

# Volt/VAr Control in Distribution Systems by Fuzzy Multiobjective and Particle Swarm

Suwit Auchariyamet<sup>1</sup> and Somporn Sirisumrannukul<sup>2</sup>, Non-members

## ABSTRACT

This paper presents the optimal dispatch for the under load tap changer (ULTC) of a substation transformer, substation capacitors, and feeder capacitors for volt/VAr control in a distribution system. Three objectives of interest in the problem consist of energy loss, total capacitor kVAr to be switched on, and total number of daily switching operations of the ULTC and all capacitors. The optimization problem is subjected to power flow equations, voltage limits, and maximum switching operations for the ULTC and the capacitors. All the objectives are fuzzified using a trapezoidal membership function and are integrated to represent the fuzzy decision value. Fuzzy multiobjective and particle swarm optimization are employed to determine the optimal dispatch schedule that provides the best compromise among all the objectives. The methodology is demonstrated by a 29-bus distribution system of Provincial Electricity Authority (PEA), Thailand.

**Keywords:** Volt/VAr Control, Fuzzy Multiobjective, Particle Swarm Optimization, Distribution System

## 1. INTRODUCTION

In a distribution system, electric power demands vary from hour to hour. The changes in the demands result in fluctuation of bus voltages and could, sometimes, cause power quality problems, e.g. under-voltage, overvoltage. Appropriate actions should be taken to keep the voltages stay within the acceptable bounds. One of the most efficient and useful methods to improve voltage magnitudes is voltage/reactive power control or volt/VAr control.

Volt/VAr control is one important scheme for a daily operation in the distribution system. It is defined as the regulation of voltage and reactive power (or power factor) along the feeders. A proper volt/VAr control can increase system efficiency, decrease system power losses, and improve voltage profile.

Volt/VAr control is implemented by incorporating an under load tap changer (ULTC) of transformer

and shunt capacitors [1]. The ULTC is normally installed at secondary side of a main transformer in a distribution substation to control secondary bus voltage under changing load conditions. Shunt capacitors consist of two types of switched capacitor: substation capacitors and feeder capacitors. Substation capacitors are installed at the secondary bus of the substation with the objective to control reactive power flow through the main transformer such that the system operates at a high power factor. For feeder capacitors, they are installed along the feeders to provide reactive power compensation.

A great deal of research work for volt/VAr control in distribution systems has been reported. In [2] and [3], only the ULTC was considered for volt/VAr control. An advanced online control method was proposed in [2] to determine the optimal tap position of the ULTC to maintain the customers' voltages within the permission limits. In [3], a fuzzy rule based controller was introduced to coordinate the cascade ULTC in the distribution system. The objective of the coordination was to improve the voltages of load buses while the tap changer should not frequently operate.

In [4-6], not only the ULTC but also substation capacitors are competed in decision variables of the search space for volt/VAr control. The objectives proposed by F. C. Lu and Y. Y. Hsu [4] were to minimize the flow of reactive power through the main transformer and the voltage deviation of the main transformer bus. The proper dispatch of the both devices was achieved by a dynamic programming while taking the limits of bus voltage and the maximum allowable number of switching operation in a day for the ULTC as practical constraints. The authors also extended their methods to solve a reactive power/voltage problem with two additional constraints [5, 6]. The first constraint was the maximum switching operation of substation capacitors and the second one was the tolerable worst power factor for the substation transformer. The uncertainty of all objectives and constraints were realized by fuzzy representation. The optimal dispatch schedule in [5] was obtained by a fuzzy dynamic programming whereas the combination of two approaches was employed in [6] to find the optimal coordination of both devices. A preliminary dispatch schedule was first defined by an artificial neural network (ANN). The obtained preliminary dispatch schedule was then further refined

Manuscript received on July 31, 2009 ; revised on October 15, 2009.

<sup>1,2</sup> The authors are with The King Mongkut's University of Technology North Bangkok, Thailand, E-mail: suwit@tistr.or.th and spss@kmutnb.ac.th

by fuzzy dynamic programming in order to reach the final schedule.

