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Optimal Reactive Power Planning for Distribution Systems Considering Intermittent Wind Power Using Markov Model and Genetic Algorithm

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OPTIMAL REACTIVE POWER PLANNING FOR DISTRIBUTION SYSTEMS

CONSIDERING INTERMITTENT WIND POWER

USING MARKOV MODEL AND GENETIC ALGORITHM

by

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ABSTRACT
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Wind farms, photovoltaic arrays, fuel cells, and micro-turbines are all considered to be Distributed Generation (DG). DG is defined as the generation of power which is dispersed throughout a utility's service territory and either connected to the utility's distribution system or isolated in a small grid. This thesis addresses modeling and economic issues pertaining to the optimal reactive power planning for distribution system with wind power generation (WPG) units. Wind farms are inclined to cause reverse power flows and voltage variations due to the random-like outputs of wind turbines. To deal with this kind of problem caused by wide spread usage of wind power generation, this thesis investigates voltage and reactive power controls in such a distribution system. Consequently static capacitors(SC) and transformer taps are introduced into the system and treated as controllers. For the purpose of getting optimum voltage and realizing reactive power control, the research proposes a proper coordination among the controllers like on-load tap changer (OLTC), feeder-switched capacitors. What's more, in order to simulate its uncertainty, the wind power generation is modeled by the Markov model. In that way, calculating the probabilities for all the scenarios is possible. Some outputs with consecutive and discrete values have been used for transition between successive time states and within state wind speeds. The thesis will describe the method to generate the wind speed time series from the transition probability matrix. After that, utilizing genetic algorithm, the optimal locations of SCs, the sizes of SCs and transformer taps are determined so as to minimize the cost or minimize the power loss, and more importantly improve voltage profiles. The applicability of the proposed method is verified through simulation on a 9-bus system and a 30-bus system respectively. At last, the simulation results indicate that as long as the available capacitors are able to sufficiently compensate the reactive power demand, the DG operation no longer imposes a significant effect on the voltage fluctuations in the distribution system. And the proposed approach is efficient, simple and straightforward.

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Chapter I Background

In recent years, with a growing concern over the environmental impact, conflicts between an increasing demand of energy and sustainability of the traditional fossil-fueled power plants, the deregulation of electric power system, and the development of renewable energy technologies, planners and policy makers think and search for ways to supplement the energy base with renewable energy sources. Distributed generations (DGs) have drawn more and more people's attention. They are predicted to increase their proportion in the electric power system in the foreseeable future [1]. The two major benefits of DG lie on their significant impact on environmental sustainability and the reduction of traditional generation expansion [2].

1.1 Wind's Characters

Wind is one of the potential renewable energy sources. It is actually a form of solar energy. Winds are caused by the heating of the atmosphere by the sun, the rotation of the earth, and the earth's surface irregularities. Compared with the other sorts of power sources, there are many vantages for the usage of wind power [3]:

(1) Wind power is fueled by the wind, which can't be used up.

(2) Wind power comes from nature. So it's a clean fuel source. It doesn't pollute the air like power plants relying on combustion of fossil fuels, such as coal or natural gas. In other words, wind turbines don't produce atmospheric emissions that can cause acid rain or greenhouse gasses.

(3) Wind energy is one of the lowest-costed renewable energy available today.

(4) Wind turbines can be placed on farms or ranches, thus benefiting the economy in rural

areas, where most of the best wind sites are found. Farmers and ranchers can continue to work the land because the wind turbines use only a fraction of the land.

With the benefits mentioned above, wind power is playing an increasingly important and promising role. The number of wind farms is rapidly increasing at present resulting in a remarkable growing contribution to electricity production and penetration of the wind power. As a consequence, the power system includes those generators with traditional power technologies like diesel and combustion turbines, and power sources of renewable technologies like wind power and photovoltaic.

Even though installing wind turbines in a distribution system will gain many advantages, we have to be aware that wind power generation may do harm to voltage profiles. Because the characteristic of wind for power generation is intermittent, uncertainty and it cannot be dispatched leading to the random-like output. It alters the power flows, which, in turn, creates a variety of well-documented impacts with voltage rise being the dominant effect feeder voltage profiles and conflicts with some operations of power systems; for instance, stability, power quality, the standard voltage, and reactive power control methods in distribution system.

1.2 Voltage and Reactive Power Control

The disadvantage implies that to ensure the power quality, the connection of DGs into a distribution system needs coordination among available voltage and reactive power control equipments. The equipments include generators, tap changing transformers, shunt capacitors/reactors, synchronous condensers, and static var compensators. For example, the distribution system will not experience the voltage drop caused by the low output of DGs when the capacitors are switched on to increase the voltage to some extent so as to allow a higher level of DG penetration. Aiming for that purpose, the proper voltage and reactive power control becomes more significant [4]. In this thesis, the impact of wind power generation on Volt/Var control is going to be studied, and the goal is to find a solution which takes voltage security, cost of SCs and power loss into account for an electric power enhancement.

A range of options have traditionally been utilized for these probabilistic load-flow methods to mitigate adverse impacts to raise the level of DG capacity. Volt/Var management is one of the important control schemes of enhancing connectable capacity at the distribution system. Reactive power (VAR) is used to regulate the voltage profile. In conventional distribution system, the voltage regulation can be achieved by incorporating network components such as on-load tap changers (OLTCs) and switched shunt static capacitors. The OLTC keeps the voltage on the secondary side of the transformer constant by adjusting the tap position. And the switched shunt capacitor is able to compensate the reactive power demand and thereby decrease the voltage drop [5].

Once the reactive power is insufficient in a distribution system or a standalone system, the voltage will degrade. In order to solve this kind of problem, transformers, new appropriate sizes and locations of VAR resources should be suggested to overcome their negative impacts on voltages. On the other hand, the interaction among these three controllers makes the solution become much more complicated.

1.3 Markov Model

Due to the random-like outputs of wind turbines, the determination of transformer tap position, the size and location of Static Capacitors is a critical problem. To avoid the probability density function and covariance, the Markov model performs definition of all operation states [6]. All scenarios with voltage fluctuation constraints need to be considered. In general, we regard Distributed Generations as PV or PQ nodes. In this paper, wind power generations are modeled as PQ nodes where their performances are combined with controlling of Load Tap Changer (LTC) and capacitor to fulfill the voltage constraints.

1.4 Genetic Algorithm

The Genetic algorithm among DGs and other traditional voltage and reactive power control equipments will be presented to find the optimal control variables. The objective of the optimization is to minimize the costs of new SCs or minimize the power loss while satisfying operational and voltage fluctuation constraints. Then the recommended model and algorithm are implemented to verify and testify on modified IEEE 9-bus and 30-bus radial distribution systems to demonstrate the application of the proposed approach.

1.5 Article Layout

This paper is set out as follows; the Markov model used for the intermittent wind generation and probabilistic load is given in Chapter II. The problem formulation in terms of OPF is provided in Chapter III. Chapter IV gives Genetic Algorithm (GA). Chapter V presents the algorithmic solution steps. First we will analysis the impacts of wind turbines on the voltage profiles of distribution system and reactive power control. Then the simulation results for a 9-bus system and a 30-bus system as test cases are employed to evaluate the algorithm from an economic point of view in Chapter VI. Concluding remarks are given in Chapter VII.

Chapter II Markov Model for Wind Farm's Multistate

2.1 Importance of Prediction of Wind Speed Statistical Parameters

Designing a proper wind energy system requires the prediction of wind speed statistical parameters. The steady growth in the utilization of wind power for electricity generation has led to increased interest in methods for synthetically predicting wind speeds which have the ability to more accurately determine the site potential. Owing to wind’s random and intermittent nature, the knowledge of its actual time-varying availability is extremely important for evaluating the electricity produced by a single wind turbine or a wind farm.

2.2 Previous Work

Wind speed databases are generally able to characterize potential sites only in terms of average and maximum annual or monthly speeds. Besides, experimental time series are lacking altogether or limited to short time periods [13]. On the contrary, the methodologies for synthetically generating wind speeds are particularly significant as they compensate for the lack of these data [14].

Relying on a stochastic approach, the most widely used methodologies comprises the autoregressive moving average models like ARMA or ARIMA, when integrated, models relied on the wavelet analysis or the Markov chains [15].

The autoregressive models have a marked capability to represent the autocorrelation properties of wind speed. Their main weak point rests with the need for complex techniques for determining the numerous model parameters. The wavelet analysis is a nonparametric method demanding signal decomposition and its own subsequent reconstruction randomly aggregating signal components. The classical modeling approach is to fit the probability distribution to a known model by estimating statistical parameters like mean and variance. These models lack the time variation properties and ignore cross-dependencies between other meteorological data.

2.3 Proposed Model

Different from the above models, the synthetic generation of wind speed data grounded on application of the Markov chains model requires the variable range of speeds to be discredited into a certain number of states. These states represent wind speeds ranging from the lowest speed to the highest speed. A matrix is then constructed whose each element defines the transition probability from one state to another. Therefore, the Markov model is an approach that can relate a state probability with its corresponding event frequency in the stochastic process. It is based upon the traditional probability matrices of various time steps. This methodology has been widely studied, largely for the aim of examining the influence of transition matrix order and state size on its performance. Due to the benefits the Markov Model can provide, a procedure is developed to model the wind speed data in the form of Markov model in this study.

The first step for usage of Markov models is to determine and define the scenarios. To calculate the Markov chain transitional probabilities, initially the wind speed variation domain is divided into many states. Such state categorization may be rather arbitrary depending on the purpose, but herein, it is determined according to the average and standard deviation of the available wind speed time series. In this research, the states have been selected as the numerically rounded wind speed values in intervals of 1 m/s except for the first and last two states. It's all because of the cut-in wind speed, the rated wind speed, and the furling or cut out wind speed. To be more specific, below the cut-in wind speed, no net power is generated. Then, power rises following the cube of wind speed. After the rated wind speed is reached, the wind turbine operates at rated power. That is at wind speeds between V_R and V_F, the output is equal to the rated power of the generator. Above the cut-out or furling wind speed, the wind is too strong to operate safely, the wind turbine must be forced to shut down, where "furling" refers to folding up the sails when winds are too strong in sail. Then the output power is directly reduced to zero, which can be integrated into the first scenario. A somewhat idealized power curve is vividly shown in Figure 1.

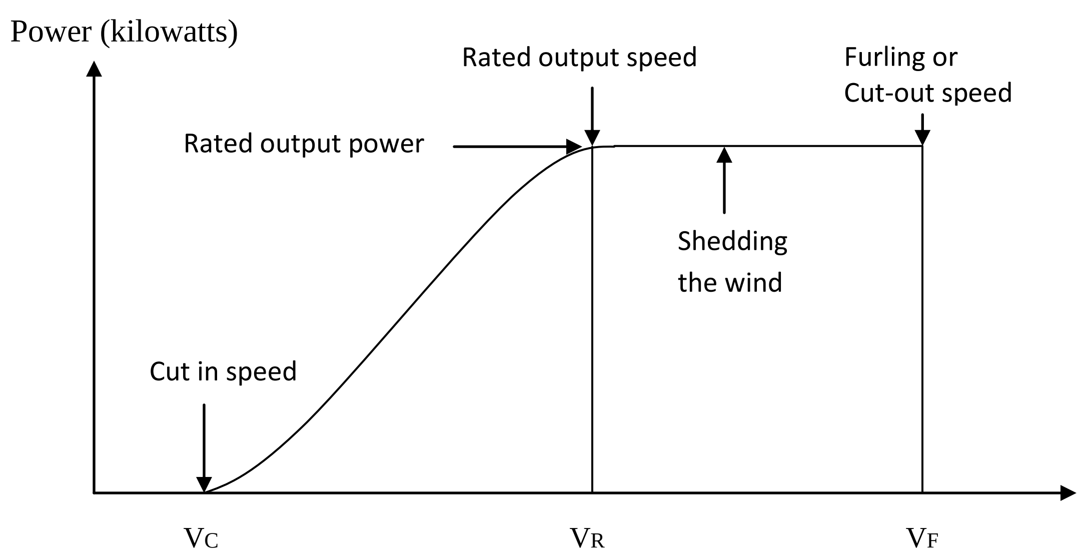

Figure 1 Idealized power curve of wind turbine

For the Markov process, the probability of the given condition in the given moment has the opportunity to be deduced from information regarding the preceding conditions. A

Markov chain represents a system with elements moving from one scenario to another over time.

In particular, for a random Markov process, the probability that wind speed at a generic instant falls into a state is a function of wind speed taking into consideration of several previous instants that determines the order of a Markov chain.

The order of the chain gives the number of time steps in the past influencing the probability distribution of the present state, which can be greater than one. Many natural processes are considered as Markov processes. In fact, the probability transition matrix is a tool to describe the Markov chains' behavior. Each element of the matrix represents probability of passage from a specific condition to the next state. According to the definition, in a first-order Markov chain, the wind speed at the current hour depends solely on the wind speed in the previous hour. To explain it more clearly, one example is shown below.

