Genetic algorithm based optimal self-tuning fuzzy logic controller for power system static VAR stabiliser

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Abstract In this study, a novel method is proposed for the compensation of loads that vary frequently in time. The proposed scheme is based on the fuzzy logic controller (FLC) that is widely used in control of nonlinear processes. FLC architecture is used for regulating the gains of the basis Proportional-Integral (PI) as a self-tuning controller. On the other hand, the constant gains of the basis: PI controller are optimised by a genetic algorithm. Experimental results demonstrate that the proposed method shows better performance than that of the conventional PI controller.

Keywords: Fuzzy logic controller (FLC); Genetic algorithms; PI controller; static VAR compensator

Many types of industrial loads on utility distribution systems adversely affect power quality on the distribution line. For example: large power supplies, motors, welders, and arc furnaces cause voltage flicker, which is experienced not only by the offending industrial power user, but also by any other utility customers receiving power from the same distribution feeder. In addition, typical poor displacement power factors of these loads result in high fundamental line currents, which must be supplied by the utility. One way to alleviate these problems is to provide static Volt-Amperes Reactive (VAR) compensation in shunt with the distribution line.[1] The static VAR compensator is one of the most important discoveries in technology that is widely used for power transmission systems applications.

In recent years many attempts have been made to improve the performance of Static Var Compensators (SVC). The SVC controller proposed in this paper contains a variable structure adaptive neural network power system static VAR stabiliser.[2] The proposed controller architecture is used for voltage regulation and enhancing power system stability. However, the use of an off-line training procedure is not practical for controlling a real power network.[3] A static VAR stabiliser based on the fuzzy adaptive model reference approach is proposed. The proposed control system consists of a feedback fuzzy controller and a model reference adaptive mechanism to make the power system speed deviation response follow a certain track.

The reactive power requirements of loads in a distribution system could vary in a wide range within a short period of time when the feeder supplies electric power to fluctuating loads, such as arc furnaces, steel rolling mills and electric trains. The reactive power not only reduces efficiency and reliability of the power system but also makes voltage regulation more difficult. Hence it is better to compensate the reactive power at the load bus. The load balancing and the power factor correction capability of a static VAR compensator is well known. A SVC adjusts the susceptance in each phase by controlling the conduction angles of the thyristor-controlled reactor (TCR). In practical applications, the formula for the desired compensation susceptances must be in terms of measurable electrical signals at the load bus.[4] On the other hand, the constant impedance load representation is not accurate and is not a good approximation in view of the strong influence of the load voltage sensitivity on the dynamic performance of power systems.[5]

It is well known that up until now, a conventional proportional-integral-derivative (PID) type controller is most widely used successfully in control of static VAR stabilisers due to its simple structure, ease of design, and low cost. The design of such a controller requires determination of three parameters. These parameters are: proportional gain, integral time constant and derivative time constant, respectively. The structure of PID controllers in the existing literature can be divided into two main categories. The first one includes the controllers that have fixed gains during the control operation. For these types of PID controllers, the controller gains are pre-defined by a known tuning method like Ziegler-Nichols[14] for linear processes; and mostly by a trial and error approach for high order linear and non-linear processes. The controllers of the second category have a structure similar to conventional PID controllers, but their control variables are not fixed during the run-time. Such controllers are called adaptive PID controllers.[6] However, the PID type controllers that have fixed controller gains cannot yield good control performance if the controlled process is highly nonlinear, ill-defined or has an non-constant structure like the loads on a distribution line.[7] On the other hand, adaptive PID controllers require an adaptation mechanism, which includes a system identifier during run time. However, a system identifier's performance is inversely proportional to the amount of harmonics and disturbances. Unlike the PID controller, fuzzy logic controllers (FLCs) have been reported to be successfully used for a number of complex and nonlinear processes.[8] Fuzzy controllers are supposed to work in situations where there are large uncertainties, disturbances or unknown variations in plant parameters and structures. Generally the basic objective of adaptive control is to maintain consistent performance of a system in the presence of these uncertainties. Therefore an advanced fuzzy control mechanism should include adaptive characteristics.

In this work, a new compensation method (self-tuning type adaptive fuzzy PI controller architecture with genetic optimised output scaling factors) is presented for the above-mentioned loads that vary within a short period of time. The adaptive mechanism uses error signal (e) and change of error signal (Δe) as input and proportional and integral coefficients as output. Figure 5 (see later) shows the proposed architecture for a reactive power control mechanism. Fixed values of G_{Ki} and G_{Kp} are optimised by using genetic algorithms (GAs).

The rest of the paper is organised as follows. In the next section, the thyristor-controlled reactors and control of fixed capacitor-thyristor controlled reactor (FC-TCR) are reviewed; details of the proposed control are then presented. The experimental results of the proposed control system with discussions are then presented; finally, conclusions are drawn.

Thyristor controlled reactor

The basic elements of a TCR are a reactor in series with a bi-directional thyristor as shown in Fig. 1. In a fixed capacitor-thyristor controlled reactor (FC-TCR), while the fixed capacitor produces reactive power, the TCR consumes reactive power. As the reactive power production of a capacitor group in a determined voltage level is fixed at a value, the reactive power production of the system is ensured by changing the firing angles of the thyristor. Changes in the firing angles control a fundamental component of the reactor current and thus the amplitude of the reactive power. Selection of non-suitable firing angles can lead to resonance-related problems which affect active harmonic production of the TCR.