Volt/VAR control using only feeder capacitors was suggested in [7] and [8]. N. I. Santoro and O. T. Tan [7] convincingly demonstrated that the need of the real time control of switched type capacitors installed in a distribution system could be effectively identified by a two-stage ANN to minimize system power losses. The first stage of ANN predicted the load profile from a set of input data and the second stage selected the optimum capacitor tap position based on the load profile obtained in the first stage. As presented in [8], the dispatch of feeder capacitors in daily system operation was investigated. The optimal capacitor dispatch schedule, performed on the basis of forecast hourly loads on the next day, was offered by a dynamic programming with the objective of power loss minimization. The constraints under imposition were the maximum switching operations for each capacitor and the voltage limits on the feeder.

The volt/VAR control devices which consist of ULTC, substation capacitors, and feeder capacitors are of interest in [9-11]. The aim of work in [9] was to properly dispatch all volt/VAR control devices such that the total loss was minimized, voltage profile was improved, and the reactive power into the substation transformer was restrained. The voltage limits on the feeders and the maximum allowable number of switching operation in a day for all control devices had to be satisfied. A dynamic programming was applied as a tool for finding the optimal dispatch schedule. The optimal control of all devices was determined with the objectives of loss minimization and voltage profile improvement [10]. The control trajectory was decomposed into two sub-problems, namely, sub-problem on substation level and sub-problem on feeder level. A simplified dynamic programming and a fuzzy logic control algorithm were suggested to deal with the two sub-problems respectively. Z. Hu et al [11] proposed a genetic algorithm to identify the coordination of ULTC and all switched capacitors. The obtained optimum dispatch schedule minimized the power loss and improved the voltage profile, ensuring that the number of switching operation was less than the maximum allowance and bus voltages were maintained within an acceptable limit.

From the aforementioned literature review, a few findings have been observed as follows. First, several studies did not simultaneously coordinate volt/VAR control devices and hence a solution may be suboptimal. Second, not much has been dealt with multi-objective optimization problems, where a number of objective functions could not be attained at the same time. They should therefore be appropriately traded off, reflecting the practical requirement of the system operator. Finally, some of the solution methods would be time consuming or complicated to arrive at the optimal solution. For example, searching for the

optimal dispatch schedule of ULTC and all switched capacitors in the distribution system by dynamic programming would take considerable computation effort due to a very large search space [11], whereas the steps of coding, encoding, selection, crossover, and mutation in the genetic algorithm could pose some difficulties when it is applied to solve volt/VAR control problems.

This paper remedies these drawbacks by formulating the coordination of key volt/VAR control devices in distribution systems, namely ULTC, substation capacitors, and feeder capacitors as a multiobjective optimization problem. The vagueness of conflicting objective functions and constraints are realized by a fuzzy set. Most importantly, a straightforward optimization technique which can provide a promising solution within a reasonable computation time is recommended to solve the problem.

## 2. PROBLEM DESCRIPTION

In practice, it is necessary to coordinate the switching operation of ULTC and capacitors for volt/VAR control because the switching of capacitors may result in the variation of secondary bus voltage and hence the movement in ULTC [9]. Without a good coordination between the operation of ULTC and capacitors, both devices will be frequently switched. Excessive switching operation introduces high maintenance costs as well as reduces their life expectancies. For this reason, the optimal dispatch is essentially required to coordinate the switching of ULTC and capacitors to minimize their operations while still achieving the advantages of volt/VAR control.

The optimal dispatch for volt/VAR control is a combinatorial optimization problem with constraints. The problem is formulated from non-continuous and non-linear functions of discrete variables. In general, possible solutions to be analyzed grow dramatically with the increase of 1) the number of load level being considered and 2) the number of ULTC and capacitors to be controlled. Most conventional optimization techniques, therefore, find it difficult to search for the optimal solution.

One efficient method that can solve volt/VAR control problem is particle swarm optimization (PSO). PSO was first introduced in 1995 [12]. It is a population based stochastic optimization technique derived from simulation of a simplified social model of swarms (e.g. bird flocks or fish schools). The interaction of particles in swarm, using common evolutionary computation algorithm, guides the direction of swarm towards the optimal regions of search space. Unlike other evolutionary techniques, PSO requires only primitive mathematical operators in its computation process. A large amount of research and development in PSO algorithms has extended its abilities to provide high quality solutions with stable conver-

gence. The advantages of PSO are computationally efficient, simplicity in concept and implementation, and robustness to control parameters.