Let X(t) be a stochastic process, possessing discrete states space S={1,2,...,K}. Generally, for a given sequence of time points $t_1 < t_2 < \cdots < t_{n-1} < t_n$ the conditional probabilities should be: P{ X(t_n) = i_n | X(t_1) = i_1 , ⋯ , X(t_{n-1}) = i_{n-1} } = P{ X(t_n) = i_n | X(t_{n-1}) = i_{n-1} } where the conditional probability P{ X(t) = j | X(s) = i } = P_{ij} (s ,t) is called as transition probability of order $r=t-s$ from state i to state j for all indices with $0 \leq s < t$ and $1 \leq i, j \leq k$. That is the probability that wind speed at the instant t is in state j, and it is in state i at time t. From the description, we can get elements for k states. The first order transition matrix T has a size of $k \times k$ and they are denoted as the transition matrix $T_{transition}$. For the sake of expressing the transition probabilities in a compact form, a state transition matrix is formed in equation (1) below:

$$T_{transition} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,k} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,k} \\ \vdots & \vdots & \vdots & \vdots \\ p_{k,1} & p_{k,2} & \dots & p_{k,k} \end{bmatrix} \tag{1}$$

Obviously, the transition probability values are between 0 and 1, and the row summation of the transition matrix must be equal to unity as expressed in equation below:

$$\sum_{j=1}^{k} p_{ij} = 1 \tag{2}$$

To make it easy to understand such kind of model, a specific wind farm with three states is considered. These three states are labeled with number 1, 2, 3, respectively as illustrated in Figure 2. The failure rate represents a state transition probability from one state (say state 1) to another state (say state 2) while the repair rate is the other state transition probability from state 2 to state 1.

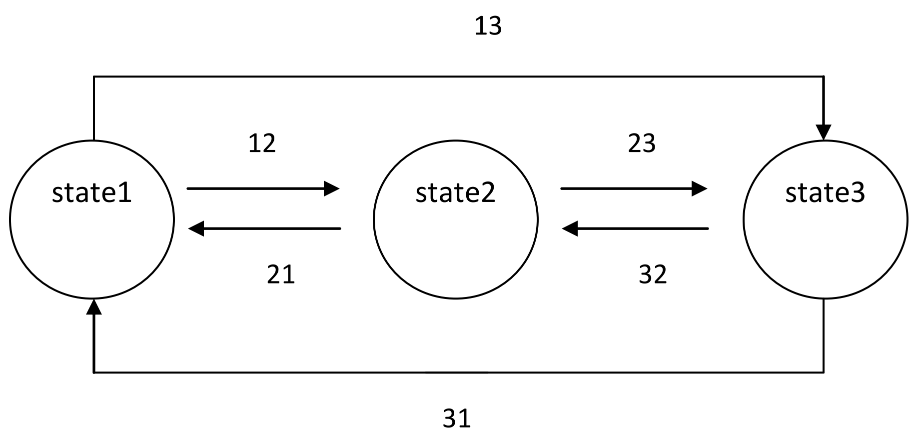

Figure 2 Three-state Markov model

Once the states are determined, the state probabilities at time t can be estimated from the relative frequencies of the *k* states. The transition probabilities between successive states must be obtained by counting in a period of observations using the experimental time series, and knowing the total number of transitions from state i to state j between two successive instants. If n_{ij} is the number of transitions from state i to state j in the sequence of speed data, the maximum likelihood estimates of the transition probabilities is:

$$p_{ij}=n_{ij}/\sum_{\mathrm{j}=1}^{\mathrm{m}} \mathrm{n_{ij}} \tag{3}$$

where n_{ij} indicates the number of transitions from state i to state j.

Let $\mathrm{P_n}$, n = 1,2,..., M, be the probabilities for N states. Then we can get

$$\sum_{\mathrm{n}=1}^{\mathrm{N}} \mathrm{P_n}=1 \tag{4}$$

$$[\mathrm{M}]\begin{bmatrix}\mathrm{P_1}\\ \vdots\\ \mathrm{P_N}\end{bmatrix}=\begin{bmatrix}0\\ \vdots\\ 0\end{bmatrix} \tag{5}$$

The elements in the upper triangle matrix of the squared matrix [M] are the repair rates among states. Meanwhile the lower triangle matrix is comprised of failure rates among states. Each diagonal term in the location (n, n) of [M] is the negative sum of all off-diagonal terms at the corresponding column. The absolute value of diagonal term for a state n in (5) is defined as the rate of departure for state n.

As n diagonal terms are determined by other off-diagonal terms at each corresponding column, at most n-1 independent equations can be derived from (5). Fortunately, equation (4) is one extra independent equation. We can obtain n independent equations. That is enough to calculate n unknown variables. Hence, solving (4) and (5) has the chance to get the values for all the N states' probabilities.

The model will be validated with wind speed measurements collected during an experimental campaign at a site in Milwaukee.

2.4 Determination of Studied States by Markov Model

Prior to applying the genetic algorithm to determine the locations and sizes of new static capacitors, and taps position of transformers in a power system with wind farms, the operation scenarios with different probabilities should be determined. The solution steps are proposed as follows:

Step 1: Give the discrete MW intervals for defining states for wind generation.

Step 2: Input MW wind generation measured in one year for wind farm. Determine all states with known MW generations.

Step 3: Determine the failure rates and the repair rates for the states related to wind farm.

Step 4: Compute the rate of departure for each state in the studied wind farm.

Step 5: Solve (4) and (5) to obtain the state probabilities for the studied wind farm.

Step 6: Run power-flow program with nominalSC_c, V_{gm} to attain the bus voltages for every operation state.

Step 7: Consider the voltage constraints and identify the operation states with voltage violations.

Step 8: Explore Optimal VAR planning for the operation states identified in Step 7 using genetic algorithm (GA).

Chapter III Problem Formulation

From the mathematical standpoint, a VAR planning problem can be formulated as an optimal power flow (OPF) problem searching the optimal control variables for a given objective function and various inequality constraints in a steady-state power system. So in this case, the OPF is a constrained and nonlinear optimization problem with discrete and continuous variables.

Several VAR control/planning algorithms have been developed. In previous works, many researchers have investigated and developed the control strategy used in the power system with wind energy [16-19]. In this thesis, an optimal VAR planning problem considering intermittent characteristics of wind generation in a power system is studied and is formulated as an objective nonlinear programming problem. The objective function is the summation of all costs of capacitor banks or power loss in the system. The value of the cost is determined by the total number of capacitors. And minimizing the swing bus generation is the same as minimizing MW loss when the system loads are fixed. The voltage regulation is achieved by tap changer and SC which are all considered as control and discrete variables. Additionally, the number of tap-changing operations and capacitors' switchings will be included in the optimization constraints. The load bus voltages are the state and continuous variables solved by an AC Newton method.

As described in Chapter II, owning to variations in intermittent wind power generations, there are many operation states for a power system. For each operation state with its own probability, the real power generations of all diesels and wind generators, and real/reactive power loads at all buses are constant. Consequently, the optimal VAR planning for an operation state can be formulated as an OPF problem as follows:

The objective function is given by equation (6) or (10).

$$\min \sum_{c=1}^{C} SC_c \tag{6}$$

subject to

$$V_i^{min} \le V_i \le V_i^{max} \qquad i=1,2,3\ldots,N \tag{7}$$

$$tap_t^{min} \le tap_t \le tap_t^{max} \qquad t=1,2,3\ldots,T \tag{8}$$

$$SC_c^{min} \le SC_c \le SC_c^{max} \qquad c=1,2,3\ldots,C \tag{9}$$

Or

$$\min P_{sw} \tag{10}$$

subject to

$$V_i^{min} \le V_i \le V_i^{max} \qquad i=1,2,3\ldots,N \tag{11}$$

$$tap_t^{min} \le tap_t \le tap_t^{max} \qquad t=1,2,3\ldots,T \tag{12}$$

$$SC_c^{min} \le SC_c \le SC_c^{max} \qquad c=1,2,3\ldots,C \tag{13}$$

where

V_i : bus voltage;

V_i^{min} : minimum voltage for each bus;

V_i^{max} : maximum voltage for each bus;

tap_t : the t-th tap changer, t=1,2,3…,T, it is a discrete integer;

tap_t^{min} : minimum tap for each transformer, a discrete integer;

tap_t^{max} : maximum tap for each transformer, a discrete integer;

SC_c : MVAR for the c-th SC, a discrete value;

SC_c^{min} : minimum reactive power for each capacitor, a discrete value;

SC_c^{max} : maximum reactive power for each capacitor, a discrete value;

N: number of buses;

T: number of transformers;

C: number of static capacitors;

Equation (6) represents the cost minimization of new static capacitors for this planning problem. And equation (10) represents power loss minimization. In (10), the MW loss is selected to be the objective because proper regulation of reactive power can reduce MW loss. Equations (6)–(9) or (10)-(13) can be considered as a single-objective nonlinear programming problem with continuous and discrete variables.

In this research, the load bus voltage deviation should be controlled within ±5% of its nominal voltage V^{nom}. To put it in another way, the low/ high limit of bus voltage is set to [0.95, 1.05] p.u. for a normal operation condition. Thus in (7) and (11), the low limit of bus voltage V_i^{min} is 0.95. And the upper limit of bus voltage V_i^{max} is 1.05p.u.. When the intermittent wind power generation is considered, the voltage may fluctuate, and the low/upper limit of bus voltage can be referred to standards. At the same time, assume $\mathrm{tap_t}$ is within [0.95, 1.05] with a discrete interval 0.01; $\mathrm{SC_C}$ is within [0, 20] Mvar with a bank size 0.5 Mvar.

Chapter IV Genetic Algorithm

Genetic Algorithm (GA), very similar to heredity selection, rules of "proper existence", and "survival of the fittest", is a generalized search and optimization technique inspired by the theory of biological evolution adaptation in nature. It is a very powerful search algorithm and has its own advantages over conventional search algorithms. The most outstanding advantage is that it does not need derivatives or other auxiliary knowledge. Therefore, the genetic algorithm has been widely used in power systems for optimization [7-9].

GA maintains a population of individuals that represent candidate solutions. Each individual is evaluated to give some measure of its fitness to the problem in line with the objective function. In each generation, a new population is formed by selecting the more fit individuals according to a particular selection strategy. Some members of the new population undergo genetic operations to form new solutions. There are a number of selection methods proposed by researchers in previous publicized works, such as fitness proportionate selection, ranking, and tournament selection [10-12]. Tournament selection is applied in this work. With tournaments selection, n individuals are selected randomly from the population, and the best of the individuals is inserted into the new population for further genetic processing.

4.1 Major Components of GA

The major components of GA consist of decoding, fitness evaluation, reproduction, crossover, and mutation operators. The abstract of genetic algorithm is expressed by the eleven-item entity as follows:

$$GA = (p^0, I, \lambda, L, F, s, c, m, elit, gray, T) \tag{14}$$

Where:

p^0: initial population

I: encoding of chromosomes

λ: population size

L: length of chromosomes

F: fitness function

s: parent-selection operation

c: crossover operation and rate

m: mutation operation and rate

elit: elitism preserving rate

gray: gray code, the better one of the coding method

T: termination criterion

The three commonly used genetic operators are reproduction, crossover and mutation. The reproduction comprises selection and process of copying individuals' genetic information to create a new population.

Crossover is a mixing operator that combines genetic material from selected parents. To be more explicit, it is the genetic information exchange of two strings that are selected from the population at random with a crossover probability at a fixed value. For binary-coded GA, there exist a number of crossover operators. Crossover can occur at a single position, we call it single crossover, or at number of different positions, we regard it as multiple crossover. In this work, two points crossover is employed in which two crossover sites are chosen and off springs are created by swapping the bits between the selected crossover sites.

Mutation acts as a background operator and is employed to search the unexplored search space by randomly altering the values at one or more positions of the selected chromosome with a crossover probability fixed at a certain value. For binary encoding, bit-wise mutation is preferred which switches a few randomly chosen bits from 1 to 0 or from 0 to 1 with a small mutation probability (P_m).

4.2 Features of GA

The features of GA are listed as follows:

(1) In the encoded process, GA must consider the limit and range of these variables, convert problem into the optimal power flow to simplify the mathematical function.

(2) The operational process just needs to check fitness function, not to have too many mathematical functions. It doesn't have to specially design system, so it can be used widely.

(3) The random process is employed in the genetic algorithm to search the optimal solution. Although it is a random process, the direction of the search must be adjusted by fitness function, so as not to search in blind.

(4) The genetic algorithm has the ability to get the global optimum. Especially, with the help of initial range settings, it can be avoided to run into local optimum.

4.3 Genetic Algorithm for OPF Problem

While applying GA to solve a particular optimization problem, firstly two main issues are obliged to be addressed. One is the representation of the solution variables. The other is the formation of the fitness function.