The most widely used static VAR control system consists of capacitor banks in parallel with thyristor-controlled reactors using reverse parallel-connected thyristors. Modelling of the thyristors and their controls is crucial for performance analyses.[9]

Thyristor controlled reactors, which have the ability to ensure a continuous and fast reactive power and voltage control, can increase the performance of the system in different ways such as control of transient over voltages at power frequency, preventing voltage collapse with increase in transient stability and decrease in the system oscillations. Static VAR compensator consisting of thyristor-controlled reactors are used for balancing the three phase systems supplying unbalanced loads and for preventing the voltage oscillations caused by short duration loads in transmission and distribution systems.

In order to develop a more accurate frequency model, the circuit in Fig. 2 is depicted. This represents a fixed capacitor-TCR static VAR compensator connected to an a.c. system configured as a system reactance, X_s and a voltage source, $v(t)$. The two parallel thyristors are gated symmetrically. They control the time over which the reactor operates and thus control a fundamental component of the current.[10]

The thyristors operate on alternate half-cycles of the supply frequency depending on the firing angle α, which is measured from a zero crossing of voltage. Full conduction is obtained with a firing angle of 90°. The current is essentially reactive and sinusoidal. Partial conduction is obtained with firing angles between 90° and 180°.

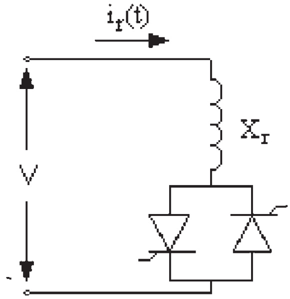

Fig. 1 *The main elements of a TCR.*

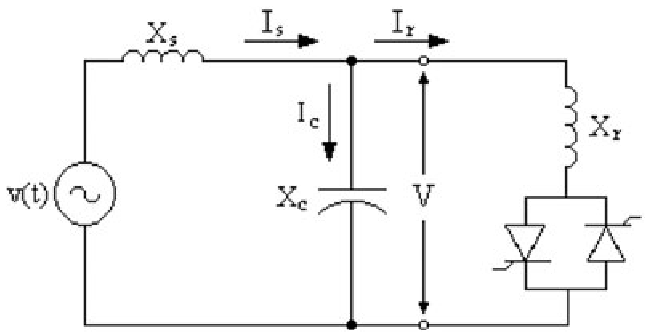

Fig. 2 *Fixed capacitor-thyristor controlled reactor static VAR compensator.*

Firing angles between 0 and 90° are not allowed since they produce asymmetrical currents with a dc component.[11]

Let σ be the conduction angle related to α by

$$\sigma = 2(\pi - \alpha) \tag{1}$$

Then instantaneous current is given by

$$i_r(t) = \begin{cases} \dfrac{\sqrt{2}\cdot V}{X_r}\left(\cos\left(\dfrac{\pi-\sigma}{2}\right) - \cos(\omega t)\right), & \dfrac{\pi-\sigma}{2} \le \omega \le \dfrac{\pi+\sigma}{2} \\ 0, & \dfrac{\pi+\sigma}{2} \le \omega t \le \dfrac{3\pi-\sigma}{2} \end{cases} \tag{2}$$

Fourier analysis of the effective current waveform gives the fundamental component:

$$I_r^{(1)} = \frac{V}{\sqrt{2}\cdot X_r}\left(\frac{\sigma - \sin\sigma}{\pi}\right), \tag{3}$$

where $I_r^{(1)}$ and V are r.m.s. values, and X_r is the reactance of the reactor at fundamental frequency. The effect of increasing α (i.e., decreasing σ) is to reduce the fundamental component $I_r^{(1)}$.[11] This is equivalent to increasing the effective inductance of the reactor. In effect, as far as the fundamental frequency current component is concerned, the TCR is controllable susceptance. The effective susceptance as a function of the firing angle α is

$$B(\alpha) = \frac{I_1}{V} = \frac{\sigma - \sin\sigma}{X_r\pi} = \frac{2(\pi-\alpha) + \sin 2\alpha}{X_r\pi}. \tag{4}$$

The maximum value of the effective susceptance is obtained at full conduction (α = 90° or σ = 180°), and is equal to $1/X_r$; the minimum value is zero, obtained with α = 180° or σ = 0°. Referring to Fig. 3, the voltage across the terminals is assumed to be a perfect sinusoidal waveform. This susceptance control principle is known as phase control. The susceptance is switched into the system for a controllable frac-

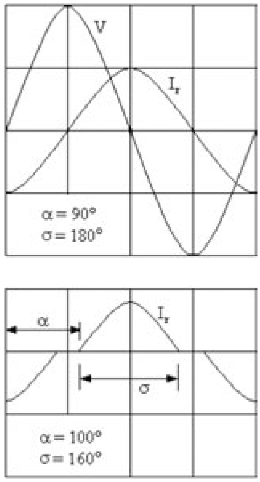

Fig. 3 *The voltage and current waveforms in a TCR* (*Ref. 11*).

tion of every half cycle. The variation in susceptance as well as the TCR current is smooth or continuous.