This paper is emphasized on the coordination of the ULTC, substation capacitors, and feeder capacitors for volt/VAr control. Three objectives taken into account are energy loss, total capacitor kVAr to be switched on, and total number of switching operations of ULTC and capacitors. The aim of the optimal dispatch schedule is to satisfy all the objectives as much as possible. It can be seen that the term “as much as possible” is a linguistic expression which can not be included in the numerical optimization algorithm. Therefore, the fuzzy set theory [13], which can handle uncertainty, vagueness, and imprecise information, is employed to translate this ambiguous linguistic expression “as much as possible” to be a mathematical expression.

In this work, the satisfaction of each objective is modeled by a fuzzy set. Then a searching process by PSO algorithm is used to find a proper combination of ULTC positions and capacitors on/off switching operations that mostly satisfies all the objectives. The system power losses and bus voltages are solved by a backward-forward sweep distribution power flow. The performance of the proposed methodology is demonstrated by a distribution system of Provincial Electricity Authority (PEA), Thailand.

### 3. PROBLEM FORMULATION

The goal of the optimal dispatch of the ULTC, substation capacitors, and feeder capacitors for volt/VAr control is to determine the setting of these devices for a given daily load pattern. To simplify the setting, the daily load pattern is divided into load levels, so the switching of ULTC and capacitors could only be done between different load levels. The objectives of interest consist of the energy loss, the total capacitor kVAr to be switched on for reactive power compensation, and the total number of switching operations of the ULTC and all capacitors.

Each objective is fuzzified using a membership function to indicate its membership value which is the real number in the interval [0, 1]. All the membership values are then combined into a fuzzy decision value expressed as:

$$\max J = \mu_E + \mu_{QC} + \mu_S \quad (1)$$

Where  $J$  = fuzzy decision value for optimal solution

$\mu_E$  = membership value for the energy loss

$\mu_{QC}$  = membership value for the total capacitor kVAr to be switched on

$\mu_S$  = membership value for the total number of switching operations of the ULTC and all capacitors

The maximization of the fuzzy decision value is

subjected to power balancing equality constraint and also the following inequality constraints.

$$V_{min} \leq |V_{j,i}| \leq V_{max} \quad (2)$$

$$N_{tap} = \sum_{i=1}^S |TAP_i - TAP_{i-1}| \leq KT \quad (3)$$

$$NCS_m = \sum_{i=1}^S |CS_{m,i} - CS_{m,i-1}| \leq KCS \quad (4)$$

$$NCF_n = \sum_{i=1}^S |CF_{n,i} - CF_{n,i-1}| \leq KCF \quad (5)$$

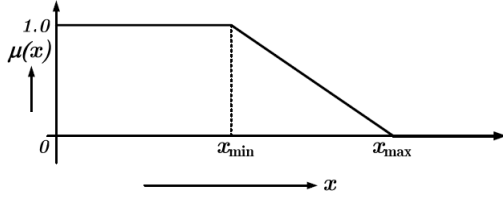
Where  $V_{min}$  = minimum limit of bus voltage (p.u.)  
 $|V_{j,i}|$  = voltage of bus  $j$  at load level  $i$  (p.u.)  
 $V_{max}$  = maximum limit of bus voltage (p.u.)  
 $N_{tap}$  = switching operations of ULTC  
 $S$  = number of load levels  
 $TAP_i$  = ULTC tap position at load level  $i$   
 $KT$  = maximum switching operation for ULTC  
 $NCS_m$  = switching operations of substation capacitor  $m$   
 $CS_{m,i}$  = number of banks for substation capacitor  $m$  at load level  $i$   
 $KCS$  = maximum switching operation for substation capacitors  
 $NCF_n$  = switching operations of feeder capacitor at bus  $n$   
 $CF_{n,i}$  = number of banks for feeder capacitor at bus  $n$  at load level  $i$   
 $KCF$  = maximum switching operation for feeder capacitors

### 4. MEMBERSHIP FUNCTIONS OF OBJECTIVES

Fuzziness in a fuzzy set is characterized by a membership function. In this paper, a trapezoidal membership function depicted in Fig.1 is applied to determine the membership value,  $\mu$ , for all objectives.