Each individual in the genetic population represents a candidate solution. In the binary-coded GA, the solution variables are represented by a string of binary alphabets. The size of the string relies on the precision of the solution required. For problems with more than one decision variable, each variable is represented by a sub-string and all the sub-strings are concatenated together to form a larger string.

The goal of the genetic algorithm is to find the best locations and outputs of a given number of SCs, and the position of the taps for all transformers in accordance with a set criterion. A configuration of SC is defined with two parameters: the location of the device and its size. Simultaneously, transformer has only one parameter: the tap position. As a consequence, in the OPF problem under consideration, the solution variables consist of locations of Static Capacitors (L_c), the reactive power generation of capacitor (SC_c) and the transformer tap setting (tap_t).

4.4 Encode and Decode

Binary string representation is utilized to code the control devices. The encoding parameters are the control devices, for instance, tap positions of on-load tap changer of transformers and shunt capacitors. Thus in this paper an individual string in genetic algorithm is presented with three substrings. The genetic length of the first substring is N_a, the second substring is N_b, while the third substring is N_c.

The first substring corresponds to the optimal location of the SC devices. It contains 1's and 0's of length N_a, number of buses in the system. 1 represents that SC device is present and 0 represents that SC device is not present. The bit number from the left gives the bus in which SC device is located or not. Hence the length of first substring is kept equal to number of buses in the system.

The second substring of the individual represents the values of all the SCs. In the proposed model, the substring represents as many values of α equal to the number of devices available in the first string. The length of this substring is taken as N_α*N_F, where N_α is the gene length for encoding the value of α in binary form and N_F is the number of SC devices to be located in the system. The total number available is retrieved from the data file to establish the number of bits required in chromosomes' string representation.

The third substring of the individual is the parameter values for existing transformers in the distribution system. The substring likes the second one represents as many value of β equal to the number of transformers located in the power system. The length of this substring is taken as N_β*N_T. Where, N_β is the gene length for encoding the value of β in binary form and N_T is the number of transformers in the power system.

With binary representation, an individual in the GA population will look like the following:

$$\underbrace{1001010111}_{L_c}\ \ldots\underbrace{011001}_{SC_1}\ \underbrace{110001}_{SC_2}\ldots.\ \underbrace{100011}_{SC_c}\ \underbrace{1100}_{tap_1}\ \underbrace{1011}_{tap_2}\ldots..\ \underbrace{0011}_{tap_t}$$

Then evaluations of the objective function for each individual string need to be generated. The population size is the number of individual strings. The GA selects the location and size of SC, the tap setting for fitness function calculation.

While evaluating the fitness value of each individual, the binary strings have to be decoded into its actual value. The control parameters here are all discrete variables. The discrete variables controls like tap changing transformer and susceptance of capacitor taking 'M' values $\mu_i^1, \mu_i^2, \cdots\ \mu_i^M$ are decoded using the expression :

$\mu_i=\mu_i^M$ with m=int[$\frac{M}{2^{N_{ui}}}\cdot$k+0.5] and $\log_2 M \le N_{ui} \le \log_2 M+1$

Where 'k' is the decimal number to which the binary number in a gene is decoded and N_{ui} is the gene length (number of bits) used for encoding control variable u_i.

For each individual, the power flow is calculated by Matpower. The constraints on the control variables are taken into account through the proper representation. Optimization toolbox in MATLAB 4.1 has been used for optimization at the simulation level.

4.5 Determine the Optimal VAR Planning by GA

This subsection describes the steps to gain the optimal locations and sizes of new static capacitors as well as tap position of transformers. Assume there are states with voltage violations subject to the voltage constraints. Let s=1 and the population size be P_s.

Step 1: If s ≤ S, then go to Step 2; otherwise go to Step 11.

Step 2: Encode the unknowns.

Step 3: Set iteration time counter of evolutionary. Iterative index t = 1.

Step 4: Randomly generate initial M individuals to form the initial population $P_1(t)$ and calculate the fitness of each individual $F_d(d = I, 2, \cdots, M)$.

Step 5: Selection operator, cross operator, and mutation operator are applied to generate population P_2 (t).

Step 6: Decode all the binary chromosomes for evaluating (6) or (10), then check the feasibility of the constraints.

Step 7: If the constraint is violated, update the evolution of algebra counter t = t + 1. All individuals in population $P_2(t)$ will be the next group of population $P_1(t)$. After that, go to step 4.

Step 8: If the best fitness at the t-th iteration is better than that at the (t-1) -th iteration, retain the best fitness at the t -th iteration and its corresponding binary chromosome.

Step 9: If the best fitness at the t-th iteration is worse than that at the (t-1)-th iteration, substitute the best fitness and its corresponding binary chromosome obtained at the t-th iteration with those obtained at the (t-1)-th iteration.

Step 10: If satisfied with the termination condition, output the calculation results and the algorithm is end.

Step 11: Compute the expected L_c, SC_c, and tap_t.

Chapter V Preparation for the Simulation

5.1 Calculating the Probabilities for Each Scenario

The experimental data were obtained from recordings of wind speed series values at meteorological station in Milwaukee as shown in the Appendix A. It has been applied for stochastic generation of wind speed data using the transition matrix approach of the Markov chain process. Model details and numerical results are presented.

Processing the measured data with equation (3), we can get every element for probability transition matrix of first order for wind speed time series. They are exhibited in Table 1. Consequently, form the probability transition matrix, we are able to further obtain the squared matrix [M] in equation (5) displayed in Table 2.

After getting the squared Matrix [M], we have the chance to calculate the probabilities for each scenario making use of Matlab. The M-file for solving equation (4) and (5) is written as follows:

```
% Script file: simul.m
%
% Purpose:
% This program solves a system of 13 linear equations in 13 unknowns (a*x = b).
%
% Record of revisions:
% Date Programmer Description of change
% ==== ======== ===============
% 3/10/13 Cheng Li Original code
```

Table 1 Probability transition matrix of first order for wind speed time series at Milwaukee

$$T=\begin{pmatrix}
0.7 & 0.2 & 0.1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.2308 & 0.3846 & 0 & 0.2308 & 0.1538 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0.3333 & 0.2222 & 0.2222 & 0.1111 & 0.1111 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0.2143 & 0.2143 & 0.1429 & 0.3571 & 0 & 0 & 0.0714 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0.3125 & 0.0625 & 0.5 & 0.0625 & 0.0625 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0.12 & 0.04 & 0.2 & 0.2 & 0.36 & 0.08 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0.037 & 0.037 & 0.2593 & 0.2593 & 0.2963 & 0.1111 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0.0333 & 0.0667 & 0.3 & 0.3333 & 0.1667 & 0.1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0.1 & 0 & 0.15 & 0.35 & 0.25 & 0.1 & 0.05 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0.0526 & 0.1579 & 0.0526 & 0.2105 & 0.3158 & 0.1053 & 0.1053 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1333 & 0.0667 & 0.2 & 0.2 & 0.4 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1765 & 0.0588 & 0.1765 & 0.2941 & 0.2941 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1364 & 0.0455 & 0.1364 & 0.6364 & 0.0455 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0.75
\end{pmatrix}$$

```
% Define variables:

% b --Constant coefficients

% x --Solution

% Define coefficients of the equation a*x = b for

% the full matrix solution.

a = [-0.3 0.2308 0 0 0 0 0 0 0 0 0 0 0 0;...

     0.2 -0.6154 0.3333 0.2143 0 0 0 0 0 0 0 0 0 0; ...

     0.1 0 -0.7778 0.2143 0 0.12 0 0 0 0 0 0 0 0; ...

     0 0.2308 0.2222 -0.8571 0.3125 0.04 0.037 0 0 0 0 0 0 0; ...

     0 0.1538 0.1111 0.3571 -0.9375 0.2 0.037 0.0333 0 0 0 0 0 0; ...

     0 0 0.1111 0 0.5 -0.8 0.2593 0.0667 0.1 0 0 0 0 0; ...

     0 0 0 0 0.0625 0.36 -0.7407 0.3 0 0.0526 0 0 0 0; ...

     0 0 0 0.0714 0.0625 0.08 0.2963 -0.6667 0.15 0.1579 0.1333 0 0 0; ...

     0 0 0 0 0 0 0.1111 0.1667 -0.65 0.0526 0.0667 0.1765 0 0; ...

     0 0 0 0 0 0 0 0.1 0.25 -0.7895 0.2 0.0588 0.1364 0; ...

     0 0 0 0 0 0 0 0 0.1 0.3158 -0.8 0.1765 0.0455 0; ...

     0 0 0 0 0 0 0 0 0.05 0.1053 0.4 -0.7059 0.1364 0; ..

    0 0 0 0 0 0 0 0 0 0.1053 0 0.2941 -0.3636 0.25; ...

    1 1 1 1 1 1 1 1 1 1 1 1 1 1];

    b=[0 0 0 0 0 0 0 0 0 0 0 0 0 1]';

    disp ('Full matrix solution:');

x = a\b
```

Table 2 Squared matrix M

$$
M = \left(\begin{array}{cccccccccccccc}
-0.3 & 0.2308 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.2 & -0.6154 & 0.333 & 0.2143 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.1 & 0 & -0.7778 & 0.2143 & 0 & 0.12 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0.2308 & 0.2222 & -0.8571 & 0.3125 & 0.04 & 0.037 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0.1538 & 0.1111 & 0.3571 & -0.9375 & 0.2 & 0.037 & 0.0333 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0.1111 & 0 & 0.5 & -0.8 & 0.2593 & 0.0667 & 0.1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0.0625 & 0.36 & -7407 & 0.3 & 0 & 0.0526 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0.0714 & 0.0625 & 0.08 & 0.2963 & -0.6667 & 0.15 & 0.1579 & 0.1333 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0.1111 & 0.1667 & -0.65 & 0.0526 & 0.0667 & 0.1765 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1 & 0.25 & -0.7895 & 0.2 & 0.0588 & 0.1364 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1 & 0.3158 & -0.8 & 0.1765 & 0.0455 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.05 & 0.1053 & 0.4 & -0.7059 & 0.1364 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1053 & 0 & 0.2941 & -0.3636 & 0.25 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0455 & -0.25
\end{array} \right)
$$

Run this program, the results are show in Table 3.

Table 3 Probabilities for each scenario

state	1	2	3	4	5	6	7
wind speed	0～5	5～6	6～7	7～8	8～9	9～10	10～11
Probability	0.0415	0.0539	0.0373	0.0581	0.0664	0.1037	0.112
state	8	9	10	11	12	13	14
wind speed	11～12	12～13	13～14	14～15	15～16	16～20	20～
Probability	0.1245	0.083	0.0789	0.0623	0.0706	0.0913	0.0166

5.2 Determine the Operation Status for Each Scenario

Hinged on Table.3, 14 operation states for 9-bus system and 30-bus system can be defined. For all operation states, the outputs of wind farm are constant, but different from each other. A power-flow program using nominal VAR control settings was employed to get the bus voltages. With the obtained bus voltage, we can determine in which scenario, the power system faces the low voltage problem or high voltage problem. In my paper, the power flow calculation is realized by Matpower. It is a simulation tool for running a simple Newton power flow in the bus system under study and also a package of MATLAB M-files for solving power flow and optimal power flow problems.

Program the M-file for operation status determination. And take the 9- bus system here as an example. The M-file is as follows:

```
for ii=1:13
  opw=120-(ii-1)*6;
  temporary=loadcase('case9modified');
  temporary.bus(5,3)=opw;
  case9modified=temporary;
```

```
 Relt=runpf(case9modified);
  if
Relt.bus(4,8)<=0.95| Relt.bus(5,8)<=0.95| Relt.bus(6,8)<=0.95| Relt.bus(7,8)<=0.95|
Relt.bus(8,8)<=0.95| Relt.bus(9,8)<=0.95| Relt.bus(4,8)>=1.05| Relt.bus(5,8)>=1.05|
Relt.bus(6,8)>=1.05| Relt.bus (7,8)>=1.95| Relt.bus(8,8)>=1.95|
Relt.bus(9,8)>=1.95
     disp(['the state has voltage problem, the state number is'  num2str(ii)]);
    else
     disp(['the state is in good condition, the state number is'  num2str(ii)]);
  end
 end
```

5.3 The Profile of MATLAB Genetic Algorithm and Direct Search Toolbox

MATLAB (Matrix Laboratory) is a kind of scientific computing software specializing processing data in the form of matrix. Genetic Algorithm and the Direct Search Toolbox, referred to as GADS, is an optimization toolbox for MATLAB. Taking advantage of GADS, we are able to enhance the ability of dealing with the optimal problems which cannot be resolved by conventional optimal technology like the problems that are difficult to be defined or not easy to be mathematically modeled. For example, the objective function is discontinuous or highly nonlinear, randomness or non-differentiable. The GADS has been used in two ways: One calls the GA function through the command-line, the other one is through a graphical interface to call the GA function. The latter method is more intuitive, directly perceived through the senses, here to introduce the use of the latter method. Before making use of Toolbox, the user needs to write an M-file for pending objective function to be optimized. Then set the options according to the requirement. At last call the GA function. GADS will optimize the minimum of the objective function in the M-file based on the options set previously. In that way, the GADS finds the optimal solution by taking the minimum value of the objective function for optimization.

