Optimal Load Shedding for Voltage Stability Enhancement by Ant Colony Optimization

Worawat Nakawiro
Institute of Electric Power Systems (EAN)
University of Duisburg Essen
Duisburg, Germany
worawat.nakawiro@uni-due.de

Istvan Erlich
Institute of Electric Power Systems (EAN)
University of Duisburg Essen
Duisburg, Germany
worawat.nakawiro@uni-due.de

Abstract— **Voltage stability has become a serious treat of modern power system operation nowadays. To tackle this problem properly, load shedding is one of the effective countermeasures. However, its consequences might result in huge technical and economic losses. Therefore, this control measure should be optimally and carefully carried out. This paper proposes an ant colony optimization (ACO) based algorithm for solving the optimal load shedding problem. Two principal concerns of the problem are addressed. The appropriate load buses for the shedding are identified by sensitivities of voltage stability margin with respect to the load change at different buses. Then, the amount of load shedding at each bus is determined by applying ACO to solve a nonlinear optimization problem formulated in the optimal power flow framework. The performance of the proposed ACO based method is illustrated with a critical operating condition of the IEEE 30-bus test system.**

Keywords- Load shedding; Ant colony optimization; Voltage stability;Optimal power flow

I. INTRODUCTION

In recent years, voltage stability has been reported as one of the reasons of the blackouts all over the world in the last three decades [1]. This phenomenon occurs as a result of a contingency, such as loss of an important transmission line or a major generator, inadequate reactive power support at critical buses due to a high loading condition or a combination of the two aspects.

Voltage collapse is the final consequence of voltage instability. This phenomenon causes huge losses in many countries throughout the world. Therefore, it has received significant attentions from many researchers both in academics and industry.

Generally voltage stability analysis involves two principal steps. First, the distance to the voltage collapse point, defined as voltage stability margin (VSM) must be assessed. In the second step, if the power system is vulnerable to the stability problem, preventive and/or corrective control actions may be required [2]. Preventive control actions can be achieved by readjusting the most effective controls in order to provide the sufficient VSM. Corrective control actions are on the other hand aimed at restoring the stable system operation when subjected to severe disturbances. Corrective load shedding may be an effective means to achieve this task but it should be deployed as the last resort when other control actions become exhausted or they are not fast enough to counteract the disturbance. In [3], the authors proposed an integrated method of MW/MVar management and minimum load shedding to satisfy voltage stability criterion. Unfortunately, the load shedding problem formulation was not clearly discussed in the paper. In [4], the so-called outage continuation power flow (OCPF) was proposed to consider the effects of branch and generator outages on voltage stability. The load shedding strategy was also developed based on sequential updating rules until the power flow solvability condition is met. In [5], the optimal load shedding problem is formulated in a more general form to minimize the total power interruption cost while maintaining system conditions with in their respective limits. Because the sufficient VSM to the collapse is of the most primary concern of the load shedding problem, however the VSM requirement was not considered in [5]. The negligence of this important constraint would finally result in an ineffective operation where the voltage stability may be still a problem even after the load curtailment.

Therefore, we have formulated the load shedding in this paper closely similar to [5] but an additional constraint on VSM is additionally included. Given the implementation flexibility and powerful capability of heuristic optimization methods applied in power system problems, this paper applies ant colony optimization (ACO)

ACO is the algorithm inspired by the foraging behavior of real ants and was initially proposed to solve combinatorial optimization problems [6]. It is only recently that there have been attempts to extend ACO to optimize a function in continuous domain. Among these methods, the method proposed by Socha and Dorigo in [7] called ACO_R, which reserves intrinsic concepts of ant algorithm, is shown to be more effective than other ant-related algorithms in dealing with global optimization problems. We have modified the original ACO_R to deal with constrained optimization problems and applied it in this paper.

The rest of this paper is organized as follows. The frame work of the proposed load shedding is discussed in section II. The modified ACO_R and constraint handling technique are explained in section III. The load shedding problem is mathematically formulated in section IV. Simulation results are discussed in section V. Finally, concluding remarks and outlooks on potential future works are given in section VI.

