District 7, HCM City, Vietnam
[2]Department of Power Systems, HCM City University of Technology
268 Ly Thuong Kiet str., 10th dist., HCM city, Vietnam
phamhuuly@tdt.edu.vn, nguyentrungthag@tdt.edu.vn, vndieu@gmail.com, trandinhcuong@tdt.edu.vn
**Corresponding Author*

Abstract

This paper presents an Adaptive Cuckoo Search Algorithm (ACSA) for solving economic load dispatch problem where thermal units with multiple fuel options and valve point loading effect are taken into account. ACSA is first developed by improving the optimal solution search ability of conventional Cuckoo search algorithm. In ACSA, the initial eggs are evaluated and classified into two groups including good group and bad group. The updated step size in ACSA at the first new solution generation via Lévy is adaptive at each iteration and therefore the selection of the parameter is not an issue in the paper. The proposed ACSA method is tested on a ten-unit system considering multiple fuel options and valve point loading effect with different load cases. The comparisons of obtained results among the proposed method with others reported in the paper have indicated that ACSA is efficient for applying to the problem.

Keywords: *Adaptive Cuckoo Search algorithm, economic load dispatch, multiple fuel options, valve point effect, good group, bad group*

Nomenclature

a_{ij}, b_{ij}, c_{ij}	fuel cost coefficients for fuel type j of unit i;
e_{ij}, f_{ij}	fuel cost coefficients for fuel type j of unit i reflecting valve-point effects;
N	total number of generating units;
m_i	number of fuel types of unit i;
P_i	power output of unit i;
$P_{i,max}$	maximum power output of unit i;
$P_{i,min}$	minimum power output of unit i;
$P_{ij,min}$	minimum power output for fuel j of unit i;
P_D	total system load demand;
P_L	total transmission loss;
randp	The random perturbation for positions of nests in $Xbest_d$.

1. Introduction

Economic load dispatch (ELD) is a very important problem to power system operation since this task decides the economy of the power system. In fact, electricity generation fuel cost of a power system mainly using fossil fuel to produce electricity is very high compared to other sources. Furthermore, the fossil

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fuel is not plentiful and exhausted in the near future. Consequently, optimal operation of thermal plants has played a significantly important role so far.

In the past, the fuel cost curve of thermal unit is expressed as a single quadratic function because each considered unit used only one fuel and the valve point loading effect was not taken into account. Nowadays, the cost curve is more complicated as considering multiple fuels and valve point loading effect [1].

Several methods have been successfully applied to ELD problem with multiple fuel options so far including lamda-iteration [2], Hopfield neural network (HNN) [3], enhanced Lagrangian neural network (ELANN) [1], augmented Lagrange Hopfield network (ALHN) method [4], approximately equivalent function based ALHN (AEALHN) [5]. Among the methods, lamda-iteration is a conventional method, which is easy to apply but the method must suffer a drawback to select an initial value for lamda. HNN is more complicated to apply but the performance is not high due to its bad solution quality and long simulation time. These disadvantages of the method are tackled by the dynamics of Lagrange multipliers, which is proposed in ELANN. Both lamda-iteration, HNN and ELANN can not deal with system where nonconvex fuel cost function is considered. The advantages of ALHN over the conventional Hopfield neural network are faster, more efficient. The equivalent fuel cost coefficients is proposed in [5] so as to simplify the search process for ALHN and obtain promising results.

Recent years, many meta-heuristic algorithms and Hopfield network based methods have attracted many attentions from researcher in applying to the economic load dispatch where multiple fuel options are considered. These methods include Particle swarm optimization (PSO) [6], Differential Evolution (DE) [7], Self-Adaptive Differential Evolution (SDE) [8], Genetic algorithm (GA) [9-10] and evolutionary programming (EP) [11]. PSO can produce high quality solutions in short period time. However, the method is sensitive to the selection of control parameters and it is not very efficient for nonconvex objective function. DE is a powerful search tool for global optimal solution. Nevertheless, the DE method is still slow for applying to large-scale problems. Compared to DE, SDE is a good method to solve ELD problem with Valve-Point Effects. Among the methods, GA is the weakest one since it is vastly dependent on the fitness function and sensitive to the mutation and crossover operations and must spend long time searching solution. The manners lead to the limitation of the GA on the complex systems. EP has a high performance for optimization problems but it is as good as DE and PSO.