Type “gatool” in the command line to open the MATLAB Genetic Algorithm and Direct Search Toolbox.

5.4 Determination of the Fitness function

The aim of the Fitness function is to obtain the minimum value of the objective function. The form for inputting fitness function is @fitnessfun, where fitnessfun.m is M file for calculating Fitness function.

For the reason that the cost of SCs is proportional to the number of capacity banks, the objective function that represents the cost can be equivalent to the function defining the number. Therefore the objective function is $G(n) = n_1 + n_2 + \cdots + n_c$.

Program the M-file of objective function. The M-file of the objective function for the cost of SCs is written as below:

```
function y=objective_function(x)
y =x(1)+x(2)+x(3)+x(4)+x(5)
```

Because the value of power loss can be indirectly revealed by the swing bus generation as long as the system load is constant. The objective function at this time is G(x) =P_{sg}. Programming the M-file of objective function, we can get the M-file of the objective function for the real power at swing bus as follows:

```
function y=objective_functionpsw(x)
 temp=loadcase('case9mod');
 intermediate1 =temp.bus(5,4);
 intermediate2=temp.bus(7,4);
 Mvar1= intermediate1-0.5*x(1)
 Mvar2= intermediate2-0.5*x(2)
 temp.bus(5,4)=Mvar1;
 temp.bus(7,4)=Mvar2;
 case9mod=temp;
 T=runpf(case9mod);
 y=T.branch(1,14)
```

Enter the name of objective function's M file in the box for Fitness function. The number of the variables is determined by the dimension of a specific problem. Here, we take the issue about 5 locations of SCs in 30-bus system as an example. The problem setup is displayed in Figure 3.

Figure 3 Interface of problem setup

5.5 Determination of Constraints

It is a constrained optimization in my thesis. The GA attempts to solve problems of the following forms:

min F(X)

subject to: A*X <= B, Aeq*X = Beq (linear constraints)

X C(X) <= 0, Ceq(X) = 0 (nonlinear constraints)

LB <= X <= UB

X(i) integer, where i is in the index vector INTCON (integer constraints)

The INTCON is not empty in respect that all the variables needed to be determined for this problem are all integers. Then no equality constraints are allowed. That is to say, Aeq and Beq must be empty. What's more, Ceq returned from NONLCON must be empty. Also, we have to set A= [] and B= [], since no inequalities exist. A set of lower and upper bounds on the design variables, X, need to be defined, so that a solution is found in the range lb <= X <= ub when we consider those variables in practice. All variables subject the minimization to the constraints defined in NONLCON. The function NONLCON accepts vector X and returns the vectors C and Ceq, representing the nonlinear inequalities and equalities respectively. The variables listed in INTCON take integer values.

Again we take the issue about 5 locations of SCs in 30-bus system as an example. Pass empty matrices for the A, b, Aeq and beq inputs. The lower and upper limits for the number of SCs are 0 and 40, respectively. Because the power system only has 30 buses, and bus 1 is the swing bus, bus 2 is a PV bus, except limited number of buses, from bus 3, the bus starts to be a PQ bus. The lower and upper limits for indices of buses are 3 and 30, respectively. While the lower and upper limits for transformer tap are 0.95 and 1.05, respectively. All the variables are integer values, pass all numbers from 1 to 16 for Integer variable indices.

Program the M-file of nonlinear constraint function. The M-file is shown in Appendix B. Enter the name of the M file of nonlinear constraint function in the corresponding box. The constraints setup is displayed in Figure 4.

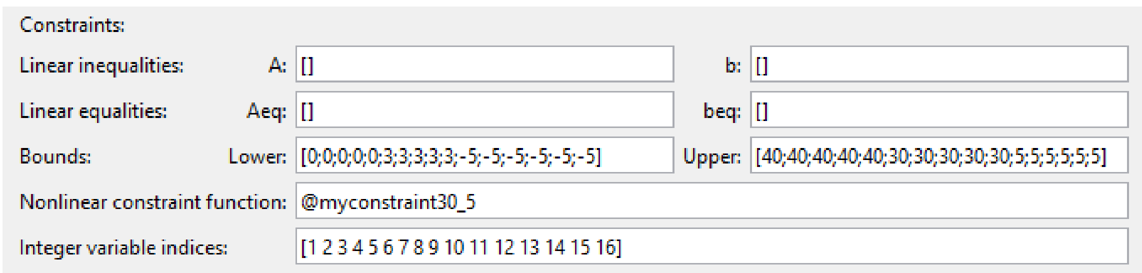

Figure 4 Interface of constraints setup

5.6 Set the GA Options

(1) Population size

Population size sets the number of individuals in each generation. The larger the population size is, the more thoroughly the genetic algorithm will search the solution space. Therefore, the larger population size can effectively reduce the probability of returning a local minimum value rather than the global minimum value by the algorithm. On the other hand, the corresponding computing speed will slow down. Population size is taken as 200 in this work.

(2) Initial range

To avoid getting the local minimum instead of global minimum, we need to increase the diversity of the generation. In other words, increase Initial range. As a consequence, the initial range for the number of Static Capacitors in each selected bus is set to [0;10], for the index of the bus needed to be selected is set to [0;10] and for the position of the tap is set to [0;3].

The initial range does not need to include the best individual. However, the range should be large enough, so as to make sure that the children around the best individual can be generated. The population setup is displayed in Figure 5.

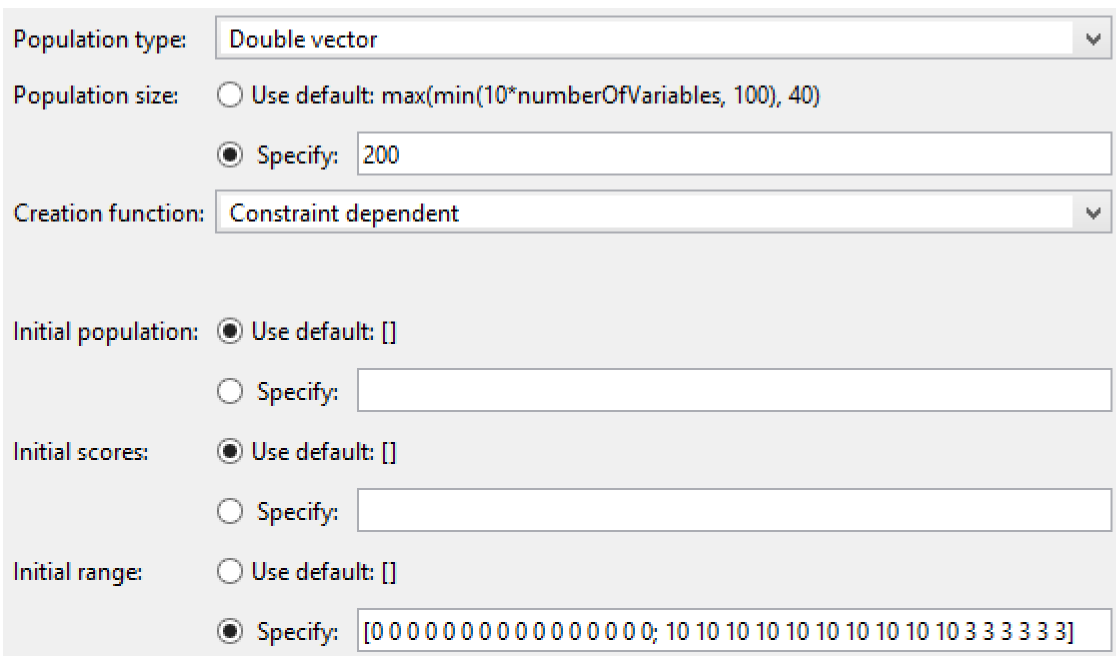

Figure 5 Interface of population setup

(3) Fitness scaling

For eliminating the influence from original fitness scores, rank approach is selected to measure the quality of each individual. It merely pays attention to the sequence of fitness scores rather than the values of fitness scores. In the light of description, the best individual ranks first, the individual which has the second lowest fitness score is the second in line. The rest can be deduced by analogy.

(4) Elite count

Elitist strategy selects a portion of the strings with best fitness values. Specify the number of Elite children in the box under "Reproduction". Here we take 20.

(5) Crossover fraction

The crossover rate is set to the default value. That is 0.8 in the Matlab. As the population size is set to 200 and Elite count is 20, the features of the next generation are listed as follows.

i. It has 20 Elite children.

ii. Except for the 20 Elite children, there are 180 individuals left. So the number of children created through crossover is $180 \times 0.8 = 144$.

iii. The remaining 36 individuals are formed by mutation.

The mutation rate is consequently set to the value of 0.2 in this paper for avoiding a local optimum.

(6) Selection function

The tournament approach is then used for selecting the rest of the strings to ensure that the number of a new generation is the same as the initial population. The Section and

Reproduction setup is displayed in Figure 6.

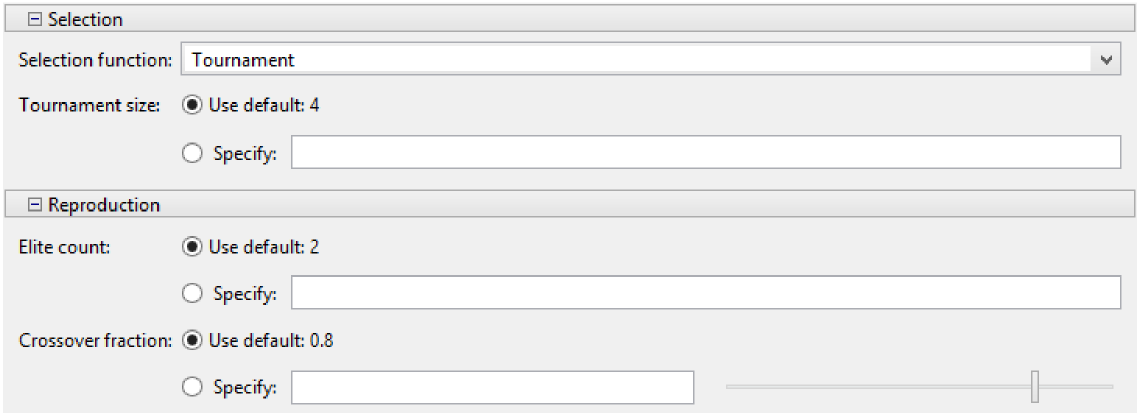

Figure 6 Interface of Selection and Reproduction setup

(7) Generations

The Generations is used to set the maximum number of generations. The default value is 100. We take 600 for this option.

(8) Stall generations

If the weighted average change of the objective function value is less than the value of Function tolerance set in (9) within the generations determined by this option, the genetic algorithm will stop running and give the final results. We make Stall generations be 200 here.

(9) Function tolerance

If the cumulative change of the objective function value is less than the value of Function tolerance within the stall generations, the genetic algorithm will stop running. In this study, the Function tolerance is assumed 1e-100.

(10) The remaining options keep the default value.

The Stopping criteria setup is displayed in Figure 7.

Figure 7 Interface of Stopping criteria setup

On the whole, stopping criteria is set by whether maximum number of generations has been attained or not. If so, stop the program, then take the best individual and its fitness function.

5.7 Plot Functions Setup

Plots can display so much relevant information through various curves during genetic algorithm running. Such information will help us change GA options to improve the capacity of algorithm. In this paper, to show the value of the best fitness and the mean of all the fitness for every generation, so that we get to know the change of operation statues in real time, we need to check the box for best fitness as shown in Figure 8.

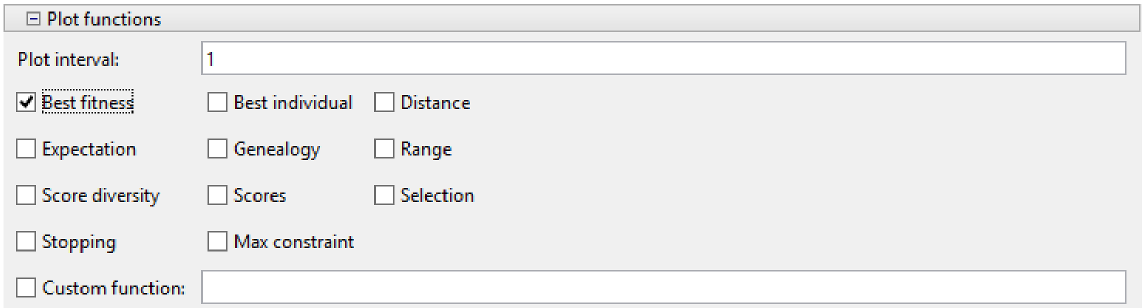

Figure 8 Interface of Plot function setup

After the algorithm begins, the plot for one of the scenarios for 30-bus system appears. It is shown in the following figure.