II. FRAMEWORK OF THE PROPOSED SCHEME

The proposed algorithm of this paper starts from the VSM assessment of the base case by the continuation power flow (CPF) method [8]. In the CPF simulation of this paper, load demands at all buses are increased in a proportional way. System generation is also scaled up to match the increasing load demand along the CPF process. These increases can be written as;

$$P_{Gi} = \lambda P_{Gi0} \qquad (1)$$
$$P_{Di} = \lambda P_{Di0} \ ; Q_{Di} = \lambda Q_{Di0}$$

where P_{Gi0}, P_{Di0} and Q_{Di0} are the base case generator and load powers, respectively; λ is the loading parameter. For long-term stability framework, λ can be applied as a good indicator of voltage stability [1]. Along the PV curve construction process, λ is increased from zero to the maximum loading condition point λ^{max}. Let suppose if $\lambda^{max} = 1.06$, that means the load powers can be increased 6% further before reaching the collapse point. It is also possible to say that the system has 6% stability (load) margin. If $\lambda^{max} < 1$, it indicates an unstable case due to the negative stability margin.

For an unstable case, load shedding might be an efficient solution. The load shedding problem principally answers two questions, namely locations and amounts. The appropriate load shedding location can be identified by sensitivities of λ with respect to parameter change at the load bus i calculated from [9]:

$$\frac{\partial \lambda}{\partial P_i} = -\left(\begin{bmatrix} \mathbf{v_{G_P}} & \mathbf{v_{G_Q}} \end{bmatrix} \begin{bmatrix} \frac{\partial \mathbf{G_P}}{\partial P_i} \\ \frac{\partial \mathbf{G_Q}}{\partial P_i} \end{bmatrix} \Big/ \begin{bmatrix} \mathbf{v_{G_P}} & \mathbf{v_{G_Q}} \end{bmatrix} \begin{bmatrix} \frac{\partial \mathbf{G_P}}{\partial \lambda} \\ \frac{\partial \mathbf{G_Q}}{\partial \lambda} \end{bmatrix} \right) \qquad (2)$$

where $\mathbf{G_P}$ and $\mathbf{G_Q}$ are the matrices of algebraic equations representing net real and reactive power injection at buses, respectively. $\mathbf{v_{G_P}}$ and $\mathbf{v_{G_Q}}$ are the zero left eigenvector associated with $\mathbf{G_P}$ and $\mathbf{G_Q}$, respectively. $\partial(\bullet)/\partial P_i$ is the partial derivative of a matrix with respect to P_i ,where P_i is a scalar representing the parameter change at load bus i. $\partial(\bullet)/\partial \lambda$ is the partial derivative of a matrix with respect to λ. $\partial(\mathbf{G_P})/\partial \lambda$ and $\partial(\mathbf{G_Q})/\partial \lambda$ correspond to the right most column of the CPF augmented Jacobian matrix.

Once the locations are identified, the amount of load to be curtailed at each effective each bus is determined by applying ACO_R to solve the problem formulated in the optimal power flow (OPF) framework. Statistical studies are undertaken to examine the effectiveness of the proposed strategy.

III. ANT COLONY OPTIMIZATION

A. Algorithm

As mentioned earlier, one of the most recent ant-based global optimization methods in the continuous domain is the ACO_R algorithm. In this section, the original ACO_R is modified to handle constrained optimization problems as demonstrated in [10].

From the global optimization viewpoint, conventional ant algorithms initially developed to deal with combinatorial optimization problems, map the entire search space of every dimension into a discretized and definite graph, namely the pheromone trail. To generate a new ant solution at each construction step, a discrete probability distribution is used to select the point on the graph representing the candidate value. On the other hand, ACO_R defines the entire search domain of each dimension by a continuous PDF. The original ACO_R algorithm uses Gaussian kernel PDF to model multiple promising search regions. A Gaussian kernel is defined as a weighted sum of k single PDFs defined by:

$$G^i(x) = \sum_{l=1}^{k} \omega_l g_l^i(x) = \sum_{l=1}^{k} \omega_l \frac{1}{\sigma_l^i \sqrt{2\pi}} e^{-(x-\mu_l^i)^2 / 2(\sigma_l^i)^2} \qquad (3)$$

where k is the number of single Gaussian PDF at i construction step; ω, μ, and σ are vectors of size k defining the weights, means and standard deviations associated with every individual Gaussian PDF at the i construction step.