The TCR requires a control system which determines the firing instants (i.e., firing angle α) measured from the last zero crossing of the voltage (synchronisation of firing angles). In some designs, the control system responds to a signal that directly represents the desired susceptance.[11]

Control of the static VAR compensator with a FC-TCR

To the a.c. system the fixed capacitor-thyristor controlled reactor (FC-TCR) compensator may be thought of as a variable reactor (controlled by conduction angle σ) in parallel with a fixed capacitor.[9] For the purpose of the reactive power requirements of loads, the reactive power generated or absorbed by the static compensator is automatically adjusted according to certain characteristics. The TCR conduction angle is therefore an unknown variable in the normal operation.[12] Figure 2 shows a FC-TCR; while a fixed capacitor produces reactive power, a TCR consumes reactive power. Reactive power versus applied voltage for steady-state characteristics is shown in Fig. 4. Three areas control the compensator. The first area is between voltages V_1 and V_2. In this area, the compensator can be capacitive or inductive.

The equation of equivalence susceptance according to the conduction angle (σ) is

$$B(\sigma) = B_C - B_L(\sigma) \quad (5)$$

Here, B_C is the capacitor susceptance and $B_L(\sigma)$ is the reactor susceptance related to the conduction angle. The reactor susceptance is as in eqn (6):

$$B_L(\sigma) = \frac{\sigma - \sin\sigma}{X_r \pi} \quad (6)$$

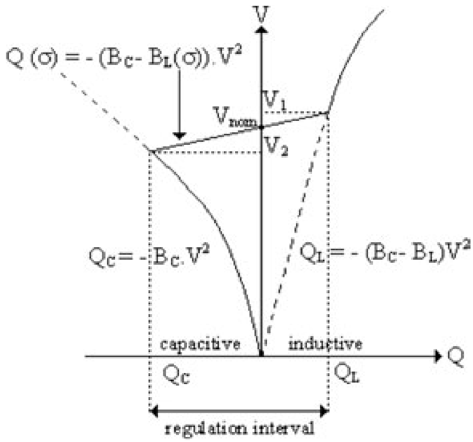

Fig. 4 *The steady-state reactive power versus voltage of the static VAR systems.*

The variation in reactive power with respect to σ is determined by

$$Q(\sigma) = -[B_C - B_L(\sigma)] \cdot V^2. \tag{7}$$

If $V > V_{nom}$, the compensator will be in inductive mode and draws capacitive power from the source ($Q(\sigma) > 0$).

If $V < V_{nom}$, the compensator will be in capacitive mode, it gives capacitive power to the system and draws inductive power ($Q(\sigma) < 0$).

If the terminal voltage $V > V_1$, this means that the system is out of control limits. The control element is limited by $\sigma = 180°$.

The second area susceptance is

$$B(180°) = B_C - B_L(180°), \tag{8}$$

and the susceptance has inductive characteristics. Reactive power changes as follows:

$$Q_L = -[B_C - B_L(180°)] \cdot V^2. \tag{9}$$

From eqn (9) it is obvious that the compensator can nolonger control changes in the conditions of voltage *V*.

The third area is where the output voltage is smaller than V_2 ($V < V_2$), that is, $\sigma = 0°$ and it is out of control limits again. Susceptance and reactive power are as follows, respectively:

$$B(0°) = B_C \tag{10}$$

$$Q_C = -B_C \cdot V^2. \tag{11}$$

From Fig. 4, the inclination of reactive power versus voltage characteristic in regulation interval can be determined by controlling the conduction angle.

Genetic based optimal self-tuning fuzzy logic controller

The best-known controllers used in industrial control processes are proportional-integral and derivative (PID) controllers, due to their simple structure and robust performance over a wide range of operating conditions. The design of such controllers requires specification of two parameters called proportional, integral and derivative gain.[13] So far, great effort has been devoted to developing methods to reduce time spent on optimising the choice of controller parameters. The PID controllers in the literature can be divided into two categories. Those in the first category are simple, but cannot always effectively control systems with changing parameters and may need frequent on-line retuning. Controllers in the second category have a structure similar to PI controllers but their parameters are adapted on-line based on parameter estimation, which requires certain knowledge of the process. Such controllers are called adaptive PID controllers in order to differentiate them from those of this category.[14]

The discrete-time equivalent expression for a PI controller has the following form:

$$u(k) = K_p e(k) + K_I T_s \sum_{i=0}^{k} e(i), \tag{12}$$

where $u(k)$ is the control signal at instant k; $e(k)$ is the error signal at instant k; T_s is the sampling period; finally, K_p and K_i are proportional and integral gains, respectively.

However the proposed control scheme serves $\Delta u(k)$ as output rather than $u(k)$; thus the first derivative of eqn (12) with respect to k yields

$$\Delta u(k) = K_p \Delta e(k) + K_I e(k). \tag{13}$$

From eqn (13), one can conclude that controlling $\Delta u(k)$, rather than $u(k)$ acts like a PD control action, where K_p and K_I substitute for derivative coefficient K_d and proportional coefficient K_p, respectively. In this work, we introduce a fuzzy adaptation mechanism, which is responsible for tuning K_p and K_I. Therefore eqn (13) can be rewritten in the form of eqn (14), where G_{Ki} and G_{Kp} are the gains of K_i and K_p, respectively. The block diagram of the proposed controller is shown in Fig. 5.

$$\Delta u(k) = K_p G_{Kp} \Delta e(k) + K_I G_{Ki} e(k). \tag{14}$$

If we substitute fuzzy K_p and fuzzy K_I, then eqn (3) can be rewritten as

$$\Delta u(k) = S_e F_{Kp}\{e, \Delta e\} G_{Kp} \Delta e(k) + S_{ce} K_{Ki}\{e, \Delta e\} G_{Ki} e(k). \tag{15}$$

Design of fuzzy controller and Rule base

In the fuzzy adaptation mechanism, all membership functions (MFs) for controller inputs, i.e., error (e) and change of error (Δe) are defined on the common interval of [–250, 250] as shown in Fig. 6 and Fig. 7, whereas the membership functions for the output of adaptation mechanism for K_I and K_p are shown in Fig. 8 and Fig. 9 which are defined on a common interval of [0,1], respectively.