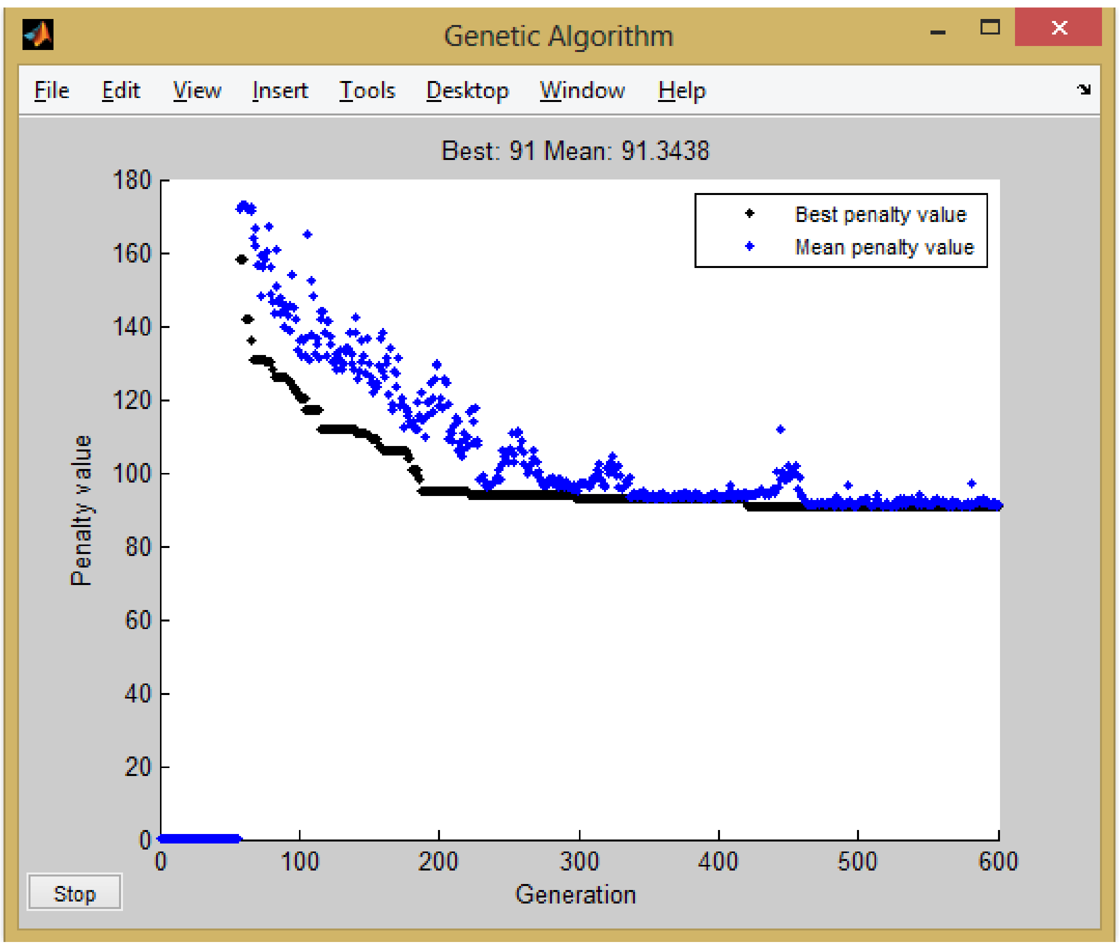

Figure 9 Plot for one of the scenarios for 30-bus system

Chapter VI Verification

6.1 Operation Results and Analysis for 9-bus System

A. Operation states obtained by Markov Model

Figure 10 illustrates the IEEE 9-bus system. The power system includes conventional generators at bus 2 and bus 3, and one wind farm at bus 7. Bus 1 is the slack bus. Voltages for these conventional generators are set to be identical. The wind farm which is controllable is located at bus 7. Three feeders are located at buses 5, 7 and 9, respectively.

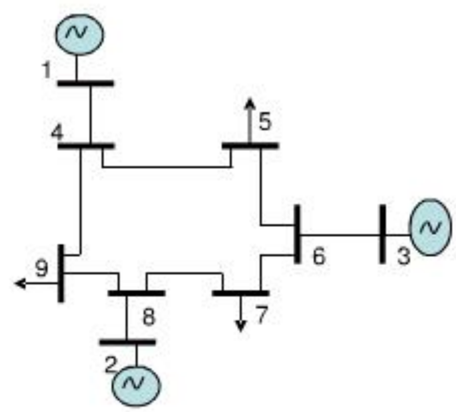

Figure 10 IEEE 9-bus system

Initially, there is no SC in this system. Realistic wind power generation measurements over one day are applied to establish the Markov model. The maximum wind power generation can be tracked within the wind speed 5m/s and 16 m/s. No MW is generated when the wind speed is below 5 m/s or above 20 m/s. On the contrary, the maximum MW is produced when the wind speed is between 16 m/s and 20 m/s. Table 4 shows the 13 states for wind farm at bus 7.

From Table 4, we can find that the interval of wind power generation is 6 MW and the power ranges from 0MW to 72MW. Correspondingly, the total real power at bus 7 is from 78MW to 150MW. The penetration rate of wind power in this system is 22.5%. The table also shows that the Markov model provides information about the probability for each state. On the basis of Table 4, operation states for the 9-bus system can be defined. As described in Step 6 in Section 2.4, a power-flow program using nominal VAR control settings was employed to screen all operation states to obtain the bus voltages. Ultimately, the results reveal that all the operation states face voltage problems subject to the low-voltage constraints. Table 5 shows these 13 operation states.

Table 4 13 states for wind farm at bus 7

state	speed (m/s)	probability	Wind Power (MW)	MW at bus 7
1	0～5, 20～	0.0581	0	150
2	5～6	0.0539	6	144
3	6～7	0.0373	12	138
4	7～8	0.0581	18	132
5	8～9	0.0664	24	126
6	9～10	0.1037	30	120
7	10～11	0.1120	36	114
8	11～12	0.1245	42	108
9	12～13	0.0830	48	102
10	13～14	0.0789	54	96
11	14～15	0.0623	60	90
12	15～16	0.0706	66	84
13	16～20	0.0913	72	78

Table 5 13 operation states for 9-bus system

State	1	2	3	4	5	6	7
V5(p.u.)	0.946	0.946	0.946	0.946	0.946	0.945	0.945
V7(p.u.)	0.945	0.946	0.946	0.947	0.948	0.949	0.949
State	8	9	10	11	12	13	\
V5(p.u.)	0.945	0.944	0.944	0.943	0.943	0.942	\
V7(p.u.)	\	\	\	\	\	\	\

B. Optimal VAR planning by GA

All the above 13 operation states need to be studied by the proposed GA. Since there is no transformer in the 9-bus system, we only need to consider the variables relating to the location and the size of SCs. Firstly, we must find the best location in the system for putting SCs. In this paper, one place and two places are studied. Only the cost of SCs has to be taken into consideration in this step. Accordingly, the objective function is the total number of all the capacitors. The GA results are shown in Table 6.

Table 6 GA results for placement of SCs in 9-bus system

S	Loc	SC (Mvar)	Num	Loc1	SC1 (Mvar)	Num 1	Loc2	SC2 (Mvar)	Num 2	Total Num
1	6	20	40	5	3	6	7	6	12	18
2	6	17.5	35	5	3.5	7	7	5	10	17
3	6	18	36	5	4	8	7	3.5	7	15
4	9	15.5	31	5	4	8	7	3	6	14
5	5	11.5	23	5	4.5	9	7	1.5	3	12
6	5	7.5	15	5	5	10	7	0.5	1	11
7	5	5.5	11	5	5	10	9	0.5	1	11
8	5	5.5	11	5	5.5	11	7	0	0	11
9	5	6	12	5	6	12	7	0	0	12
10	5	6.5	13	5	6.5	13	7	0	0	13
11	5	7	14	5	7	14	7	0	0	14
12	5	7.5	15	5	7.5	15	7	0	0	15
13	5	8.5	17	5	8.5	17	7	0	0	17

According to the Table.6, for the case of selecting a single location, the probability of choosing the bus 5 as the best location to put static capacitors is the summation of all probabilities from state 5 to state 13. The total value is 0.7927. Applying the same principle, the probability for bus 6 is 0.1493. And the probability for bus 9 is 0.0581. Obviously, Bus 5 has the largest probability, so we select bus 5. In the same way, for the issue of two places, the pair bus 5 and bus 7 has the largest probability with 0.888. There is no doubt that we would select that pair for this case.

The next step is to calculate the size of each SC based on the locations we calculated in the first step. The GA is applied again for this step. But the sizes will be determined separately for two different purposes. One is to minimize the cost of SCs, The other is to minimize the power losses. Thus, two different objective functions are used here individually. One is the total number of all capacitors. The other is the power generation at the swing bus. As bus 5 is not the best location for state 1, that bus needs much more Mvar than bus 6. Moreover, the cost is not considered while minimizing the power loss. It'd be better to raise the upper limit of SC sizes. So 50Mvar is taken here. The sizes of static capacitors for the 13 operation states were individually calculated using the proposed method with the first objective function being expressed in Table 7.

Table 7 Sizes of SCs for the 13 operation states to minimize the cost

	Case 1			Case2						
S	Loc	SC(Mvar)	Num	L1	Mvar1	N1	L2	Mvar2	N2	Total Num
1	5	31	62	5	3	6	7	6	12	18
2	5	25.5	51	5	3.5	7	7	5	10	17
3	5	20.5	41	5	4	8	7	3.5	7	15
4	5	16	32	5	4	8	7	3	6	14
5	5	11.5	23	5	4.5	9	7	1.5	3	12
6	5	7.5	15	5	5	10	7	0.5	1	11
7	5	5.5	11	5	5.5	11	7	0	0	11
8	5	5.5	11	5	5.5	11	7	0	0	11
9	5	6	12	5	6	12	7	0	0	12
10	5	6.5	13	5	6.5	13	7	0	0	13
11	5	7	14	5	7	14	7	0	0	14
12	5	7.5	15	5	7.5	15	7	0	0	15
13	5	8.5	17	5	8.5	17	7	0	0	17

The result of GA with the second objective function is shown in Table 8.

The goal of this study is to improve the voltage quality with less low or high voltage issues. It is not necessary to totally solve the voltage problems and guarantee that all voltages are within voltage constraints at any time for all scenarios.

Table 8 Sizes of SCs for the 13 operation states to minimize the power loss

S	L	Case3 SC(Mvar)	P_{sw}	L1	Case4 SC1(Mvar)	L2	SC2(Mvar)	P_{sw}
1	5	41.5	126.9589	5	43	7	50	126.5444
2	5	41.5	120.9729	5	42.5	7	50	120.5612
3	5	41.5	115.0095	5	42.5	7	50	114.5999
4	5	41.5	109.0686	5	42.5	7	50	108.6602
5	5	41.5	103.15	5	42.5	7	50	102.7422
6	5	41.5	97.2537	5	43	7	50	96.8456
7	5	42	91.3796	5	43	7	50	90.9704
8	5	42	85.5276	5	43.5	7	50	85.1166
9	5	42.5	79.6975	5	43.5	7	50	79.2839
10	5	43	73.8894	5	44	7	50	73.4725
11	5	43.5	68.1032	5	44.5	7	50	67.6822
12	5	44	62.3387	5	45	7	50	61.913
13	5	45	56.596	5	46	7	50	56.1648

As a consequence, it is possible to place the static capacitors with fixed values at the selected buses. We calculate the value in accordance with the Table 7 and Table 8. Here, the fixed value is set to the expected SCs. For example, the expected $\mathrm{SC_c}$ for the c-th static capacitor is

$$\mathrm{dis}(\textstyle\sum_{s=1}^{S} \mathrm{SC_c}(s) \times \mathrm{P}(s))$$

where dis$(\cdot)$ denotes the nearest and larger discrete value.

And the optimal solution expressed with the expected values of SCs aiming for the single location and two locations together with two different objective functions are shown in the Table 9.

Table 9 Expected values of SCs for the cases of one place and two places

objective	SC(Mvar)	Num	SC1(Mvar)	Num1	SC2(Mvar)	Num2	Mvar	Num
cost	10.5	21	6	12	1.5	3	7.5	15
PL	42.5	85	44	88	50	100	94	188

From Table.9, we can find that when the objective is to minimize the cost for the same voltage constraints, the case of two locations always requires a lower investment for installing new static capacitors. More importantly, so much more investment is required to minimize the power loss in the power system for both cases of one single location or two locations.

For the purpose of testing the results, a power-flow program using obtained VAR control settings will be applied to display all operation states to obtain the bus voltages as well as the real power generation at the swing bus. The values of the lowest voltage magnitude violating voltage constraints, the number of low voltages, and power generation at the swing bus are exhibited from Table 10 to Table 13.