For each ant, a new variable value can be developed at each construction step by a random sampling technique of a given PDF based on mean μ and standard deviation σ. Since the global optimization in a continuous domain involves an indefinite number of candidate solutions, the pheromone trail concept of conventional ACO is no longer applicable. Therefore, ACO_R stores the knowledge gained from previous searches in a table format called the archive (**T**).

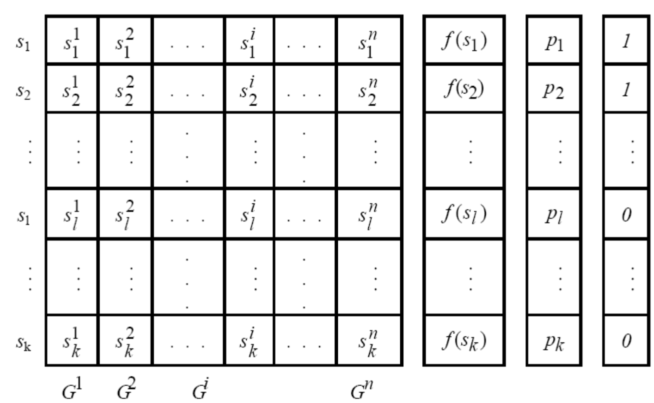

Fig. 1 Data structure of the archive solution

Fig. 1 shows the data structure of the solution archive **T** designed to handle constrained optimization problems. The archive stores the set of good ant solutions that have been discovered from the previous generations. The first part of **T** contains the set of k candidate solutions $\mathbf{s}_i$, i=1,2,…,k where $\mathbf{s}_i \in \Re^n$; n is the problem dimension. The next column of **T** stores the corresponding fitness value of ith candidate solution $f(s_i)$. The probability of selecting the ith solution as a mean p_i is recorded in the next column. The last column holds the binary indicating feasibility status of the the ith solution (1 if feasible and 0 if infeasible).

If the Gaussian kernel is directly applied for random sampling, it is necessary to determine the inverse of cumulative distribution function (CDF), $D^{-1}(x)$. However, this is not always straightforward for an arbitrary PDF. Therefore, an alternative sampling technique is used in this paper in order to increase the implementation flexibility. This can be done in two steps. In the first step, a single component of the kernel is probabilistically selected for each ant. The weight ω_l of the solution l is the Gaussian PDF value with mean of 1 and standard deviation of qk. It is computed according to:

$$\omega_l = \frac{1}{qk\sqrt{2\pi}} e^{-(l-1)^2 / 2q^2k^2} \tag{4}$$

where q is a parameter of the algorithm and k is the size of solution archive. When q is small, the solutions with lower ranks in the archive have very strong influences in guiding new search directions whereby a larger q allows the wider search diversification over the entire space. For each archive solution of rank l in **T**, the corresponding probability is calculated by:

$$p_l = \frac{\omega_l}{\sum_{r=1}^{k} \omega_r} \; ; \forall l = 1,2,...,k \; ; \; p_l \in \mathbf{p} \tag{5}$$

where **p** is the vector of probability of selection. Then, to generate an ant l of the descent ant population, the Roulette wheel selection method [11] is applied to randomly select which candidate solution of **T** should be set as the vector of mean values expressed by:

$$\boldsymbol{\mu}_l = \mathbf{s}_j \; ; \; \forall l = 1,2,...,n_{ant} \; ; \; j = \text{Roulette}(\mathbf{p}) \tag{6}$$

where n is the problem dimension; n_{ant} is the size of ant population; Roulette(**p**) is the Roulette selection function with **p** as the input and returning the selected rank. Standard deviation σ for every construction step i is calculated from the average distance from the chosen solution s_l to the other solutions in **T** according to:

$$\sigma_l^i = \xi \sum_{e=1}^{k} \frac{\left| s_e^i - s_l^i \right|}{k-1} \; ; \; \forall l = 1,2,...,n_{ant} \; ; \forall i = 1,2,...,n \tag{7}$$

where ξ is the pheromone evaporation coefficient; and n is the problem dimension. Based on determined mean and standard deviation, a corresponding random variable can be generated by a technique, such as Box and Mueller [12].