The values normalised by K_I and K_p are determined by rules of the form:

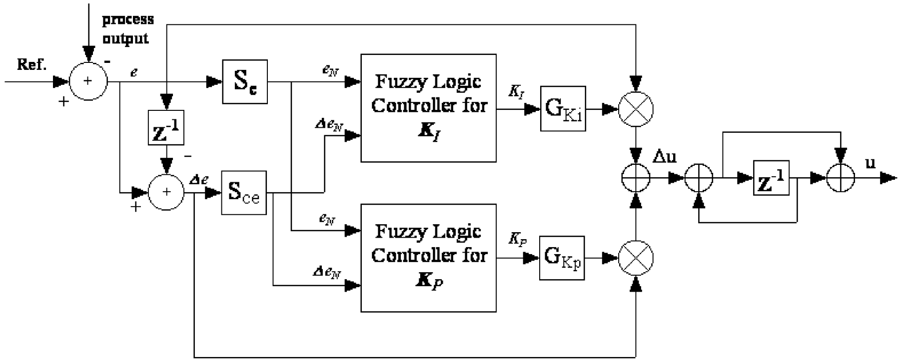

Fig. 5 *Proposed controller architecture.*

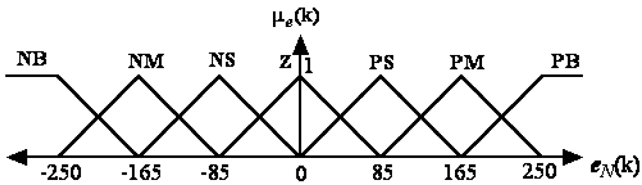

Fig. 6 *Membership functions of error.*

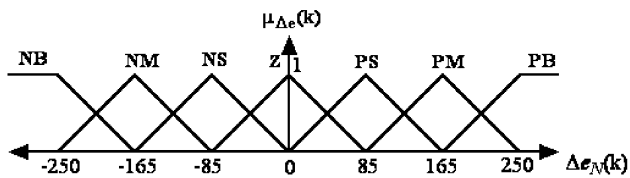

Fig. 7 *Membership functions of change of error* (Δe).

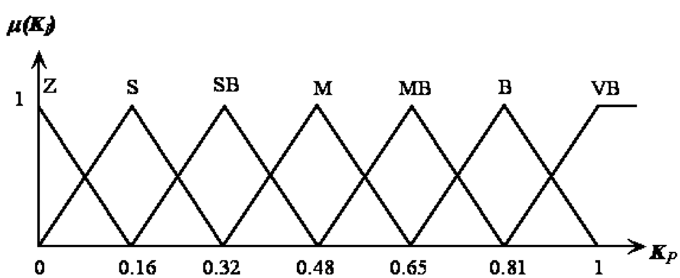

Fig. 8 *Membership functions for* K_I.

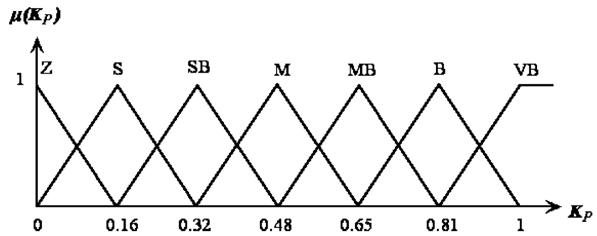

Fig. 9 *Membership functions for* K_p.

Δe/e	NB	NM	NS	Z	PS	PM	PB
NB	VB	VB	B	Z	Z	Z	Z
NM	VB	B	MB	Z	Z	Z	S
NS	B	B	M	Z	Z	S	SB
Z	VB	VB	M	Z	M	B	VB
PS	SB	S	Z	Z	M	B	B
PM	S	Z	Z	Z	MB	B	VB
PB	Z	Z	Z	Z	B	VB	VB

Fig. 10 *Fuzzy rules for computation of* K_I.

Δe/e	NB	NM	NS	Z	PS	PM	PB
NB	VB	B	MB	VB	B	M	Z
NM	B	M	M	M	M	Z	Z
NS	B	SB	SB	S	Z	Z	Z
Z	Z	Z	Z	Z	Z	Z	Z
PS	Z	Z	Z	S	SB	SB	M
PM	Z	Z	S	M	M	M	B
PB	Z	S	M	VB	B	B	VB

Fig. 11 *Fuzzy rules for computation of* K_p.

R_{KI}: If e is E and Δe is ΔE then K_I is K_I.
R_{Kp}: If e is E and Δe is ΔE then K_p is K_p.

The rule base for computing both K_I and K_p are shown in Fig. 10 and Fig. 11, respectively. Some of the important considerations that have been taken into account for determining the rules are as follows:

If the error is NB, and the rate of error is NB, then this means that the output of the process is not only far away from the reference, but also diverging from it. For this situation the controller gains are set to very big values in order to reduce the control signal immediately. The same situation is valid when the error is PB, and the rate of error is PB. This time, the fuzzy gain-schedules try to increase the controller effort in order to avoid a probable undershoot.