Table 10 Power generation at the swing bus and voltages violating limits throughout all states for case 1

State	1	2	3	4	5	6	7
P_{sw}(MW)	127.11	121.12	115.16	109.22	103.3	97.4	91.53
Number	1	1	1	1	0	0	0
V_{min}/V_{max} (p.u.)	0.947	0.947	0.948	0.949	\	\	\
State	8	9	10	11	12	13	\
Number	0	0	0	0	0	0	\
P_{sw}(MW)	85.68	79.86	74.05	68.27	62.51	56.78	\
V_{min}/V_{max} (p.u.)	\	\	\	\	\	\	\

Table 11 Power generation at the swing bus and voltages violating limits throughout all states for case 2

State	1	2	3	4	5	6	7
P_{sw}(MW)	127.14	121.15	115.19	109.25	103.33	97.43	91.56
Number	1	1	1	0	0	0	0
V_{min}/V_{max} (p.u.)	0.947	0.948	0.949	\	\	\	\
State	8	9	10	11	12	13	\
P_{sw}(MW)	85.71	79.89	74.08	68.3	62.55	56.81	\
Number	0	0	0	0	0	0	\
V_{min}/V_{max} (p.u.)	\	\	\	\	\	\	\

Table 12 Power generation at the swing bus and voltages violating limits throughout all states for case 3

State	1	2	3	4	5	6	7
P_{sw}(MW)	126.96	120.97	115.01	109.07	103.15	97.25	91.38
Number	0	0	0	0	0	0	0
V_{min}/V_{max}(p.u.)	\	\	\	\	\	\	\
State	8	9	10	11	12	13	\
P_{sw}(MW)	85.53	79.7	73.89	68.1	62.34	56.6	\
Number	0	0	0	0	0	0	\
V_{min}/V_{max}(p.u.)	\	\	\	\	\	\	\

Table 13 Power generation at the swing bus and voltages violating limits throughout all states for case 4

State	1	2	3	4	5	6	7
P_{sw}(MW)	126.54	120.56	114.60	108.66	102.74	96.85	90.97
Number	0	0	0	0	0	0	0
V_{min}/V_{max}(p.u.)	\	\	\	\	\	\	\
State	8	9	10	11	12	13	\
P_{sw}(MW)	85.12	79.28	73.47	67.68	61.91	56.17	\
Number	0	0	0	0	0	0	\
V_{min}/V_{max}(p.u.)	\	\	\	\	\	\	\

Through these tables, the expected values of power generation at the swing bus for cases from case 1 to case 4 are 88.754MW, 88.7846MW, 88.597MW, 88.1819MW, respectively. And the probabilities under normal operation for them are 0.7926, 0.8507, 1, and 1.

For comparison of those values, the power losses are almost the same showing little difference between each other. Even though the P_{sw} for case 3 and case 4 is less than case 1 and case 2, respectively; the method cannot effectively reduce the power loss with the second objective function. In addition, the cost experiences a tremendous increase, much higher than it in case 1 and 2 individually, if we want to lower the power losses, because under such circumstances, the aim is achieved regardless of expense. For this reason, setting the cost as an objective function is much better at least for this bus system. Furthermore, compared with one location, the case of two locations has higher probability of normal operation and much less cost. This may lead to less static capacitor investment and smaller voltage violation. In conclusion, putting the Static Capacitors at two different locations along with the goal of minimizing cost is the best choice among all four options.

6.2 Operation Results and Analysis for 30-bus System

A. Operation states obtained by Markov Model

Figure 11 illustrates the IEEE 30-bus system. In this power system, conventional generators are located at bus 2, bus 13, bus 22, bus 23, and bus 27. Meanwhile, one wind farm is at bus 8. Bus 1 is the swing bus. Voltages for these generators are set to be identical. The wind farm is located at bus 8 whose voltage is controllable. There are 20 feeders at most of the buses in the power system.

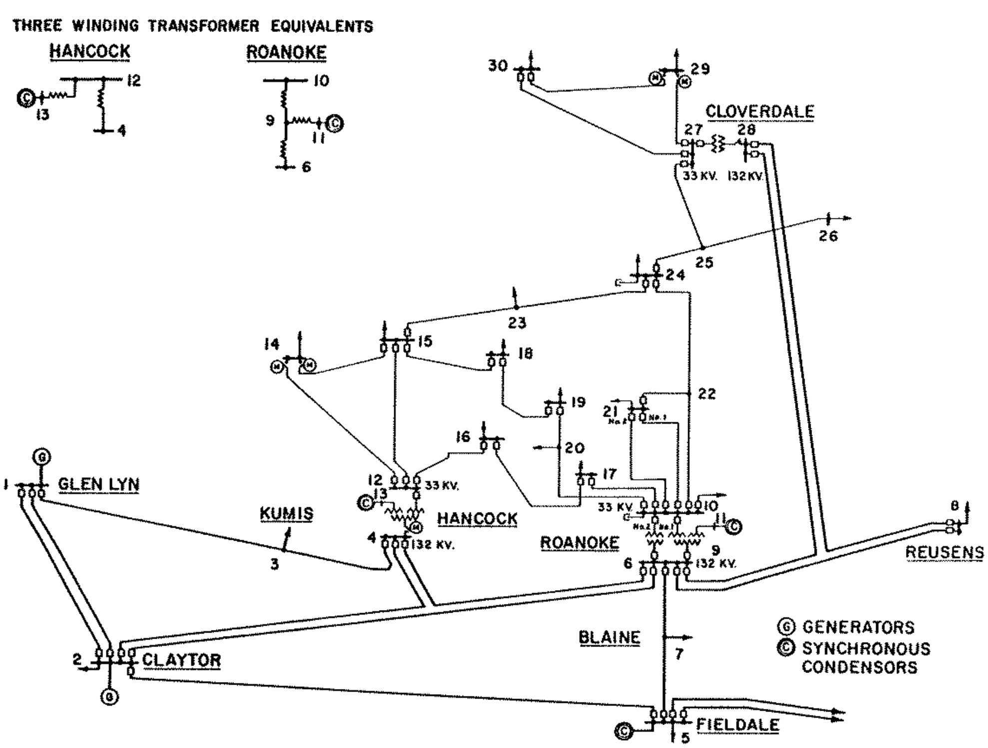

Figure 11 IEEE 30-bus system

At first, no SC is in this system. We utilize the same Markov model of realistic wind power generation as used in the 9-bus system except for the interval of wind power generation. The interval is assumed to be 5 MW for 30-bus system. And the minimum output and maximum output are 10MW and 70MW, respectively. As the total real power generation of conventional generators is 259.21MW, the penetration rate of wind power in this system, consequently, is 27.01%. Table 14 exhibits the 13 states for wind farm at buses 8 and their probabilities.

Table 14 13 states for wind farm at bus 8

state	speed (m/s)	probability	Wind Power (MW)	MW at bus 8
1	0～5, 20～	0.0581	0	70
2	5～6	0.0539	5	65
3	6～7	0.0373	10	60
4	7～8	0.0581	15	55
5	8～9	0.0664	20	50
6	9～10	0.1037	25	45
7	10～11	0.112	30	40
8	11～12	0.1245	35	35
9	12～13	0.083	40	30
10	13～14	0.0789	45	25
11	14～15	0.0623	50	20
12	15～16	0.0706	55	15
13	16～20	0.0913	60	10

With Table 14, operation states in the 30-bus system have the chance to be defined. Also relying on Step 6 in Section 2.4, a power-flow program with nominal VAR control settings was employed to screen all operation states including the bus voltages. Table 15 shows the number of voltages violating the low voltage constraint and the minimum voltage among them. From the results, we can see that all the operation states have low voltage problems.

Table 15 13 operation states for 9-bus system

State	1	2	3	4	5	6	7
Number	11	11	11	11	11	11	10
V_{min} (p.u.)	0.893	0.893	0.893	0.893	0.893	0.893	0.893
State	8	9	10	11	12	13	\
Number	9	8	8	8	8	8	\
V_{min} (p.u.)	0.893	0.893	0.893	0.893	0.893	0.893	\

B. Optimal VAR planning by GA (30-Bus System)

Each operation state defined above must be studied by the proposed GA. But different from 9-bus system, this bus system has several transformers. So, one extra variable must be considered this time. This variable is transformer tap position. At the first step, we must find the best place for putting SCs like what we did for 9-bus system. Three, four and five locations are studied for this bus system due to its much more buses compared with 9-bus system. Still only the cost of SCs needs to be taken into account in this step. The results are displayed in Table 16-18 below.

Table 16 GA results for placement of SCs with 3 locations in 30 bus system

S	Loc1	SC1 (Mvar)	Num1	Loc2	SC2 (Mvar)	Num2	Loc3	SC3 (Mvar)	Num3	Total Num
1	\	\	\	\	\	\	\	\	\	\
2	\	\	\	\	\	\	\	\	\	\
3	\	\	\	\	\	\	\	\	\	\
4	\	\	\	\	\	\	\	\	\	\
5	\	\	\	\	\	\	\	\	\	\
6	\	\	\	\	\	\	\	\	\	\
7	\	\	\	\	\	\	\	\	\	\
8	\	\	\	\	\	\	\	\	\	\
9	\	\	\	\	\	\	\	\	\	\
10	\	\	\	\	\	\	\	\	\	\
11	18	20	40	26	9.5	19	30	5.5	11	70
12	18	19.5	39	26	9.5	19	30	5.5	11	69
13	18	20	40	26	9.5	19	30	5.5	11	70

Table 17 GA results for placement of SCs with 4 locations in 30 bus system

S	Loc1	SC1	Nu 1	Loc2	SC2	Nu 2	Loc3	SC3	Nu 3	Loc4	SC4	Nu 4	N
1	8	19.5	39	18	20	40	26	9.5	19	30	5.5	11	109
2	14	19	38	19	19	38	26	9.5	19	30	5.5	11	106
3	14	11	22	19	16	32	26	9.5	19	30	5.5	11	84
4	14	9.5	19	19	15.5	31	26	9.5	19	30	5.5	11	80
5	14	8	16	19	15	30	26	9.5	19	30	5.5	11	76
6	14	8.5	17	19	14.5	29	26	9.5	19	30	5.5	11	76
7	14	5	10	19	14.5	29	26	9.5	19	30	5.5	11	69
8	14	4	8	19	14	28	26	9.5	19	30	5.5	11	66
9	14	4	8	19	13.5	27	26	9.5	19	30	5.5	11	65
10	14	3	6	19	13	26	26	9.5	19	30	5.5	11	62
11	14	3	6	19	12.5	25	26	9.5	19	30	5.5	11	61
12	14	2.5	5	19	12.5	25	26	9.5	19	30	5.5	11	60
13	14	2.5	5	18	12	24	26	9.5	19	30	5.5	11	59

Table 18 GA results for placement of SCs with 5 locations in 30 bus system

S	L1	SC1	L2	SC2	L3	SC3	L4	SC4	L5	SC5	Num
1	8	12/24	14	4/8	19	14.5/29	26	9.5/19	30	5.5/11	91
2	8	11/22	14	4/8	19	14/28	26	9.5/19	30	5.5/11	88
3	8	5/10	14	6.5/13	19	15/30	26	9.5/19	30	5.5/11	83
4	8	5.5/11	14	5/10	19	14.5/29	26	9.5/19	30	5.5/11	80
5	15	0.5/1	14	7.5/15	19	15/30	26	9.5/19	30	5.5/11	76
6	8	4/8	14	3.5/7	19	14/28	26	9.5/19	30	5.5/11	73
7	8	0/0	14	5/10	19	14.5/29	26	9.5/19	30	5.5/11	69
8	9	0.5/1	14	3/6	19	14/28	26	9.5/19	30	5.5/11	65
9	8	0/0	14	4/8	19	13.5/27	26	9.5/19	30	5.5/11	65
10	18	1.5/3	14	2.5/5	19	12/24	26	9.5/19	30	5.5/11	62
11	12	0.5/1	14	2.5/5	19	13/26	26	9.5/19	30	5.5/11	62
12	8	0/0	14	2.5/5	19	12.5/25	26	9.5/19	30	5.5/11	60
13	20	0.5/1	14	2.5/5	19	11.5/23	26	9.5/19	30	5.5/11	59

In Table 16, the values for states from 1 to 10 are not able to be worked out by the Genetic Algorithm owing to the upper limit for the size of SCs. It demonstrates that only three locations are not enough for problem solving. As a consequence, this option will be discarded. From Table.17, with probability of 0.9419, the group including bus 14, bus 19, bus 26 and bus 30, is undoubtedly chosen as the locations for putting Static Capacitors.

For the case of five locations, the probability for selecting group, bus 8, bus 14, bus 19, bus 26 and bus 30, is 0.5767 also accounting for most proportion. This group is determined as best locations.

The reason why the sizes of SCs for Bus 26 and Bus 30 remain the same throughout all scenarios is that bus 22, bus 23 and bus 27 are all PV buses. The magnitudes of these buses keep constant. Therefore, the unchanged $|V_{22}|$ and $|V_{23}|$ have isolation effect for bus 26. And the bus 30 is isolated by constant $|V_{27}|$.