After a complete generation, all solutions in **T** are ranked according to their feasibility status (the fourth column of Fig.1), and fitness value (the second column of Fig.1). Because the archive solutions with lower ranks have the greater influence in guiding the search directions, feasible solutions are first ranked based on their fitness values found by the self-adaptive penalty scheme in [13]. The same process is repeated for infeasible solutions which are placed in the lower portion of **T**. The same ranking procedure is repeated on the rest member of the ant population.

B. Constraint handling technique

For constrained optimization problems, the attraction of a solution $\mathbf{s}_i$ is measured by the value of fitness function instead of the value of original objective function. Therefore, the objective function of ACO_R is modified to the sum of the distance value, $d(\mathbf{x})$ and the penalty value, $p(\mathbf{x})$.

$$\text{Minimize} \;\; f''(\mathbf{x}) = d(\mathbf{x}) + p(\mathbf{x}) \tag{8}$$

The distance function is defined as follows:

$$d(\mathbf{x}) = \begin{cases} v'(\mathbf{x}) & \text{if } r_f = 0 \\ \sqrt{f'(\mathbf{x})^2 + v'(\mathbf{x})^2} & \text{otherwise} \end{cases} \tag{9}$$

where r_f is the ratio of the number of feasible solutions in the archive or ant population. $f'(\mathbf{x})$ is the normalized value of $f(\mathbf{x})$ and $v'(\mathbf{x})$ is the sum of normalized violation of each constraint divided by the number of constraints. When there is no feasible solution in the population, the objective function is now to minimize the constraint violation. If there are feasible solutions, then the distance value becomes the root mean square of the sum of the objective value and constraint violations. This process can help improve the search performance of ACO_R because it guides the ants to concentrate only on the distance to feasible space when there is a drought of feasible solutions. When a number of feasible solutions have been explored, the ants still continues to search for further feasible region and simultaneously trace the optimal area.

The second term of (10) is called the penalty value. This term is very helpful at a given generation of ACO_R to identify which ant can help the exploration. The idea of this term is to ensure that the most useful ant both in terms of infeasible solutions (at the early stage) and feasible solutions (toward the end) are assigned lower penalties relative to other ant solutions. Therefore $p(\mathbf{x})$ can be defined as shown below:

$$p(\mathbf{x}) = (1 - r_f) X(\mathbf{x}) + r_f Y(\mathbf{x}) \tag{10}$$

where

$$X(\mathbf{x}) = \begin{cases} 0 & \text{if } r_f = 0 \\ v'(\mathbf{x}) & \text{otherwise} \end{cases} \tag{11}$$

$$Y(\mathbf{x}) = \begin{cases} 0 & \text{if } \mathbf{x} \text{ is feasible} \\ f'(\mathbf{x}) & \text{if } \mathbf{x} \text{ is infeasible} \end{cases} \tag{12}$$

IV. PROBLEM FORMULATION

The solution of optimal load shedding involves the determination of the effective locations and optimal load reductions subject to various system constraints. This optimization task can be carried out in two stages: planning and operation. In the planning stage, system behaviors of different scenarios are analyzed and if necessary different control strategies may be determined. During the operation, an optimization algorithm is used to suggest the efficient operation scheme as per grid requirements.