The cuckoo search algorithm (CSA) developed by Yang and Deb in 2009 [12] is a new meta-heuristic algorithm inspired from the obligate brood parasitism of some cuckoo species. To validate the performance of the CSA, results obtained from it were compared to particle swarm optimization (PSO) and GA for ten standard optimization benchmark functions [12]. As observed from the obtained results, the CSA method is superior to both PSO and GA methods for all test functions in terms of success rate and the number of iterations for searching obtimal solution.

In this paper, an adaptive cuckoo search algorithm (ACSA) is proposed for solving the economic load dispatch where multiple fuels are used and the fuel cost function is approximately represented as a multi-quadratic curve, and valve-point loading effects are taken into consideration. ACSA is tested on two systems and the results obtained from ACSA are compared to those from other methods available in the paper.

2. Problem Formulation

The objective of the ED problem with multiple fuel options is to minimize the total cost of thermal generating units while satisfying different constraints including power balance and generation limits.

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Mathematically, the problem is formulated as follows:

$$\text{Min } F = \sum_{i=1}^{N} F_i(P_i) \quad (1)$$

Where:

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2, \text{ fuel } 1, P_{i,\min} \le P_i \le P_{i1,max} \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2, \text{ fuel } 2, P_{i2,\min} \le P_i \le P_{i2,\max} \\ \ldots \\ a_{ij} + b_{ij}P_i + c_{ij}P_i^2, \text{ fuel } j, P_{ij,\min} \le P_i \le P_{ij,\max} \end{cases} \quad (2)$$

where the fuel cost function for fuel type *j* of unit *i* is determined by:

$$F_i(P_i) = a_{ij} + b_{ij}P_i + c_{ij}P_i^2 + \left| e_{ij} \times \sin(f_{ij} \times (P_{ij,\min} - P_i)) \right|$$

Subject to:

1. Power balance constraints: the power generated by all thermal units must be equal to load demand

$$\sum_{i=1}^{N} P_i - P_D = 0 \quad (4)$$

2. Generator operating limits: the power output of each generators must be within its limitations as below

$$P_{i\min} \le P_i \le P_{i\max} \quad (5)$$

3. Adaptive Cuckoo Search Algorithm for the Considered Problem

3.1. Implementation of ACSA

1) *Initialization:* Similar to other meta-heuristic algorithms, each cuckoo nest in N_p nests is represented by a vector $X_d = [P_{d2}, \ldots\ldots, P_{dN}]$ $(d = 1, \ldots, N_p)$. Certainly, the upper and lower limits of each nest are respectively $X_{dmin}=[P_{imin}]$ *and* $X_{dmax}=[P_{imax}]$. Consequently, each nest X_d is randomly initialized within the limits $P_{i,min} \le P_{i\,d} \le P_{i,max}$ $(i=2, \ldots, N_1)$ as follows.

$$X_d = X_{d\min} + rand * (X_{d\max} - X_{d\min}) \quad (6)$$

Note that the power output of thermal unit 1 is not included in the initial solutions due to the equality constraint (4), which must be exactly satisfied. Therefore, the value of thermal unit 1 is considered as a slack variable and obtained as the following equation

$$P_{1d} = P_D - \sum_{i=2}^{N} P_{id}; d = 1, 2, \ldots, Np \quad (7)$$

Where P_{1d} is the generation of thermal unit 1 corresponding to the nest *d* and P_{id} is the generation of thermal unit i corresponding to nest *d*.