If the error is Z, then the integral controller does not have any effect on the control signal, thus all the rules having Z error produce Z gain for K_I. Similarly, Z values for the error rate results in ineffective proportional control action, therefore all the rules having *Z* error rate produce *Z* gains for K_P.

If the conditions are such that *e* will go to zero at a satisfactory rate, then the present control setting must be kept. These kinds of rules fall into the group that is settled along the diagonal connecting the first quadrant to the third, in both rule bases.

If the error is PS and the error rate is NB, this means that the controlled variable is approaching the reference very fast and it is probable that it will produce an overshoot; therefore K_I is set to Z and K_P is set to *B* in order to decrease the present control signal.

By using the same idea, one can easily form the rule bases as shown in Fig. 10 and Fig. 11. The rule bases shown in Fig. 10 and Fig. 11 can also be shown in the 3-dimensional plane as shown in Fig. 12 and Fig. 13, respectively. Further modification of the rule base for both K_I and K_P may be required, depending on the type

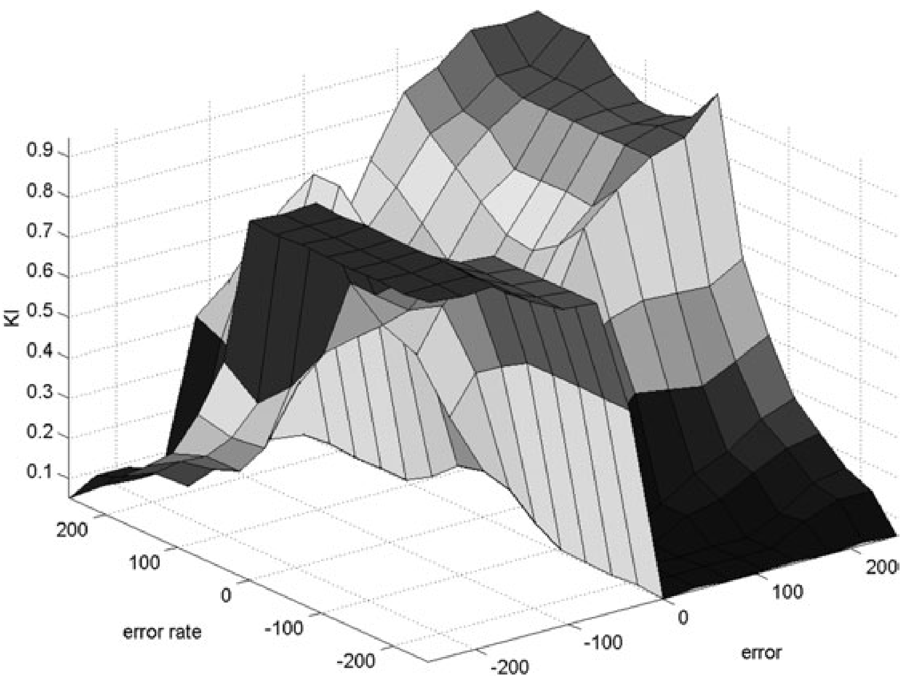

Fig. 12 *Rule surface for computation of* K_I.

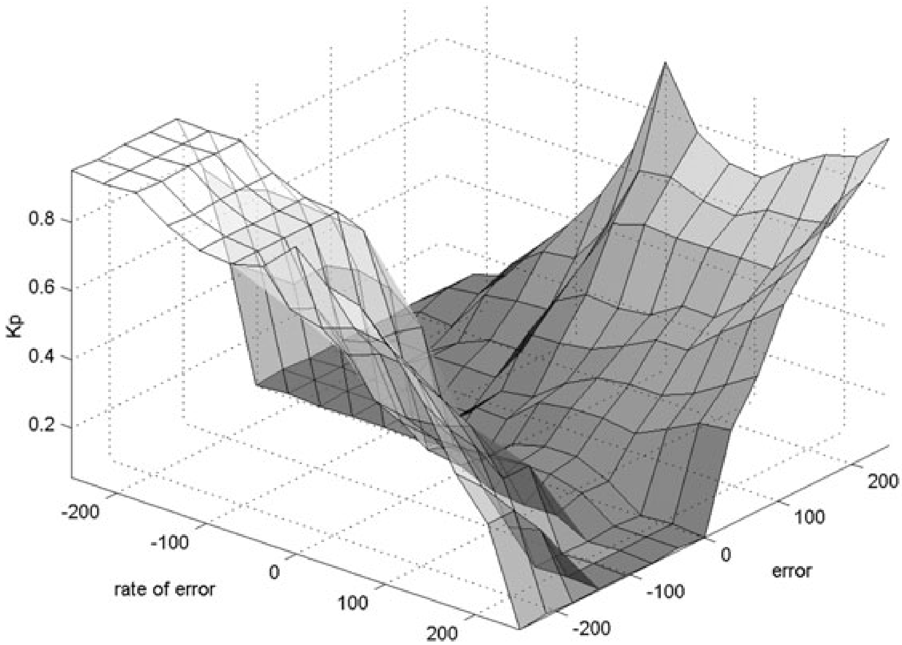

Fig. 13 *Rule surface for computation of* K_p.

of response the designer wishes to achieve. But it is very important to note that any change in one of the rule bases may cause a related change in the other one.