As seen in Fig.1, the unity membership value is assigned as long as the value of  $x$  is less than  $x_{min}$ . The membership value linearly decreases if  $x$  lies between  $x_{min}$  and  $x_{max}$ . The zero membership value is given if  $x$  is greater than  $x_{max}$ . Therefore, the membership values derived from this membership function can be mathematically written as:

$$\mu = \begin{cases} 1 & \text{for } x \leq x_{min} \\ \frac{x_{max} - x}{x_{max} - x_{min}} & \text{for } x_{min} < x < x_{max} \\ 0 & \text{for } x \geq x_{max} \end{cases} \quad (6)$$



**Fig.1:** Trapezoidal Membership Function.

Note that the fuzzy parameters  $x_{min}$  and  $x_{max}$  are different for each objective.

The value of  $x$  depends on a dispatch pattern and the objective under question. Let the superscript  $k$  be the dispatch pattern. Consequently, the value of  $x$  used to calculate  $\mu_E$ ,  $\mu_{QC}$ , and  $\mu_S$  for a dispatch pattern  $k$  can be expressed as in (7), (8), and (9), respectively.

$$x_E^k = \left( \sum_{i=1}^S T_i P_i^k \right) / \left( \sum_{i=1}^S T_i P_i^0 \right) \quad (7)$$

$$x_{QC}^k = \left( \sum_{i=1}^S Q_{C,i}^k \right) / (S \times Q_T) \quad (8)$$

$$x_S^k = N_{top}^k + \sum_{m=1}^{C_s} NCS_m^k + \sum_{n \in SCF} NCF_n^k \quad (9)$$

Where  $x_E^k = x^k$  that calculates  $\mu_E$   
 $x_{QC}^k = x^k$  that calculates  $\mu_{QC}$   
 $x_S^k = x^k$  that calculates  $\mu_S$   
 $T_i$  = time duration for load level  $i$  (hr)  
 $P_i^k$  = power loss for load level  $i$  in dispatch pattern  $k$  (kW)  
 $P_i^0$  = power loss for load level  $i$  without dispatch (kW)  
 $Q_{C,i}^k$  = capacitor kVAR to be switched on in dispatch pattern  $k$  for load level  $i$   
 $Q_T$  = total existing capacitor kVAR in the system  
 $C_s$  = number of substation capacitors  
 $SCF$  = set of buses for feeder capacitor placement

## 5. PARTICLE SWARM OPTIMIZATION (PSO)

PSO is a population based stochastic optimization technique. In PSO, the population is called “swarm” and the individual in swarm is called “particle”. PSO algorithm conducts searching process using swarm of particles. Each particle is represented by its position and velocity and is referred as a potential solution in  $n$ -dimensional search space of the problem. Particles have knowledge of formerly moved directions, their previous best solutions, and the best solution found

by the best particle in swarm. Based on this knowledge, particles can explore different regions of search space to locate a good optimum.

In general, PSO algorithm consists of three main steps, namely, 1) generate initial particle’s positions and velocities, 2) evaluate fitness value of each particle, and 3) update velocity and position of all particles [14].

At the beginning, the positions and velocities of the initial swarm of particles are randomly generated to allow all particles arbitrarily distributed across the search space. The fitness value of each particle is evaluated in the second step to determine the best position of each particle and also to reveal the particle that has the best global fitness value in the current swarm.

Next, the velocities of all particles are updated from iteration  $t$  to  $(t+1)$  by: [15]

$$v_{id}(t+1) = wv_{id}(t) + c_1 r_{1d} [y_{id}(t) - x_{id}(t)] + c_2 r_{2d} [\hat{y}_d(t) - x_{id}(t)] \quad (10)$$

Where  $x$  = position of particle  
 $v$  = velocity of particle  
 $w$  = inertia weight  
 $c_1, c_2$  = positive acceleration constants  
 $r_{1d}, r_{2d}$  = uniformly distributed random variables in the range  $[0,1]$   
 $y$  = personal best position;  $Pbest$   
 $\hat{y}$  = global best position;  $Gbest$   
 $i$  =  $i^{th}$  particle  
 $d$  =  $d^{th}$  dimension  
 $id$  = particle  $i$  in dimension  $d$

In the right hand side of (10), the first term is an inertia weight from the current velocity. The second term represents the knowledge based on the best solution of each particle while the third term is the information of the best solution found by the best particle in swarm.