Each nest or each solution is evaluated via its fitness function which contains the values of objective function and penalty for slack thermal unit 1. The fitness function is obtained as below.

$$FT_d = \sum_{i=1}^{N} (F_{id}) + K_s (P_{1d} - P_{1d}^{\lim})^2 \quad (8)$$

The limit of $P_{1d}^{\lim}$ in the fitness function is obtained by:

$$P_{1d}^{\lim} = \begin{cases} P_{1\max} & if\ P_{1d} > P_{1\max} \\ P_{1\min} & if\ P_{1d} < P_{1\min} \\ P_{1d} & \text{otherwise} \end{cases} \quad (9)$$

where P_{1max} and P_{1min} are the maximum and minimum generation of thermal unit 1. The initial population of the host nests is set to the best value of each nest $Xbest_d$ (d = 1, …, N_d) and the nest corresponding to the best fitness function in (8) is set to the best nest

Gbest among all nests in the population.

All the solutions are ranged in increasing order of fitness value. It means that the solution with the lowest fitness value is ranged at the first position meanwhile the one with the highest fitness value is located at the end. There is a ratio to divide the number of solutions into two groups including good solution group, called X_{dgood} and bad solution group, called X_{dbad}

2) *The first new solution generation* via *Lévy flights*

a. New solution generation for the good egg group

The new solution by each nest is calculated as follows:

$$X_d^{new} = Xbest_d + \alpha_1 \times rand \times \Delta X_{dgood}; d = 1,..., Nogood \tag{10}$$

where $\alpha_1 = 1/\sqrt{G}$ and the increased value ΔX_{dgood} is determined by:

$$\Delta X_{dgood} = \nu \times \frac{\sigma_x(\beta)}{\sigma_y(\beta)} \times \left(Xbest_d - Gbest \right); d = 1,..., Nogood \tag{11}$$

b. New solution generation for the bad egg group

The new solution by each nest is calculated as follows:

$$X_d^{new} = Xbest_d + \alpha_2 \times rand \times \Delta X_{dbad}; d = Nogood + 1,..., N_P \tag{12}$$

where $\alpha_2 = 1/\mathrm{G}\wedge 2$ and the increased value ΔX_{dbad} is determined by:

$$\Delta X_{dgood} = \nu \times \frac{\sigma_x(\beta)}{\sigma_y(\beta)} \times \left(Xbest_d - Gbest \right); d = Nogood + 1,..., N_P \tag{13}$$

For the newly obtained solution, its lower and upper limits should be satisfied according to the generating unit's limits:

$$P_{id}^{new} = \begin{cases} P_{i\max} & \text{if} \quad P_{id}^{new} > P_{i\max} \\ P_{i\min} & \text{if} \quad P_{id}^{new} < P_{i\min}; i = 2, 3, ..., \mathrm{N} \\ P_{id}^{new} & otherwise \end{cases} \tag{14}$$

The new solution is evaluated by using eq. (8) above. The fitness function value of the new solutions is compared to that from the old one and better one is kept

3) The second new solution generation via the discovery of alien egg:

In the strategy of the second new solution, only a fraction of kept solutions above are newly generated using the probability Pa as the following equation.

$$X_d^{dis} = \begin{cases} X_d + rand.\Delta X_d^{dis} & \text{if} \quad rand < Pa \\ X_d & otherwise \end{cases} \tag{15}$$

where the increased value ΔX_d^{dis} is determined by:

$$\Delta X_d^{dis} = rand \times \left(randp \ (Xbest_d) - randp(Xbest_d) \right) \tag{16}$$

Similar to the solution obtained via Lévy flights, this new solution is also redefined as in (14), and each nest $Xbest_d$ and the best value of all nests *Gbest* are set based on fitness value obtained from (8).

4) Stopping Criteria: The proposed algorithm is terminated when the current iteration is equal to the maximum number of iteration.

3.2. The Overall Procedure

The overall procedure of the proposed ACSA for solving the ELD problems is described as follows.

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Step 1: Select parameters for ACSA including number of host nests N_p, probability of a host bird to discover an alien egg in its nest P_a, and maximum number of iterations N_{max}, and the ratio of the solutions in good group to that in bad group.

Step 2: - Initialize a population of N_p host nests and calculate the generation of thermal unit 1 as in Section 3.1.1.
- Evaluate the fitness function using (8)
Set the initial iteration counter $G = 1$.

Step 3: Put better solutions with lower fitness function value in the good group and other in the bad group.