A. Problem Formulation

In the OPF framework, the main objective of optimization is to minimize the cost of power interruption at buses:

$$\text{Minimize} \qquad f(\Delta p_d) = \sum_{i \in \mathbf{n_s}} C_i \cdot \left(\frac{\Delta p_{di}}{\partial \lambda / \partial p_{di}} \right) \tag{13}$$

subject to

a) Load bus voltage limits

- Base condition

$$u_{Li,b}^{\min} \le u_{Li,b} \le u_{Li,b}^{\max} \quad \forall i \in \mathbf{n_{pq}} \qquad (14)$$

- Max. loading condition

$$u_{Li,m}^{\min} \le u_{Li,m} \le u_{Li,m}^{\max}$$

b) Line power flow limits

- Base condition

$$s_{Li,b}^{\min} \le s_{Li,b} \le s_{Li,b}^{\max} \quad \forall i \in \mathbf{n_l} \qquad (15)$$

- Max. loading condition

$$s_{Li,m}^{\min} \le s_{Li,m} \le s_{Li,m}^{\max}$$

c) Fixed power factor

$$\frac{\Delta p_{di}}{p_{di}^{0}} = \frac{\Delta q_{di}}{q_{di}^{0}} \quad \forall i \in \mathbf{n_s} \qquad (16)$$

d) Allowable load curtailment

$$\Delta p_{di}^{\min} \le \Delta p_{di} \le \Delta p_{di}^{\max} \quad \forall i \in \mathbf{n_s} \qquad (17)$$

e) Voltage stability margin limit

$$1 \le \lambda_0 + \sum_{i=1}^{N} \frac{\partial \lambda}{\partial p_{di}} \Delta p_{di} + \sum_{i=1}^{N} \frac{\partial \lambda}{\partial q_{di}} \Delta q_{di} \le 1.06 \qquad (18)$$

where C_i is the power interruption cost at bus i (\$/kW) ; $\mathbf{n_{pq}}$ is the set of load (PQ) buses; $\mathbf{n_l}$ is the set of transmission lines; $\mathbf{n_s}$ is the set of effective load buses selected for load shedding. In this paper, the control variables are the active power load curtailment at effective buses represented by Δp_{di}. and the dependent variables listed in (14)-(15). To simplify the problem, power factor at the load shedding buses are maintained by proportionately curtailing the reactive power load Δq_{di} according to (16), where p_{di}^{0} and q_{di}^{0} are initial active and reactive power demand of bus i, respectively. The value of λ is calculated based on the linear estimation technique in [11]. Because the power system may become unstable (λ<1) after a severe disturbance, therefore the load shedding algorithm must be able to bring the system back to the boundary of stable operation (λ=1). However, it may not be necessary in the practical viewpoint to guarantee a great distance to the collapse. Therefore, the maximum stability margin of 6% is set (λ=1.06).

B. Implementation

The implementation steps of the proposed ACO_R based algorithm can be written as follows;

Step 1: At the generation *Gen* =0; store ACO_R parameters and randomly initialize k individuals within respective limits and save them in the archive.

Step 2: For each individual in the archive, evaluate the original objective as shown in (13) and determine the corresponding λ from the middle term of (18).

Step 3: To maintain constant power factor at load buses, reactive power demand is additionally curtailed (assumed at no cost) according to (16).

Step 4: Run power flow to determine load bus voltages and calculate line power flows in (14) and (15) at base- and maximum loading condition (at the λ found from step 2).

Step 5: Evaluate the fitness of each individual based on the strategy section III.B.

Step 6: Sort individuals of the archive based on feasibility and fitness values.

Step 7: To generate ant population, perform random sampling based on in the method discussed in section III.A and evaluate the corresponding fitness according to steps 2-5.

Step 8: Sort individuals of the ant population based on feasibility and fitness values.

Step 9: Find the generation (local) best $\mathbf{x_{local}}$ and global best $\mathbf{x_{global}}$ ant based on the following criteria;

a) Any feasible solution is preferred to any infeasible solution;
b) Between two feasible solutions, the one having better objective value is preferred;
c) Between two infeasible solutions, the one having smaller fitness value (smaller constraint violation) is preferred.

Step 10: Store $\mathbf{x_{local}}$ and $\mathbf{x_{global}}$

Step 11: In the archive, update the individuals by replacing a pre-specified number of worse solutions (n_{rp}) by n_{rp} better ant solutions, re-evaluate the fitness, and resort the archive.

Step 12: Increase the generation counter *Gen* = *Gen*+1.

Step 13: If one of stopping criterion have not been met, repeat steps 7-12.