As an inference engine, we use individual-rule based inference with union combination, Mamdani's minimum implication, *min* for all *t*-norm operators and *max* for all *s*-norm operators. As a defuzzifier, a centre of average defuzzifier is used. Then the nonlinear transfer function of the adaptation mechanisms for K_I and K_p can be defined as in eqns (16) and (17) respectively, where $\mathbf{x}^T = [e_N, \Delta e_N]$ denotes the input vector, $\bar{y}^l \in \Re$ are the output index values for K_I and K_p for *l*th rule, *n* stands for the number of inputs to the fuzzy system and finally *M* stands for the number of rules in the rule-base.

$$F_{K_I}(x) = \frac{\sum_{l=1}^{M} \bar{y}^l \left(\prod_{i=1}^{n} \mu_{A_i^l}(x_i) \right)}{\sum_{l=1}^{M} \left(\prod_{i=1}^{n} \mu_{A_i^l}(x_i) \right)} \tag{16}$$

$$F_{K_p}(x) = \frac{\sum_{l=1}^{M} \bar{y}^l \left(\prod_{i=1}^{n} \mu_{A_i^l}(x_i) \right)}{\sum_{l=1}^{M} \left(\prod_{i=1}^{n} \mu_{A_i^l}(x_i) \right)} \tag{17}$$

In this work the values for *n* is 2 and *M* is 49; thus, eqn (16) and eqn (17) can be rewritten as in eqn (18) and eqn (19) respectively.

$$F_{K_1}(x) = \frac{\sum_{l=1}^{49} \bar{y}^l \left(\prod_{i=1}^{2} \mu_{A_i^l}(x_i)\right)}{\sum_{l=1}^{49} \left(\prod_{i=1}^{2} \mu_{A_i^l}(x_i)\right)} \tag{18}$$

$$F_{K_p}(x) = \frac{\sum_{l=1}^{49} \bar{y}^l \left(\prod_{i=1}^{2} \mu_{A_i^l}(x_i)\right)}{\sum_{l=1}^{49} \left(\prod_{i=1}^{2} \mu_{A_i^l}(x_i)\right)} \tag{19}$$

Genetic optimization of output scaling factors

Genetic algorithms (GAs) are general-purpose optimisation algorithms based on Darwinian *survival of the fittest* theory.[15] The pioneering work of J. H. Holland in the 1970s proved to be a significant contribution for scientific and engineering applications. Since then, the output of research work in this field has grown exponentially. It is inspired by the mechanism of natural selection, a biological process in which stronger individuals are likely be the winner in a competing environment.[16] They are useful approaches to problems requiring effective and efficient searching, and their use is widespread in applications to business, scientific, and engineering fields. A mayor advantage of GAs is their global optimisation solution even for non-linear, high dimensional, multimodal (many peaked), and discontinuous problems. They consider many points in the search space simultaneously and therefore have a reduced chance of converging to local optima. In most conventional search techniques, a single point is considered based on some decision rule. These methods can be dangerous in multimodal search spaces because they may converge to a local optimum, rather than a global one.[17]

Before GA is applied, the requirements of the optimisation problem should be formulated by a function called the ‘fitness function’. This represents the performance of the problem. A positive value, generally known as the fitness value, is used to reflect the degree of ‘goodness’ of the chromosome for solving the problem, and its value is closely related to the objective value. The design of the fitness function may vary, according to the performance requirements of the problem. The higher the fitness value, the better the system’s performance.[18] The purpose of the GA is to manipulate the genetic operation, e.g., reproduction, crossover, or mutation, to obtain a solution corresponding to the fitness value.

In order to use GAs to find an optimal solution to a specific problem the string of a ‘chromosome’ should first be defined. The optimisation parameters are called the ‘genes’ of the chromosome. They may be binary coded or real coded. Their union forms the chromosomes. Each chromosome represents a different solution for the problem. N sets of chromosomes should be randomly generated before using a GA operation. These are called the initial population. For a large population size a typical value for N is 100, and for a small population size N can be chosen to be about 30. In each cycle of genetic operation, a subsequent generation is created from the chromosomes in the current population. This can only be successful if a group of those chromosomes, generally called ‘parents’ or a collective term ‘mating pool’, are selected via a specific selection routine. This stage is called reproduction. The genes of the parents are to be mixed and recombined for the production of offspring in the next generation. This is called the crossover stage. It is expected that from this process of evolution (manipulation of genes), the 'better' chromosome will create a larger number of offspring, and thus have a higher chance of surviving in the subsequent generation. The cycle of evolution is repeated until a desired termination criterion is reached.[19]

In order to facilitate the GA evolution cycle, one more fundamental stage, which is called mutation, is also required. The mutation operator is used to avoid the possibility of being trapped in a local optimum rather than a global one. It is an occasional random change at some string position based on the mutation probability.[20]

As a selection mechanism a method called 'roulette wheel selection' is one of the most commonly used techniques. In this technique, the fitness of all population members is added up to give a value called total fitness *TF*. A random number, *m*, is generated between 0 and total fitness, *TF*. Finally, the population member whose fitness, added to the fitness of the preceding population members, is greater than or equal to *m*, is returned as a selected member.[19]

The choice of crossover probability p_c, and mutation probability p_m, is a complex problem. Also their settings are critically dependent upon the nature of the objective function. For large population size, some typical values might be $p_c = 0.6$ and $p_m = 0.001$, respectively. For small population size, the typical values for p_c, p_m might be 0.9 and 0.01, respectively.[19]

In a fuzzy logic controller mechanism, it is a hard job to tune the controller parameters like scaling factors, membership functions and construction of the rule base. In literature, the majority of the research work is related with solving this problem. In recent years, tuning of these variables is made with GAs. Well results are obtained with this optimisation method. But all of these methods use fitness functions, which need computations based on mathematical model of the process. This is a drawback for the systems, which do not have an explicit mathematical formula. In this work we propose a new method, which does not need any information about the system.