Step 4: Generate a new solution via Lévy flights as described in Section 3.1.2 and calculate generation of thermal unit 1 as in eq. (7).

Step 5: - Evaluate the fitness function using (8) for the newly obtained solution
- Compare each new solution and old one at the same nest to retain the better one.
- Set each kept solution in the two groups to $Xbest_d$

Step 6: Generate a new solution based on the probability of P_a as in Section 3.1.3 and calculate generation of thermal unit 1 as in eq. (7)

Step 7: - Evaluate the fitness function using (8)
- Compare each new solution and old one at the same nest to retain the better one.
- Determine the best solution with the lowest fitness function value, *Gbest*

Step 8: If $G<G_{max}$, $G = G + 1$ and return to Step 3. Otherwise, stop.

4. Results and Discussions

To validate the performance of ACSA, two systems with ten units where system 1 neglects valve point-loading effects and system 2 considers the effects are employed. ACSA is coded in Matlab platform and fifty independent trials for each test case on a 2 GHz Laptop with 2 GB of RAM.

4.1. System I with Ten Units Neglecting Valve Point Effect

In the section, the proposed ACSA method is run on one system consisting of 10 generating units [1] where multiple fuel options with quadratic function and load demand changed from 2,400 MW to 2,700 MW in steps of 100 MW are considered.

For the study cases, the nest and iterations number are fixed at 9 and 400. Note that the good quality group accounts for 3 meanwhile the eggs in bad group are 6 whereas the probability P_a is ranged from 0.1 to 0.9.

The result obtained including minimum cost, average cost, maximum cost, standard deviation and computational time by the method are given in Tables 1, 2, 3 and 4.

As meticulously observed from the tables, the best values of Pa is in range from 0.2 to 0.9 and the standard deviation costs corresponding to the Pa values are equal to 0 as well as the minimum cost are the same and obtained at the Pa=0.2-0.9. The best cost from ACSA is then compared to other methods reported in table 5. Clearly, ACSA obtains better cost than ELANN [1], SDE [8], ARCGA [9] and IEP [11] and appriximate cost with others for all load demands.

With respect to execution time comparison, ACSA is faster than other methods except ALHN and RCGA. Table 6 shows the best optimal generations obtained by ACSA for different load demands.

Table 1. Result Obtained for 2400 MW Load

Pa	Min total	Average	Max total	Std.	Avg.

	cost ($)	total cost ($)	cost ($)	dev. ($)	CPU (s)
0.1	481.7226	481.7231	481.7330	0.0004	086
0.2	481.7226	481.7226	481.7226	0	0.75
0.3	481.7226	481.7226	481.7226	0	0.96
0.4	481.7226	481.7226	481.7226	0	0.83
0.5	481.7226	481.7226	481.7226	0	0.78
0.6	481.7226	481.7226	481.7226	0	0.82
0.7	481.7226	481.7226	481.7226	0	0.83
0.8	481.7226	481.7226	481.7226	0	0.79
0.9	481.7226	481.7226	481.7226	0	0.9

Table 2. Result Obtained for 2500 MW Load

Pa	Min total cost ($)	Average total cost ($)	Max total cost ($)	Std. dev. ($)	Avg. CPU (s)
0.1	526.2388	526.4530	526.5110	0.0023	0.98
0.2	526.2388	526.4478	526.4680	0.0016	0.94
0.3	526.2388	526.4530	526.5110	0	0.88
0.4	526.2388	526.4530	526.5110	0	0.87
0.5	526.2388	526.4530	526.5110	0	0.94
0.6	526.2388	526.4530	526.5110	0	0.94
0.7	526.2388	526.4530	526.5110	0	0.88
0.8	526.2388	526.4530	526.5110	0	0.86
0.9	526.2388	526.4530	526.5110	0	0.92