In this paper, two stopping criterion are set up. The algorithm stops if the maximum number of generations is reached ($Gen = Gen_{max}$) or there is no solution improvement over a specified number of generations.

V. SIMULATION RESULTS

The IEEE 30-bus system is used to test the effectiveness of the proposed algorithm. The test system used in this study has six generation buses, 21 load buses, 4 transformers and 41 transmission lines. The network topology, generator, load and transmission line data can found in [14]. The reactive power sources are connected to buses 10 13 15 16 18 20 25 27 and 30. The system loading is increased to 2 times of the base case to 566.8 MW where all voltage profiles and line flows are within the limits and the corresponding λ is 1.5353. The N-1 contingency analysis was conducted to identify the most critical line. It reveals that the outage of line connected between buses 28 and 27 results in an unstable case where λ=0.7533 (see Fig.4).This means that the system is being driven to instability. If no control actions are deployed, collapse is inevitable.

The software package namely, PSAT [15], is used as the simulation tool. Fig. 2 shows the VSM sensitivity with respect to active and reactive power demand changes at each load bus calculated at an operating point closed to the saddle node bifurcation. Buses with high sensitivities are very effective for the VSM enhancement. Therefore, five buses with the highest sensitivities (load buses number 17-21 corresponding to buses 23, 24,26,29 and 30, respectively) are selected to participate in the load shedding program. By pre-screening the effective buses, the computation efforts can be significantly reduced because of fewer decision variables are required for the optimization.

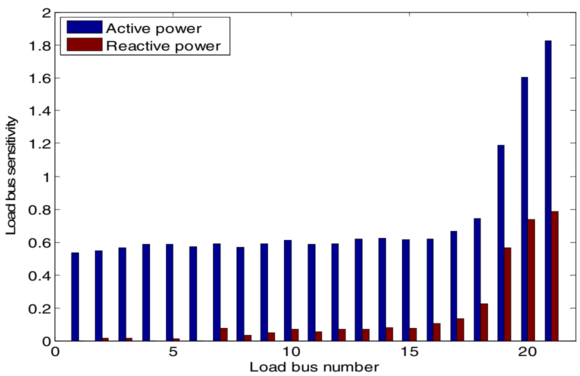

Fig. 2 Sensitivity of load buses

Costs of power interruption incurred by power consumers in different sectors according to [16] are given in Table A.1 of appendix. The permissible range of load shedding at buses and load configuration are listed in Table A.2. From this table, load bus 30, as an example, has the configuration of 0.6t+0.2i+0.2r. This means 60% of total demand of this bus comes from the transportation (t) sector, 20% from the industrial (i) sector and 20% from the residential (r) sector. Costs per 100 kW power interruptions at every bus showing different cost characteristics are also listed in Table A.2.

The ACO_R algorithm developed in MATLAB is applied for solving the NLP optimization problem defined in (11) to (16). The ACO_R parameter settings used in this study are tuned based on experimental knowledge and listed in Table I.

TABLE I
ACO_R PARAMETER SETTINGS

Parameter	Value
Archive size (k)	40
Number of ants (n_{ant})	20
Number of replancement (n_{rp})	8
Convergence rate factor (q)	0.1
Pheromone evaporation (ξ)	0.99

The voltage stability constraint in (18) is determined from the linear approximation of VSM subject to load reductions. Fig.3 (a) shows the comparison between actual VSMs determined by CPF and estimated values of 100 random load shedding conditions in order to examine the accuracy of (16). Corresponding absolute estimation errors are calculated as shown in Fig.3 (b) and good accuracies are demonstrated.