Next, the size of each SC based upon the locations we got previously, and the transformer tap settings need to be calculated. Once again the sizes will be determined separately with two different objective functions mentioned in 6.1. For the same reason, the upper limit of SC's size is raised. Here it is assumed to be 55Mvar. In the same way, the two values for all states were individually calculated with the first objective function for 4 locations. This case is numbered as case 5. The results are shown in Table 19 and 20 below.

Table 19 Sizes of SCs for 13 operation states for case 5

S	L1	SC1	N1	L2	SC2	N2	L3	SC3	N3	L4	SC4	N4	Num
1	14	26	52	19	32.5	65	26	9.5	19	30	5.5	11	147
2	14	19	38	19	19	38	26	9.5	19	30	5.5	11	106
3	14	11	22	19	16	32	26	9.5	19	30	5.5	11	84
4	14	9.5	19	19	15.5	31	26	9.5	19	30	5.5	11	80
5	14	8	16	19	15	30	26	9.5	19	30	5.5	11	76
6	14	8.5	17	19	14.5	29	26	9.5	19	30	5.5	11	76
7	14	5	10	19	14.5	29	26	9.5	19	30	5.5	11	69
8	14	4	8	19	14	28	26	9.5	19	30	5.5	11	66
9	14	4	8	19	13.5	27	26	9.5	19	30	5.5	11	65
10	14	3	6	19	13	26	26	9.5	19	30	5.5	11	62
11	14	3	6	19	12.5	25	26	9.5	19	30	5.5	11	61
12	14	2.5	5	19	12.5	25	26	9.5	19	30	5.5	11	60
13	14	2.5	5	19	12	24	26	9.5	19	30	5.5	11	59

Table 20 Transformer taps for 13 operation states for case 5

S	Trans4_12	Trans12_13	trans6_9	Trans9_10	Trans9_11	Trans28_27
1	1.05	1.05	1.05	1.05	1.02	1.05
2	1.05	1.05	1.05	1.05	0.96	1.05
3	1.04	1.05	1.05	1.05	0.98	1.05
4	1.02	1.05	1.05	1.05	0.96	1.05
5	1	1.05	1.05	1.05	0.99	1.05
6	1.01	1.05	1.04	1.04	1	1.05
7	0.97	1.05	1.05	1.05	1.03	1.05
8	0.96	1.05	1.04	1.05	0.99	1.05
9	0.96	1.05	1.05	1.03	0.95	1.05
10	0.95	1.05	1.04	1.03	0.97	1.05
11	0.95	1.05	1.04	1.02	1.02	1.05
12	0.95	1.05	1.04	1.01	0.95	1.05
13	0.95	1.05	1.02	1.02	1.01	1.05

Calculate each expected SC and tap position, the expected values are exhibited in Table 21.

Table 21 Expected SCs and tap positions for case 5

SC	Size1	Num1	Size2	Num2	Size3	Num3	Size4	Num4	Num
Value	7.5	15	15.5	31	9.5	19	5.5	11	76

Trans	4_12	12_13	6_9	9_10	9_11	28_27
Value	0.99	1.05	1.05	1.04	0.99	1.05

Like what is done in 6.1, the bus voltages and the real power generation at the swing bus for all states calculated with obtained control settings are finally gotten in Table 22. The only bus below 0.95 p.u. is Bus 8.

Table 22 Power generation at the swing bus and the lowest voltage violating limits throughout all states for case 5

state	1	2	3	4	5	6	7
P_{sw} (MW)	150.89	145.27	139.68	134.12	128.58	123.07	117.58
Number	1	1	1	1	1	0	0
$V_{\text{min}}/V_{\text{max}}$(p.u.)	0.942	0.944	0.945	0.947	0.948	\	\
State	8	9	10	11	12	13	\
P_{sw} (MW)	112.12	106.68	101.27	95.88	90.52	85.18	\
Number	0	0	0	0	0	0	\
$V_{\text{min}}/V_{\text{max}}$(p.u.)	\	\	\	\	\	\	\

Case 6 is defined here when there are 5 locations in which to put SCs in the 30-bus system and the objective function is the summation of all capacitors' numbers. As what we did for case 5, applying the genetic algorithm, we can get the results from Table 23 to 26.

Table 23 Sizes of SCs for 13 operation states for case 6

S	Loc1	SC1	Loc2	SC2	Loc3	SC3	Loc4	SC4	Loc5	SC5	Num
1	8	12/24	14	4/8	19	14.5/29	26	9.5/19	30	5.5/11	91
2	8	11/22	14	4/8	19	14/28	26	9.5/19	30	5.5/11	88
3	8	5/10	14	6.5/13	19	15/30	26	9.5/19	30	5.5/11	83
4	8	5.5/11	14	5/10	19	14.5/29	26	9.5/19	30	5.5/11	80
5	8	0/0	14	7.5/15	19	15.5/31	26	9.5/19	30	5.5/11	76
6	8	4/8	14	3.5/7	19	14/28	26	9.5/19	30	5.5/11	73
7	8	0/0	14	5/10	19	14.5/29	26	9.5/19	30	5.5/11	69
8	8	0/0	14	4/8	19	14/28	26	9.5/19	30	5.5/11	66
9	8	0/0	14	4/8	19	13.5/27	26	9.5/19	30	5.5/11	65
10	8	0/0	14	3/6	19	13/26	26	9.5/19	30	5.5/11	62
11	8	0/0	14	2.5/5	19	13.5/27	26	9.5/19	30	5.5/11	62
12	8	0/0	14	2.5/5	19	12.5/25	26	9.5/19	30	5.5/11	60
13	8	0/0	14	2.5/5	19	12/24	26	9.5/19	30	5.5/11	59

Table 24 Transformer taps for 13 operation states for case 6

State	4_12	12_13	6_9	9_10	9_11	28_27
1	0.96	1.05	1.05	1.05	0.98	1.05
2	0.95	1.05	1.05	1.05	0.95	1.05
3	0.99	1.05	1.05	1.05	0.99	1.05
4	0.97	1.05	1.05	1.05	1	1.05
5	1	1.05	1.05	1.05	0.99	1.05
6	0.95	1.05	1.05	1.05	1.02	1.05
7	0.97	1.05	1.05	1.05	0.98	1.05
8	0.95	1.05	1.05	1.05	0.97	1.05
9	0.95	1.05	1.04	1.04	1	1.05
10	0.95	1.05	1.05	1.02	1	1.05
11	0.95	1.05	1.05	1.03	0.96	1.05
12	0.95	1.05	1.01	1.03	0.99	1.05
13	0.95	1.05	1	1.03	0.99	1.05

Table 25 Expected SCs and expected tap positions for the case 6

SC	size1	n1	size2	n2	size3	n3	size4	n4	size5	n5	Num
value	2.5	5	4.5	9	14	28	9.5	19	5.5	11	72
tram	4_12		12_13		6_9		9_10		9_11		28_27
value	0.96		1.05		1.05		1.05		0.99		1.05

Table 26 Power generation at the swing bus and voltages violating limits throughout all states for case 6

state	1	2	3	4	5	6	7
P_{sw} (MW)	151.1	145.48	139.89	134.32	128.78	123.27	117.78
Number	3	3	2	2	2	0	0
$V_{\min}/V_{\max}$(p.u.)	0.942	0.944	0.945	0.947	0.949	\	\
State	8	9	10	11	12	13	\
P_{sw}	112.32	106.88	101.46	96.08	90.71	85.37	\
Number	0	0	0	0	0	0	\
$V_{\min}/V_{\max}$(p.u.)	\	\	\	\	\	\	\

Employing the same principle for case 7 where the goal is aiming at minimizing the power loss, and only four locations in 30-bus system, we will obtain the results shown from Table 27 to 30. The single bus violating the low voltage constraint again is Bus 8.

Table 27 Sizes of SCs for 13 operation states for case 7

S	L1	SC1	N1	L2	SC2	N2	L3	SC3	N3	L4	SC4	N4	P_{sw}-MW
1	14	29	58	19	29.5	59	26	11	22	30	8	16	150.4629
2	14	25	50	19	24.5	49	26	11	22	30	8	16	144.7802
3	14	25	50	19	24.5	49	26	11	22	30	8	16	139.1295
4	14	26.5	53	19	25	50	26	11	22	30	8	16	133.5203
5	14	25	50	19	23.5	47	26	11	22	30	8	16	127.9603
6	14	26.5	53	19	24.5	49	26	11	22	30	8	16	122.4206
7	14	25	50	19	22.5	45	26	11	22	30	8	16	116.9191
8	14	25	50	19	22	44	26	11	22	30	8	16	111.4526
9	14	24.5	49	19	21.5	43	26	11	22	30	8	16	106.0167
10	14	24.5	49	19	21.5	43	26	11	22	30	8	16	100.6094
11	14	24.5	49	19	21.5	43	26	11	22	30	8	16	95.2282
12	14	24.5	49	19	21.5	43	26	11	22	30	8	16	89.871
13	14	24.5	49	19	21	42	26	11	22	30	8	16	84.5375

Table 28 Transformer taps for 13 operation states for case 7

State	Trans4_12	Trans12_13	trans6_9	Trans9_10	Trans9_11	Trans28_27
1	1.05	1.05	1.05	1.05	1	1.05
2	1.05	1.05	1.04	1.05	1	1.05
3	1.04	1.05	1.03	1.04	0.95	1.05
4	1.05	1.05	1	1.05	1.03	1.05
5	1.05	1.05	0.99	1.05	0.97	1.05
6	1.05	1.05	0.97	1.05	1.05	1.05
7	1.05	1.05	0.96	1.05	0.98	1.05
8	1.05	1.05	0.95	1.05	1.05	1.05
9	1.04	1.05	0.95	1.04	1.04	1.05
10	1.05	1.05	0.95	1.03	1	1.05
11	1.05	1.05	0.95	1.03	0.98	1.05
12	1.05	1.05	0.95	1.03	0.98	1.05
13	1.05	1.05	0.95	1.03	1.04	1.05

Table 29 Expected SCs and expected tap positions for the case 7

SC	size1	num1	size2	num2	size3	num3	size4	num4	Num
value	25.5	51	23.5	47	11	22	8	16	136
Tram	4_12	12_13	6_9	9_10	9_11	28_27			
value	1.05	1.05	0.98	0.98	1.02	1.05			

Table 30 Power generation at the swing bus and voltages violating limits

throughout all states for case 7

state	1	2	3	4	5	6	7
P_{sw}(MW)	150.18	144.57	138.99	133.43	127.90	122.40	116.92
Number	1	1	1	1	1	1	1
V_{min}/V_{max}(p.u.)	0.935	0.937	0.938	0.940	0.942	0.943	0.945
State	8	9	10	11	12	13	\
P_{sw}(MW)	111.46	106.03	100.63	95.25	89.89	84.56	\
Number	1	1	1	0	0	0	
V_{min}/V_{max}(p.u.)	0.946	0.948	0.949	\	\	\	\

Case 8 differs from case 6 in that the objective function is the power generation at the swing bus. Repeating the procedure, the results are clearly shown in the following Tables.

According to table 21, 25, 29 and 33, the expected values of power generation at the swing bus for case 5 to 8 are 115.0128MW, 115.2119MW, 114.3525MW, 113.961MW, respectively. And the probabilities under normal operation for them are 0.7262, 0.7262, 0.2242, and 1.