Table 3. Result Obtained for 2600 MW Load

Pa	Min total cost ($)	Average total cost ($)	Max total cost ($)	Std. dev. ($)	Avg. CPU (s)
0.1	574.3808	574.4100	574.4632	0.0006	0.92
0.2	574.3808	574.3921	574.4374	0.0004	0.95
0.3	574.3808	574.3808	574.3808	0	0.89
0.4	574.3808	574.3808	574.3808	0	0.88
0.5	574.3808	574.3808	574.3808	0	0.89
0.6	574.3808	574.3808	574.3808	0	0.97
0.7	574.3808	574.3808	574.3808	0	1.02
0.8	574.3808	574.3808	574.3808	0	0.96
0.9	574.3808	574.3808	574.3808	0	0.94

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Table 4. Result Obtained for 2700 MW Load

Pa	Min total cost ($)	Average total cost ($)	Max total cost ($)	Std. dev. ($)	Avg. CPU (s)
0.1	623.8092	623.9876	624.321	0.004	0.89
0.2	623.8092	623.8912	623.9356	0.002	0.93
0.3	623.8092	623.8092	623.8092	0	0.88
0.4	623.8092	623.8092	623.8092	0	0.94
0.5	623.8092	623.8092	623.8092	0	0.89
0.6	623.8092	623.8092	623.8092	0	0.96
0.7	623.8092	623.8092	623.8092	0	0.93
0.8	623.8092	623.8092	623.8092	0	0.94
0.9	623.8092	623.8092	623.8092	0	0.94

Table 5. Comparison for System with Quadratic Fuel Cost Function

Method	P_D=2400 (MW)		P_D=2400 (MW)		P_D=2400 (MW)		P_D=2400 (MW)	
	Cost ($/h)	CPU time (s)	Cost ($/h)	CPU time (s)	Cost ($/h)	CPU time (s)	Cost ($/h)	CPU time (s)
ELANN[1]	481.74	11.53	526.27	12.25	574.41	~9.99	623.88	21.36
SDE [8]	481.8628	-	526.3232	-	574.538	-	623.9225	-
ARCGA [9]	481.743	0.85	526.259	0.85	574.405	0.85	623.828	0.85
IEP [11]	481.779	-	526.304	-	574.473	-	623.851	-
DE [7]	481.723	-	526.239	-	574.381	-	623.809	-
ALHN [4]	481.723	0.008	526.239	0.043	574.381	0.047	623.809	0.057
MPSO [6]	481.723	-	526.239	-	574.381	-	623.809	-
ACSA	481.7226	0.75	526.2388	0.86	574.3808	0.88	623.8092	0.88

Table 6. The Best Optimal Generations Obtained by ACSA for System with Quadratic Fuel Cost Function

Unit i	P_D=2400 MW	P_D=2500 MW	P_D=2600 MW	P_D=2700 MW
	Pi (MW)	Pi (MW)	Pi (MW)	Pi (MW)
1	189.7410	206.5215	216.5409	218.2496
2	202.3380	206.4580	210.9076	211.6593
3	253.8940	265.7270	278.5337	280.7214
4	233.0456	235.9544	239.0982	239.6297
5	241.8284	258.0036	275.5269	278.4967
6	233.0459	235.9570	239.0989	239.6370
7	253.2789	268.8678	285.7218	288.5794
8	233.0430	235.9478	239.0968	239.6292
9	320.3845	331.4926	343.4888	428.5280
10	239.4006	255.0704	271.9863	274.8697

4.2. System with Multiple Fuel Options and Valve Point Effect

In this section, a system with 10-unit considering valve point effect is considered [13]. The load demand is 2700 MW. The control parameters for the method are set to the same values with those for the study case above. The results in detail obtained by the proposed methods are indicated in Table 7. The best value of fuel cost is compared to other methods such as improved genetic algorithm with multiplier updating (IGA-MU), conventional genetic algorithm (CGA) with multiplier

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updating (CGA-MU) [13], new PSO (NPSO), PSO with a simple local random search (PSO-LRS), new PSO with a simple local random search (NPSO-LRS) [14] in Table 8.

Obviously, ACSA obtains the best solution among the available methods because the fuel cost by the method is the lowest. Furthermore, the proposed method is much faster than CGA-MU [13] and IGA-MU [13] and slower than the others. Consequently, ACSA is very efficient for solving the problem with nonconvex fuel cost function. The best optimal generation by the method is reported in Table 9.