Position update is the last step. The new position of each particle is calculated by: [15]

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (11)$$

The step of fitness value evaluation including the step of velocity and position updating are repeated until a stopping criterion is met. Many criteria can be applied to terminate the iterative process of PSO; for example, maximum number of iteration is reached, an acceptable solution is found, or no improvement in solution is observed over a number of iteration. The important point for stopping criterion selection is that it should not cause the PSO to prematurely converge. More explanations about PSO algorithm are covered in [15].

## 6. COMPUTATION PROCESS

### 6.1 Distribution Power Flow

Power flow calculation is a computation procedure to find power losses and bus voltages of a network. The specific technique in [16], employed in this work, is based on the backward-forward sweep technique and tailored for radial distribution systems. This power flow algorithm is simple since it does not require any complex mathematical computations or any matrix inversion.

A branch-to-node matrix is first developed based on the topological structure of the system to indicate the relationship between load currents and branch currents. All bus voltages are then computed by iterative process using the branch-to-node matrix. Bus voltages in the  $k^{th}$  iteration of power flow calculation are stated by:

$$[\mathbf{V}]^{(k)} = [\mathbf{V}_0] - [\mathbf{C}]^T [\mathbf{Z}] [\mathbf{C}] [\mathbf{I}]^{(k)} \quad (12)$$

Where  $[\mathbf{V}]^{(k)}$  = vector of bus voltages  
 $[\mathbf{V}_0]$  = vector of voltage at the slack bus  
 $[\mathbf{C}]$  = branch-to-node matrix  
 $[\mathbf{Z}]$  = primitive impedance matrix  
 $[\mathbf{I}]^k$  = vector of load currents

$[\mathbf{V}]^{(k)}$  and demand load at every bus are used to calculate  $[\mathbf{I}]^{(k+1)}$ , so that  $[\mathbf{V}]^{(k+1)}$  in the next iteration can be evaluated. This process is repeated until the difference of bus voltages between a current iteration and the previous one is smaller than an acceptable tolerance.

### 6.2 Particle's Representation

Each particle consists of three segments to represent candidate solutions. The first segment defines the setting of the ULTC. The number of digits in the first segment is equal to the number of load levels. The second and third segments respectively represent the setting of substation capacitors and feeder capacitors. In these two segments, the number of digits depends on the number of load levels and the number of capacitors. Thereby, the dimension of particle is:

$$L = S \times (1 + C_S + C_F) \quad (13)$$

Where  $L$  = dimension of particle  
 $S$  = number of load levels  
 $C_S$  = number of substation capacitors  
 $C_F$  = number of feeder capacitors

### 6.3 Selection of Feasible Solutions

For the methodology proposed in this paper, one particle requires power flow calculation to determine power losses and bus voltages for every load level. If there are  $N$  load levels and there are particles in

swarm, power flow calculation must be performed  $S \times N$  times for each iteration of PSO. This is a computationally time-consuming process. However, it should be emphasized that many solutions in the search space violate the constraints of maximum switching operations as mentioned in (3), (4), and (5) [11]. Therefore, we should first calculate the switching operations of ULTC, substation capacitors, and feeder capacitors for every particle to classify them into qualified and unqualified particle. The qualified particles are those which do not violate all the switching operation constraints. Otherwise, they are defined as unqualified particles and will be discarded. This step greatly helps reduce the computational burden because power flow calculations are only performed for the qualified particles.

### 6.4 Computation Procedure

The computation procedure can be described by the following steps.