Table 31 Sizes of SCs for 13 operation states for case 8

S	L1	SC1	L2	SC2	L3	SC3	L4	SC4	L5	SC5	P_{sw}(MW)
1	8	51.5/103	14	23.5/47	19	19/38	26	11/22	30	8/16	149.6992
2	8	50.5/101	14	23.5/47	19	19/38	26	11/22	30	8/16	144.1065
3	8	51/102	14	23.5/47	19	19/38	26	11/22	30	8/16	138.5393
4	8	50.5/101	14	23.5/47	19	19/38	26	11/22	30	8/16	132.9972
5	8	49.5/99	14	23.5/47	19	19/38	26	11/22	30	8/16	127.48
6	8	49/98	14	23/46	19	19/38	26	11/22	30	8/16	121.9874
7	8	46.5/93	14	21.5/43	19	17.5/35	26	11.5/23	30	8.5/17	116.5296
8	8	48/96	14	23/46	19	19/38	26	11/22	30	8/16	111.0751
9	8	47.5/95	14	23/46	19	19/38	26	11/22	30	8/16	105.6549
10	8	47.5/95	14	23/46	19	18.5/37	26	11/22	30	8/16	100.2584
11	8	46/92	14	23/46	19	18.5/37	26	11/22	30	8/16	94.8852
12	8	45.5/91	14	23/46	19	18.5/37	26	11/22	30	8/16	89.5352
13	8	45.5/91	14	22.5/45	19	18.5/37	26	11/22	30	8/16	84.208

Table 32 Transformer taps for 13 operation states for case 8

State	4_12	12_13	6_9	9_10	9_11	28_27
1	1.02	1.05	0.95	0.99	1.02	1.01
2	1.02	1.05	0.95	0.99	0.97	1.01
3	1.02	1.05	0.95	0.99	1	1
4	1.02	1.05	0.95	0.99	1.03	1
5	1.02	1.05	0.95	0.99	1.03	1
6	1.02	1.05	0.95	0.99	1.03	1
7	1.01	1.05	0.96	0.97	1.01	1.02
8	1.02	1.05	0.95	0.99	1.01	1
9	1.02	1.05	0.95	0.99	1	1
10	1.02	1.05	0.95	0.99	1.02	1
11	1.02	1.05	0.95	0.99	0.96	1.01
12	1.02	1.05	0.95	0.99	1.01	1.01
13	1.02	1.05	0.95	0.99	1.01	1.01

Table 33 Expected SCs and expected tap positions for the case 8

SC	size1	n1	size2	n2	size3	n3	size4	n4	size5	n5	Num
Value	48.5	97	23	46	19	38	11.5	23	8.5	17	221
Tram	4_12		12_13		6_9		9_10		9_11		28_27
value	1.02		1.05		0.96		0.99		1.01		1.01

Table 34 Power generation at the swing bus and voltages violating limits throughout all states for case 8

state	1	2	3	4	5	6	7
P_{sw}(MW)	149.71	144.11	138.55	133.00	127.49	121.99	116.53
Number	0	0	0	0	0	0	0
V_{min}/V_{max}(p.u.)	\	\	\	\	\	\	\
State	8	9	10	11	12	13	\
P_{sw}(MW)	111.08	105.66	100.27	94.89	89.54	84.22	\
Number	0	0	0	0	0	0	\
V_{min}/V_{max}(p.u.)	\	\	\	\	\	\	\

Comparing calculated values above, the power generation at the swing bus actually cannot efficiently be reduced. These cases result in almost the same power loss even with the help of objective function for minimizing it as a goal. What's more, the cost increases largely for case 7 and 8 where both set the power generation at the swing bus as objective function. Thus it is still reasonable to make the cost to be the objective function for 30-bus system. In other words, we have to abandon case 7 and case 8. The remaining case 5 and case 6 have the same probability under normal operation. Nevertheless, the expected cost for case 6 is less than case 5. So case 6 is better than case 5.

In summary, compared with other options, putting the Static Capacitors at five different locations along with the aim of minimizing the cost is the best choice for this power system.

Chapter VII Conclusions

A new method based on the Markov model and the genetic algorithm is proposed to explore the optimal VAR planning considering intermittent wind generations in a power system in this research. The Markov model provides information about the probability for each operation state. And the genetic algorithm is able to obtain an effective solution. The contributions of this paper can be summarized as follows.

(1) The wind power generation is modeled by the Markov process considering one wind farm at specific bus. 13 states for the wind power generations are determined.

(2) There are no probability density functions and covariance required for the wind generation in the proposed method. Hence, no complicated convolution computation is needed here.

(3) The probabilities of the critical operation states with voltage violations are considered to conduct the VAR planning study. Traditionally, only the most severe operation state is considered for VAR planning. However, for the most severe operation state, the corresponding probability may be very small.

All in all, the simulation results indicate that the approach is efficient, simple and straightforward.

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Appendix A: Recordings of hourly wind speed series values of meteorological station in Milwaukee

Time （hr）	Wind (m/s)	Time （hr）	Wind (m/s)	Time （hr）	Wind (m/s)	Time （hr）	Wind (m/s)
0.1	10.892	1.1	7.058	2.1	5.854	3.1	7.5
0.2	10.911	1.2	5.869	2.2	5.765	3.2	8.1
0.3	10.116	1.3	5.806	2.3	5.185	3.3	9.978
0.4	11.754	1.4	7.958	2.4	8.458	3.4	10.565
0.5	8.601	1.5	8.875	2.5	10.207	3.5	11.678
0.6	7.349	1.6	9.107	2.6	11.301	3.6	12.315
0.7	7.401	1.7	9.22	2.7	10.142	3.7	12.878
0.8	8.137	1.8	8.789	2.8	9.54	3.8	12.943
0.9	9.092	1.9	7.594	2.9	10.325	3.9	13.397
1.0	8.955	2.0	6.82	3.0	8.685	4.0	14.515

Time （hr）	Wind (m/s)	Time （hr）	Wind (m/s)	Time （hr）	Wind (m/s)	Time （hr）	Wind (m/s)
4.1	15.198	5.1	15.381	6.1	16.197	7.1	10.408
4.2	16.343	5.2	15.577	6.2	19.532	7.2	10.343
4.3	15.206	5.3	14.996	6.3	17.459	7.3	9.198
4.4	15.872	5.4	15.561	6.4	18.929	7.4	11.54
4.5	14.816	5.5	12.462	6.5	18.526	7.5	10.727
4.6	11.554	5.6	12.781	6.6	14.733	7.6	9.574
4.7	12.315	5.7	14.432	6.7	11.419	7.7	7.358
4.8	13.115	5.8	13.449	6.8	10.692	7.8	5.871
4.9	14.072	5.9	14.039	6.9	10.614	7.9	5.174
5.0	15.637	6.0	15.747	7.0	11.197	8.0	4.608

Time （hr）	Wind (m/s)	Time （hr）	Wind (m/s)	Time （hr）	Wind (m/s)	Time （hr）	Wind (m/s)
8.1	5.976	9.1	10.025	10.1	11.741	11.1	8.688
8.2	5.954	9.2	11.485	10.2	11.113	11.2	9.507
8.3	7.966	9.3	12.664	10.3	10.428	11.3	8.246
8.4	8.495	9.4	13.867	10.4	12.767	11.4	9.01
8.5	9.242	9.5	14.053	10.5	14.646	11.5	8.314
8.6	8.888	9.6	15.295	10.6	13.47	11.6	7.219
8.7	9.229	9.7	12.592	10.7	11.479	11.7	6.398
8.8	9.551	9.8	15.129	10.8	10.13	11.8	8.099
8.9	10.371	9.9	17.073	10.9	10.28	11.9	9.1
9.0	10.56	10.0	13.408	11.0	7.907	12.0	10.67

Time（hr）	Wind (m/s)	Time（hr）	Wind (m/s)	Time（hr）	Wind (m/s)	Time（hr）	Wind (m/s)
12.1	9.74	13.1	11.995	14.1	7.326	15.1	9.779
12.2	10.358	13.2	11.759	14.2	11.747	15.2	10.823
12.3	11.54	13.3	13.519	14.3	12.416	15.3	11.544
12.4	11.046	13.4	13.101	14.4	12.305	15.4	11.045
12.5	13.501	13.5	15.492	14.5	11.558	15.5	11.564
12.6	16.134	13.6	13.787	14.6	10.961	15.6	11.685
12.7	16.278	13.7	10.437	14.7	9.948	15.7	11.48
12.8	15.952	13.8	9.198	14.8	10.466	15.8	13.367
12.9	16.259	13.9	6.438	14.9	12.169	15.9	15.164
13.0	13.926	14.0	6.778	15.0	11.717	16.0	14.346

Time（hr）	Wind (m/s)	Time（hr）	Wind (m/s)	Time（hr）	Wind (m/s)	Time（hr）	Wind (m/s)
16.1	14.012	17.1	16.693	18.1	17.819	19.1	15.146
16.2	12.776	17.2	17.775	18.2	16.529	19.2	17.098
16.3	11.192	17.3	17.154	18.3	16.958	19.3	16.533
16.4	11.802	17.4	18.429	18.4	13.845	19.4	15.443
16.5	12.983	17.5	20.84	18.5	14.343	19.5	15.582
16.6	12.684	17.6	20.905	18.6	14.569	19.6	12.914
16.7	13.093	17.7	20.089	18.7	13.81	19.7	9.195
16.8	13.345	17.8	20.507	18.8	14.796	19.8	6.748
16.9	13.882	17.9	19.101	18.9	14.457	19.9	5.942
17.0	17.362	18.0	19.164	19.0	15.916	20.0	4.894

Time（hr）	Wind (m/s)	Time（hr）	Wind (m/s)	Time（hr）	Wind (m/s)	Time（hr）	Wind (m/s)
20.1	2.974	21.1	6.135	22.1	9.581	23.1	9.131
20.2	1.789	21.2	7.999	22.2	9.662	23.2	6.878
20.3	1.511	21.3	5.868	22.3	10.799	23.3	6.132
20.4	0.024	21.4	8.791	22.4	12.164	23.4	5.927
20.5	1.806	21.5	8.789	22.5	13.668	23.5	4.762
20.6	2.824	21.6	11.053	22.6	12.241	23.6	6.82
20.7	3.404	21.7	10.703	22.7	12.254	23.7	9.343
20.8	5.724	21.8	11.617	22.8	12.005	23.8	11.276
20.9	7.215	21.9	11.337	22.9	9.28	23.9	11.294
21.0	7.961	22.0	10.806	23.0	9.587	24.0	9.358

Appendix B: M-file of nonlinear constraint function

```
function [c,ceq]=myconstraint30_5(x)
 temp=loadcase('case30modified');
  intermediate 1=temp.bus(x(6),4);
  loc1=x(6)
  x(7)~=x(6);
  loc2=x(7)
  x(8)~=x(6);
  x(6)~=x(7);
  loc3=x(8)
  x(9)~=x(6);
  x(9)~=x(7);
  x(9)~=x(8);
  loc4=x(9)
  x(10)~=x(6);
  x(10)~=x(7);
  x(10)~=x(8);
  x(10)~=x(9);
  loc5=x(10)
  intermediate 2=temp.bus(x(7),4);
  intermediate 3=temp.bus(x(8),4);
  intermediate 4=temp.bus(x(9),4);
  intermediate 5=temp.bus(x(10),4);
```

```
Mvar1= intermediate 1-0.5*x(1)

Mvar2= intermediate 2-0.5*x(2)

Mvar3= intermediate 3-0.5*x(3)

Mvar4= intermediate 4-0.5*x(4)

Mvar5= intermediate 5-0.5*x(5)

temp.bus(x(6),4)=Mvar1;

temp.bus(x(7),4)=Mvar2;

temp.bus(x(8),4)=Mvar3;

temp.bus(x(9),4)=Mvar4;

temp.bus(x(10),4)=Mvar5;

tap4_12=1+0.05*x(11)

tap12_13=1+0.05*x(12)

tap6_9=1+0.05*x(13)

tap9_10=1+0.05*x(14)

tap9_11=1+0.05*x(15)

tap28_27=1+0.05*x(16)

temp.branch(15,9)=tap4_12;

temp.branch(16,9)=tap12_13;

temp.branch(11,9)=tap6_9;

temp.branch(14,9)=tap9_10;

temp.branch(13,9)=tap9_11;

temp.branch(36,9)=tap28_27;

case30modified=temp;
```

```
T=runpf(case30modified);

V3=T.bus(3,8);

V4=T.bus(4,8);

V5=T.bus(5,8);

V6=T.bus(6,8);

V7=T.bus(7,8);

V8=T.bus(8,8);

V9=T.bus(9,8);

V10=T.bus(10,8);

V11=T.bus(11,8);

V12=T.bus(12,8);

V14=T.bus(14,8);

V15=T.bus(15,8);

V16=T.bus(16,8);

V17=T.bus(17,8);

V18=T.bus(18,8);

V19=T.bus(19,8);

V20=T.bus(20,8);

V21=T.bus(21,8);

V24=T.bus(24,8);

V25=T.bus(25,8);

V26=T.bus(26,8);

V28=T.bus(28,8);
```

```
V29=T.bus(29,8);
V30=T.bus(30,8);
c=[-1*V3-(-0.95);-1*V4-(-0.95);-1*V5-(-0.95);-1*V6-(-0.95);-1*V7-(-0.95);-1*V8-(-
0.95);-1*V9-(-0.95);-1*V10-(-0.95);-1*V11-(-0.95);-1*V12-(-0.95);-1*V14-(-0.95);-
1*V15-(-0.95);-1*V16-(-0.95);-1*V17-(-0.95);-1*V18-(-0.95);-1*V19-(-0.95);-1*V20-(-
0.95);-1*V21-(-0.95);-1*V24-(-0.95);-1*V25-(-0.95);-1*V26-(-0.95);-1*V28-(-0.95);-
1*V29-(-0.95);-1*V30-(-0.95);V3-1.05;V4-1.05;V5-1.05;V6-1.05;V7-1.05;V8-1.05;V9-
1.05;V10-1.05;V11-1.05;V12-1.05;V14-1.05;V15-1.05;V16-1.05;V17-1.05;V18-
1.05;V19-1.05;V20-1.05;V21-1.05;V24-1.05;V25-1.05;V26-1.05;V28-1.05;V29-
1.05;V30-1.05];
% No nonlinear equality constraints:
ceq = [];
```