Table 7. Result Obtained by ACSA for System with Nonconvex Fuel Cost Function and 2700 MW Load

Pa	Min. cost ($)	Aver. cost ($)	Max. cost ($)	Std. dev. ($)	Avg. CPU (s)
0.1	623.8941	624.2512	626.4898	0.7665	2.24
0.2	623.8597	624.1287	626.3968	0.6629	2.24
0.3	623.8805	623.9751	626.3815	0.3432	2.24
0.4	623.8828	624.0522	626.4011	0.536	2.24
0.5	623.899	624.0952	626.4535	0.5823	2.25
0.6	623.8978	624.2003	626.6556	0.719	2.25
0.7	623.8985	624.1776	626.5711	0.6435	2.42
0.8	623.9036	624.3279	626.6909	0.7801	2.40
0.9	623.9527	624.8219	635.8982	1.8314	2.45

Table 8. Comparison of Fuel Cost and CPU Time for System with Valve Point Effect of Thermal Units

Method	Min cost ($)	Average cost ($)	Max cost ($)	Std. dev. ($)	Avg. CPU (s)
CGA-MU [13]	624.7193	627.6087	633.8652	-	25.65
IGA-MU [13]	624.5178	625.8692	630.8705	-	7.14
PSO-LRS [14]	624.2297	625.7887	628.3214	-	0.93
NPSO [14]	624.1624	625.218	627.4237	-	0.41
NPSO-LRS [14]	624.1273	624.9985	626.9981	-	1.08
ACSA	623.8597	624.1287	626.3968	0.6629	2.24905

Table 9. The Best Optimal Generations Obtained by ACSA for System with Nonconvex Fuel Cost Function

i	P_i (MW)
1	217.0696
2	212.6491
3	279.6713
4	239.6856
5	279.9483
6	238.8554
7	290.0692
8	239.2837
9	427.3783
10	275.3895

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6. Conclusion

In this paper, an adaptive version of conventional Cuckoo search algorithm is proposed for solving the economic load dispatch problems with multiple fuel options and valve point effect on thermal units. In the method, the solution in the population is ranked and put in two different groups so as to generate diversity of new solution. ACSA has been tested on two system with different load cases and the result comparison with other methods have revealed that ACSA is very efficient for solving ELD problem with multiple fuel options considering either quadratic or nonconvex fuel cost function.

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Authors

Ly Huu Pham, He has graduated from the University of Technology Ho Chi Minh city, Ho Chi Minh city, VietNam. He received her B.Eng and M.Eng degrees in electrical Engineering in 2004 and 2009, respectively. Now, He is teaching at department of electrical and electronics engineering, Ton Duc Thang University, Ho Chi Minh city, Vietnam. His research interests include Renewable Energy, transformer loss minimization

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Thang Trung Nguyen, He received his B.Eng. and M.Eng degrees in Electrical Engineering from University of Technical education HCM City in 2008 and 2010, respectively. Now, he is teaching at department of electrical and electronics engineering, Ton Duc Thang University. His research interests include optimization of power system, power system operation and control and Renewable Energy.

Dieu Ngoc Vo, He received B.Eng. and M.Eng. Degrees in electrical engineering from HCM City University of Technology, Vietnam, in 1995 and 2000, respectively and his D. Eng. degree in energy from Asian Institute of Technology (AIT), Pathumthani, Thailand in 2007. He is now teaching at Faculty of Electrical and Electronic Engineering, HCM City University of Technology, Vietnam. His interests are applications of AI in power system optimization, power system operation and control, power system analysis, and power systems under deregulation.

Cuong Dinh Tran, He has graduated from the University of Technology Ho Chi Minh city, Ho Chi Minh city, Vietnam. He received her B. Eng and M. Eng degrees in Electrical Engineering in 2005 and 2008, respectively. Now, he is teaching at department of electrical engineering, Ton Duc Thang University, Ho Chi Minh city, Vietnam. His research interests include intelligent control system, power system operation and control and Renewable Energy.

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