- Step 1: Input line data and bus data of a distribution system, load pattern, all operational constraints and PSO parameters.
- Step 2: Generate an initial population of particles with random positions and velocities.
- Step 3: Set iteration index = 0.
- Step 4: For every particle, find the number of switching operations for ULTC, substation capacitors, and feeder capacitors to define the qualified and unqualified particles.
- Step 5: Perform AC distribution power flow for each qualified particle to obtain system power loss and bus voltages for all the load levels.
- Step 6: For each qualified particle, evaluate the membership values of all the objectives and then integrate them into the fuzzy decision value.
- Step 7: Check the voltage constraint. If it is violated, a penalty term is identified, or else a penalty term is zero.
- Step 8: Evaluate the fitness value for each qualified particle using the sum of fuzzy decision value and penalty term.
- Step 9: Compare the fitness value of qualified particle with the personal best,  $P_{best}$ . If the fitness value is better than  $P_{best}$ , set this value as the current  $P_{best}$ , and record the particle corresponding to this  $P_{best}$  value.
- Step 10: Select the maximum value of  $P_{best}$  from all qualified particles to be the current global best,  $G_{best}$ , and record the particle corresponding to this  $G_{best}$  value.
- Step 11: Update the velocity and position of all particles.
- Step 12: If the maximum number of iteration has been reached, the particle associated with the current  $G_{best}$  is the optimal solution

and then go to Step 13. Otherwise,  
set  $t=t+1$  and return to Step 4.

Step 13: Identify the setting of the ULTC, substation capacitors, and feeder capacitors using the optimal solution obtained in Step 12.

Step 14: Print out the results.

## 7. CASE STUDY

The proposed technique is tested with a 29-bus distribution system designated as KWA F6 (Khleng Fang Feeder 6). This test system is modified from a practical distribution system of Provincial Electricity Authority (PEA), Thailand [17]. Its configuration, load data, and feeder data are shown in Fig. A1 and Table A1 of appendix. The total demand of the system is 3,890 kW.

It is assumed that all load points have the same profile as shown in Fig. 2. The 1.0 per unit load in this figure is the demand given in Fig. A1. The base value for voltage and power are 22 kV and 100 MVA. The power factors of all load points are assumed as 0.7 lagging. The ULTC has 17 possible positions ( $TAP_i$  -8, -7, ..., 0, 1, 2, ..., 8) which can change the voltage from -5% to +5%.

The data of the existing capacitors in the network is given in Table 1. All the operational constraints are shown in Table 2. The fuzzy parameters for the membership function associated with the three objectives are listed in Table 3 and the PSO parameters are provided in Table 4.

**Table 1: Data of Existing Capacitors in the Network**

Capacitor type	Bank size (kVAr)	Number of banks
Substation capacitors		
-No.1	100	3
-No.2	100	3
Feeder capacitors		
bus No.8	300	6
bus No.11	300	6
bus No.17	300	6
bus No.29	300	6

**Table 2: Operational Constraints**

Minimum voltage limit ( $V_{min}$ )	0.95 p.u.
Maximum voltage limit ( $V_{max}$ )	1.05 p.u.
Maximum switching operation	
- for ULTC ( $KT$ )	15
- for substation capacitors ( $KCS$ )	10
- for feeder capacitors ( $KCF$ )	4

**Table 3: Fuzzy Parameters for Each Objective**

Membership function for	$x_{min}$	$x_{max}$
$\mu_E$	0.1	1
$\mu_{QC}$	0.2	1
$\mu_S$	12	51

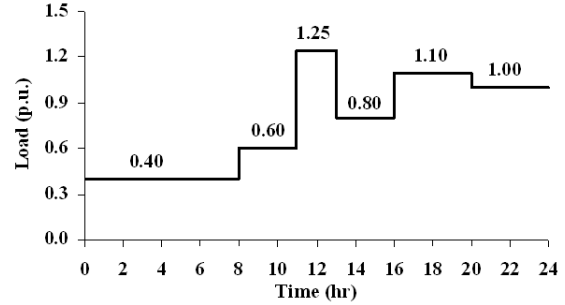
The following five cases are examined for comparison purpose.

Case 1: The system is without volt/VAr control

Case 2: A dispatch schedule of this case minimizes the energy loss.

**Table 4: PSO Parameters**

Number of particles in swarm	50
Maximum iteration of computation	50
Acceleration constants, $c_1, c_2$	2.0, 2.0
Inertia weight, $w$	linearly decreased from 0.9 to 0.4 in each iteration



**Fig.2: Daily Load Pattern**

Case 3: A dispatch schedule of this case minimizes the total capacitor kVAr to be switched on for all load levels.