Experimental results

To illustrate the operation of the TCR with an a.c. system on the MATLAB only the single-phase case is studied. We assume that the a.c. system can be represented by a 220 V (rms), 50 Hz voltage source, an inductance and a resistance. In the experimental study, the value of compensation capacitor is chosen as 455 VAR, the variable inductance which is used during the correction process of the power factor via thyristor circuit, is chosen to be 308 VAR. The block diagram of the system that is handled is shown in Fig. 14. In order to investigate the efficiency of the proposed controller, two independent loads are applied to the system at different intervals. The reactive power values of the loads are chosen to be 218 VAR, whereas the active powers are chosen to be 347 W.

To the a.c. system the FC–TCR compensator may be thought of as variable reactor (controlled by conduction angle σ) in parallel with a fixed capacitor. In this partic-

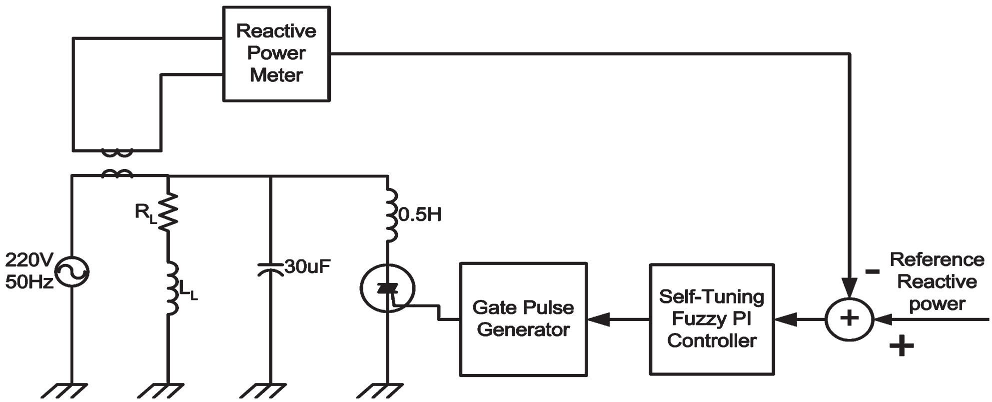

Fig. 14 *Block diagram experimental closed loop system.*

ular example the regulated range is between a capacitive Q of 237 VAR to an inductive Q of 81 VAR, with $\sigma = 0$ providing the full capacitive VARs and a $\sigma = 180°$ providing the full inductive VARs.

During the GA based optimisation procedure, each chromosome's fitness value is computed by eqn (20) where IAE stands for the integral of absolute value of error, %OS stands for percentage overshoot and ITAE stands for integral of time weighted absolute error.

$$F(\text{IAE}, \text{ITAE}, \%\text{OS}) = \frac{100}{0.001 + \omega_1 \times \text{IAE} + \omega_2 \times \%\text{OS} + \omega_3 \times \text{ITAE}} \tag{20}$$

Here ω_1, ω_2 and ω_3 stand for the weighting factors for each performance criteria. In order to provide equal importance for each criterion, they are chosen as 10 in this study. On the other hand each performance variable is normalised between [0, 1].

IAE and ITAE values are computed for 1 s duration and updated every sampling instant. The sampling interval is chosen to be 1 ms. Chromosomes are formed by concatenating two pieces of unsigned binary strings each 16 bits in length. These are G_{Ki} and G_{Kp} respectively. In other words, a chromosome which is coded to carry genetic information for a 2-input, 2-output system requires ($16 \times 2 = 32$) 32 binary bits. As the selection mechanism, roulette wheel selection is used. For the optimisation process, GA parameters are chosen as follows: $P_c = 0.91$, $P_m = 0.02$ and $N = 30$. Figure 15 shows that after 25 generations the GA converges to near-optimal values in the domain of scaling factors.

After 25 generations the near-optimal values of G_{Ki} and G_{Kp} are found to be 0.17 and 0.6, respectively. In fitness function (20), normalised values of IAE and ITAE are used.

After the near-optimal values for the constant gains are obtained, the proposed control system is applied to the process with the conventional PID controller. The conventional PID controller and the proposed controller are compared in terms of