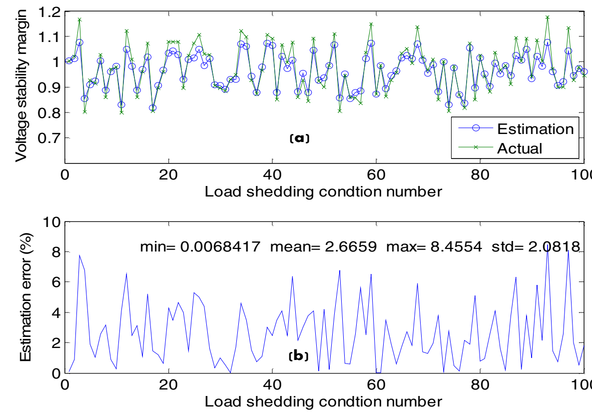

Fig. 3 Voltage stability margin vs. load shedding (a) comparison (b) estimation error

Following the optimization process, the PV profile of the most critical bus (bus 30) obtained by the CPF is plotted in Fig.4 against pre- and post-contigency (with no control actions) conditions. It is demonstrated that the proposed ACO_R technique is able to restore voltage stability of the system while maintaining a number of constraints within their limits.

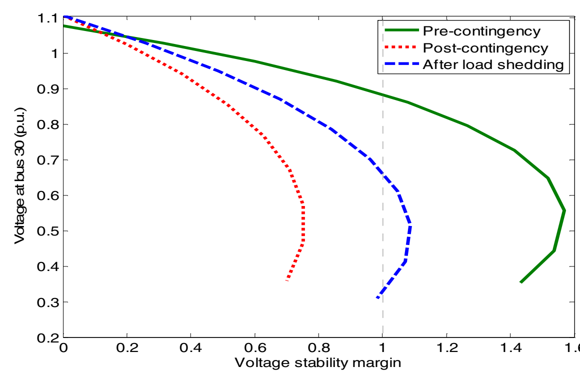

Fig. 4 PV curves of different operating conditions

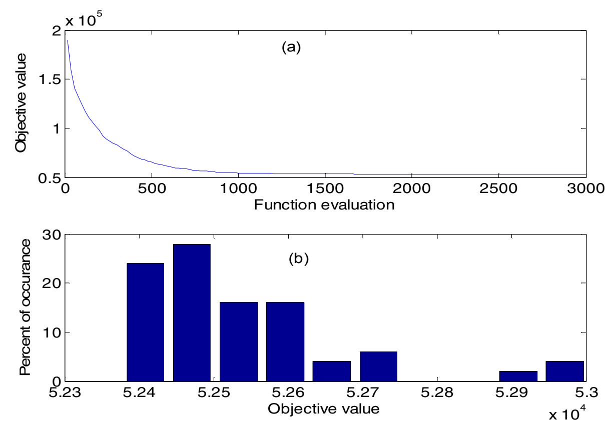

Fig. 5 ACO_R performance (a) convergence property (average of 50 independent runs) (b) histogram of optimal objective values

The average convergence property obtained from 50 independent runs is shown in Fig. 5 (a). It is obvious that the proposed algorithm is capable of discovering the optimal solution at a very fast speed. Statistical evaluation has been performed and the histogram of the optimal objective value is depicted in Fig. 5(b). It is quite obvious that the ACO_R nearly converges to the same solution. The optima results of each indpendent run, the final λ after load shedding and CPU time are averaged and given in Table II. Statistical values of the final objective values are shown in Table III.

TABLE II
OPTIMAL RESULTS AND SIMULATION TIME

Optimal control variables (kW)					λ	Time (s)
Δp_{d23}	Δp_{d24}	Δp_{d26}	Δp_{d29}	Δp_{d30}		
1.142	1.043	3493.378	2333.508	6081.638	1.046	144.425

TABLE III
STATISTICAL DATA

Min	Mean	Max	Std.
52377.4765	52536.2404	53003.3872	142.9681

CONCLUSION

This paper presents an ant colony optimization (ACO) based algorithm for optimal load shedding problem to enhance power system voltage stability. The proposed method is flexible to study technical and economic aspects of the problem. The former goal is accomplished by analyzing sensitivities of the voltage stability margin with respect to power demand changes at different buses. Only few effective load buses are selected to participate in the load shedding program. Cost of power interruption is minimized to achieve the second requirement. The recent ACO variant for global search in continuous domain namely ACO_R is modified to handle constrained optimization problems. The developed ACO_R is applied to solve the optimization problem formulated in the optimal power flow (OPF) framework with the full consideration of various network constraints. It is shown from the simulation results that the proposed method can effectively improve voltage stability of the power system. The developed ACO_R also processes at a fast speed. Statistical studies based on multiple independent runs also reveal that ACO_R is a quite robust tool because of its ability to generate nearly identical results. Because the present ACO_R algorithm was initially developed to solve unconstrained optimization problems, therefore some conceptual modifications could be very useful when handling constrained optimization problems. If some of parameters, which normally require tuning, were eliminated, the algorithm would become more powerful. These are our current domain of investigation.