Case 4: A dispatch schedule of this case minimizes the total number of switching operations of the ULTC and all capacitors.

Case 5: A dispatch schedule of this case is obtained from the procedure given in the previous section.

## 8. RESULTS AND DISCUSSIONS

A computer program, developed based on the computation procedure detailed in Section 6.4, has been run on Pentium M processor 1.60 GHz, 1.00 GB of RAM. The optimal dispatch of case 5, taken all objectives into account, is shown in Table 5. The summary of numerical results for all cases is presented in Table 6.

**Table 5: Dispatch Schedule of Case5**

Devices	Load levels						Number of switching
	1	2	3	4	5	6	
1) Tap position of ULTC	2	2	2	4	4	4	4
2) Number of banks for substation capacitors							
-No. 1	1	1	2	2	2	1	2
-No. 2	1	1	1	1	1	1	0
3) Number of banks for feeder capacitors							
-bus No.8	2	2	4	3	3	3	4
-bus No.11	2	2	2	2	2	2	0
-bus No.17	3	3	5	5	5	4	4
-bus No.29	2	3	4	4	4	4	4

Table 6 indicates that fastest computation time in case 1 can be expected since its computation process is no more than power flow calculation. The computation time of cases 2 to 4 is not much different because only one objective is concentrated in each case. Case 5 takes around 30 seconds as much computation time as cases 2 to 4 because its optimization process has to cope with all the three objectives.

From the results shown in Table 6, the energy loss in case 1 is highest and some bus voltages in this case are found violating the lower limit of 0.95 per

**Table 6:** Results of Case Study

	Case 1	Case 2	Case 3	Case 4	Case 5
1) Computation time (seconds)	1.2	229	234	231	265
2) Energy loss (kWh)	6,074.91	2,308.77	2,648.21	2,991.91	2,510.40
3) Saving in energy loss (%)	-	61.99	56.41	50.75	58.68
4) Total capacitor kVAr from all load levels (kVAr)	-	23,200	20,400	27,600	24,000
5) Minimum voltage found in the system (p.u.)	0.8122	0.9842	0.9501	0.9577	0.9504
6) Maximum voltage found in the system (p.u.)	1.0000	1.0500	1.0286	1.0471	1.0250
7) Number of switching operations					
- ULTC	-	10	4	2	4
- Substation capacitors	-	6	10	-	2
- Feeder capacitors	-	14	12	6	12
- Total	-	30	26	8	18

unit. It can be seen that the implementation of the optimal schedules in cases 2 to 5 can decrease the energy losses and can develop all bus voltages to stay within the allowable range. The energy loss, the total capacitor kVAr to be switched on, and the total number of switching operations of the control devices are at minimum in cases 2, 3 and 4 respectively. This is because the optimization process is able to provide the solutions that serve the targeted objective of each case. However, it is observed that the achievement in one objective can take effects on the others. As seen in Table 6, the lowest energy loss in case 2 comes at the expense of the highest total number of switching operations of the ULTC and the capacitors. The minimum total capacitor kVAr in case 3 gives a higher energy loss compared with that of case 2. The lowest total number of switching operations for all control devices in case 4 introduces the maximum total capacitor kVAr and also the minimum saving in energy loss.

A trade-off among all the objectives is offered by the application of fuzzy multiobjective illustrated in case 5. In this case, the membership value for energy loss, total capacitor kVAr, and number of switching operations are 0.652, 0.609, and 0.846 respectively. The saving in energy loss and the total capacitor kVAr of case 5 are slightly lower and slightly higher than those of case 2 but the number of switching operations in case 5 are significantly lower. Although case 5 requires more total capacitor kVAr for reactive power compensation than that of case 3, it can present a higher value of saving in energy loss and also a lower number of switching operations. Finally, ten more switching operations of case 5, against those of case 4, can decrease the values of energy loss and the required total capacitor kVAr. These demonstrate the performance of the fuzzy multiobjective model to compromise all the objectives.