APPENDIX

TABLE A.1 INTERRUPTION COST IN DIFFERENT SECTORS

Interruption cost ($/kW)			
Transportation (t)	Industrial (i)	Commercial (c)	Residential (r)
16.42	13.93	12.87	0.15

TABLE A.2 LOAD SHEDDING DATA

Bus	$\Delta P_{Di,min}$(pu)	$\Delta P_{Di,max}$(pu)	Configuration	Cost ($/100 kW)
23	0	0.032	0.5c+0.5r	651
24	0	0.087	0.3t+0.7i	1467.7
26	0	0.035	1r	15
29	0	0.024	0.4i+0.2c+0.4r	820.6
30	0	0.070	0.6t+0.2i+0.2r	1266.8

REFERENCES

[1] Voltage stability assessment: concepts, practises and tools, Aug. 2002, www.power.uwaterloo.ca [online]

[2] T.Van Cutsem and C. Vournas, *Voltage stability of electric power systems* , Kluwer Academic Publisher, 1998

[3] C.M. Affonso, L.C.P. da Silva, F.G.M. Lima and S. Soares, “MW and Mvar management on supply and demand side for meeting voltage stability margin criteria,” *IEEE Trans. on Power Systems,* vol.19, no.3, pp.1538-1545, 2004

[4] H.Song, S.D. Park and B. Lee, “Determination of load shedding for power flow solvablity and outage continuation power flow (OCPF),” *IEE Proc. Gener Transm Distrib*, vol. 153, no.3 , pp. 321-325, 2006

[5] T. Amraee, A.M Ranjbar, B. Mazafari and N. Sadati, “An enhanced under voltage load shedding scheme to provide voltage stability”, *Elec. Power Syst. Res.*,vol.77, 2007, pp. 1038-1046

[6] M. Dorigo and T.Stützle, *Ant colony optimization,* MIT press, Cambridge, MA, 2004

[7] K. Socha and M. Dorigo, “Ant colony optimization for continuous domains,” European Journal of Operational Research, vol.185, 2008, pp. 1155-1173

[8] V.Ajjarapu, C.Christy, “The continuation power flow: a tool to study steady state voltage stability,” *IEEE Trans. on Power Systems,* vol.7, no.1, pp.416-423, 1992

[9] V. Ajjarapu, *Computational techniques for voltage stability assessment and control* , Springer-Verlag, 2006

[10] W.Nakawiro and I. Erlich, “Voltage security assessment and control using a hybrid intelligent method”, In.Proc. *IEEE Power Tech 2009*, Bucharest, Romania, July 2009

[11] D.E. Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*, Kluwer Academic Publishers, Boston, MA.,1989

[12] G.E.P. Box and M.E. Müller,“A note on the generation of reandom normal deviates,” Annals of mathematical statistics, vol. 29, no.2, pp.610-611, 1958

[13] B.Tessema, G.G. Yen, “A self adaptive penalty function based algortihm for constrained optimization,” in proc. *IEEE Congress on Evolutionary Computation*, 2006, 16-21 July 2006, pp. 246-253

[14] H.Saadat, *Power system analysis*, McGraw-Hill, 1999

[15] F. Milano, L. Vanfretti, J. C. Morataya, “An Open Source Power System Virtual Laboratory: The PSAT Case and Experience,” *IEEE Trans on Education*, vol. 51, no. 1, pp. 17-23, Feb. 2008.

[16] P.J. Balducci, J.M. Roop, L.A. Schienbein, J.G. Desteese and M.R. Weimar, “Electrical power interruption cost estimates for individual industries, sectors and U.S. economy,” Pacific Northwest National Lab, Feb. 2002