## 9. CONCLUSION

This paper has presented a methodology based on fuzzy multiobjective and PSO to determine the optimal dispatch of the ULTC, substation capacitors, and feeder capacitors for volt/VAr control in a distribution system. Three objectives considered were the system energy loss, the total capacitor kVAr, and

the total number of switching operations of the ULTC and the capacitors. All objectives were fuzzified using a trapezoidal membership function to indicate their membership values and were integrated into a fuzzy decision value. The searching process by a developed PSO algorithm was performed to find the dispatch schedule that maximizes the sum of each of the fuzzified objectives. The test results revealed the effectiveness of the fuzzy models in compromising the benefits obtained from the conflicting objectives. Therefore, the fuzzy models were able to offer flexibility for the decision maker, who can adjust some of the fuzzy parameters to reflect the importance of each of the objectives on the basis of his or her intuition.

## 10. ACKNOWLEDGEMENTS

The first author would like to express his sincere thanks to the followings organizations for their supports; Ministry of Science and Technology (MOST)-Thailand, Coordinating Center for Thai Government Science and Technology Scholarship Students (CSTS)-Thailand, and Thailand Institute of Scientific and Technological Research (TISTR)-Thailand.

## References

- [1] T. A. Short, *Electric Power Distribution Handbook*, CRC, Boca Raton FL, 2004, p.238.
- [2] J.H. Choi and J. C. Kim, "The Online Voltage Control of ULTC Transformer for Distribution Voltage Regulation," *Electrical Power and Energy Systems*, Vol. 23, No.2, pp. 91-98, 2001.
- [3] A. Tajfar, M. Kalantar, R. Iravani and K. Zare, "Coordinated Fuzzy Logic Voltage/VAr Controller in Distribution Networks," *Proc. IEEE International Conf. on Industrial Technology*, April. 2008, pp.1-5.
- [4] F.C. Lu and Y. Y. Hsu, "Reactive Power/Voltage Control in a Distribution Substation using Dynamic Programming," *IEE Proc. Gener. Transm. Distrib.*, Vol. 142, No.6, pp. 639-645, 1995.
- [5] F.C. Lu and Y. Y. Hsu, "Fuzzy Dynamic Programming Approach to Reactive Power/Voltage Control in a Distribution Substation," *IEEE*

- 

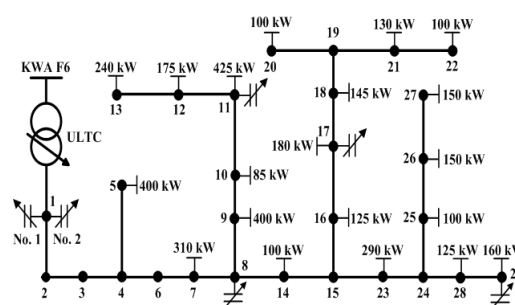
timization technique



**Suwit Auchariyamet** is a research officer at Thailand Institute of Scientific and Technological Research (TISTR), Pathumthani, Thailand. He is now working towards his Ph.D. degree in Electrical Engineering at the Department of Electrical Engineering, Faculty of Engineering, King Monkut's University of Technology North Bangkok (KMUTNB), Bangkok, Thailand. His research areas are the applications of op- for power system planning and control.

## APPENDICES

This section provides data of the test system, which consists of network configuration, load data, and feeder data.



**Fig.A1: Configuration and Load Data of the Test System**

Table A1: Feeder Data for the Test System

From bus	To bus	Length (km)	Cable type	From bus	To bus	Length (km)	Cable type
1	2	8.740	SAC185	15	16	0.312	AAC50
2	3	0.383	SAC185	16	17	0.051	AAC50
3	4	0.429	SAC185	17	18	0.466	AAC50
4	5	0.289	SAC185	18	19	0.091	AAC50
5	6	3.006	SAC185	19	20	0.410	AAC50
6	7	0.190	AAC50	20	21	0.166	AAC50
7	8	1.069	AAC50	21	22	0.319	AAC50
8	9	0.854	AAC50	15	23	0.505	AAC50
9	10	0.017	AAC50	23	24	0.130	AAC50
10	11	0.222	AAC50	24	25	0.394	AAC50
11	12	0.518	AAC50	25	26	0.693	AAC50
12	13	0.081	AAC50	26	27	0.430	AAC50
8	14	0.508	AAC50	24	28	0.291	AAC50
14	15	0.064	AAC50	28	29	0.091	AAC50