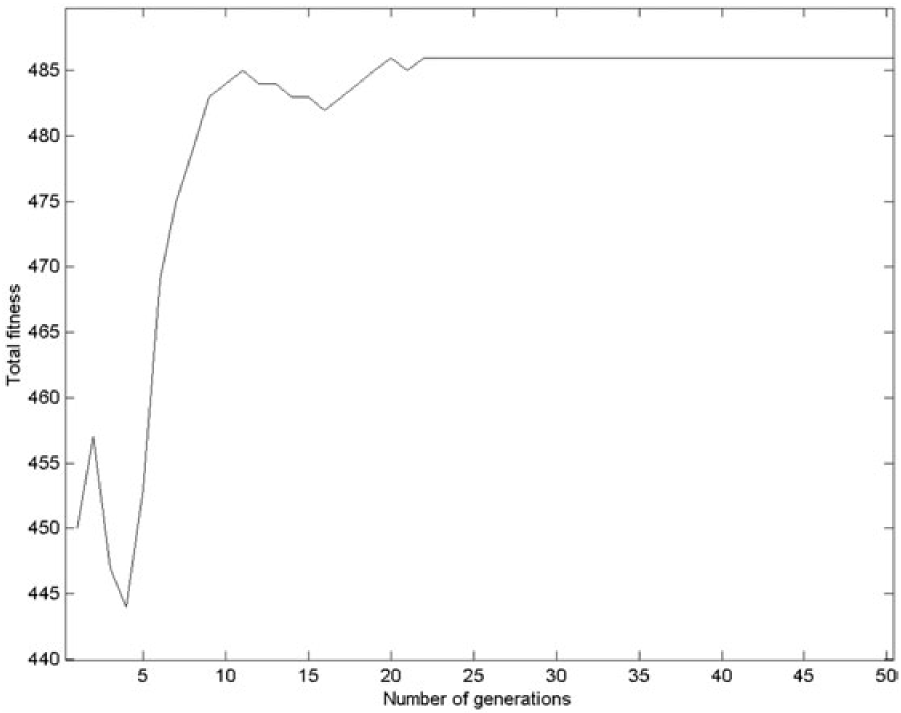

Fig. 15 *Variation of total fitness of mating pool in each generation.*

three criteria. These are: rise time, settling time and overshoot. When the first criterion (rise-time) is taken into account, the system that is controlled with the PID controller reaches the desired reactive power set value at 70 ms, whereas the process that is controlled with the proposed method rises to the set value 18 ms before. Our proposed controller scheme demonstrates similar performance when the settling time is taken into consideration. This time, the process that is controlled with the proposed control method settles to the desired reactive power in almost half the time when it is controlled with the PID. On the other hand, when the performance criterion that is related to the overshoot is considered, the system that is controlled with the PID produces less overshoot at the start up than the proposed controller; whereas when a parallel load that is at the same value with a constant load is inserted into the load system as a disturbance at 0.4 s, the system produces less overshoot with the proposed control method than the conventional PID. Table 1 summarises the performances of both controllers that are taken into consideration. Figure 16 shows the reactive power variation of the controlled system when it is controlled with the proposed method and the conventional PID, Fig. 17 shows the control efforts of the proposed method together with the conventional PID, Fig. 18 shows the reactive power error variation of the proposed and the conventional PID and finally Fig. 19 shows the percentage harmonics variation with respect to time. Here, the system that

TABLE 1 *Performance results of the proposed controller and conventional PID controller*

Controllers	Rise time t_r (ms)	Settling time t_S (ms)	Overshoot at startup (VAR)	Overshoot with load disturbance (VAR)
Proposed control	52	68	11.5	150
PID control	70	100	5	168

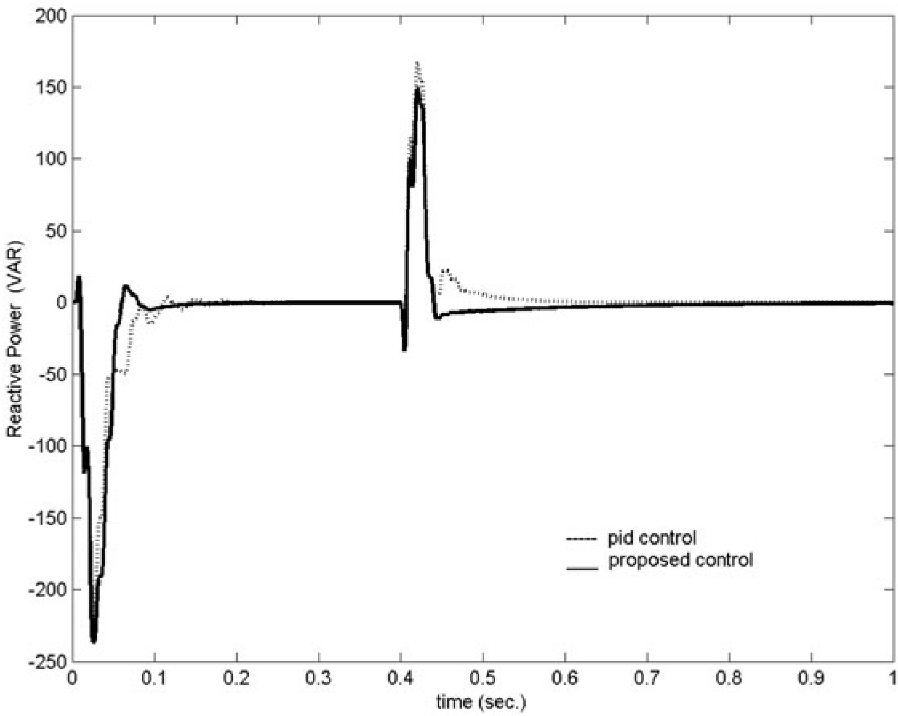

Fig. 16 *Reactive power variation with proposed controller* (—) *and PID controller* (······).

is controlled with the proposed method and the conventional PID showed the over-fitting harmonic variation.

Conclusion

In this study, a novel self-tuning fuzzy PI controller scheme for the VAR stabilisation of the power system is developed. It is well known that the power networks include nonlinear time varying loads that change its behaviour frequently. Fuzzy controllers are supposed to work in situations where there is a large uncertainty or unknown variation in plant parameters and structures. Generally, the basic objective

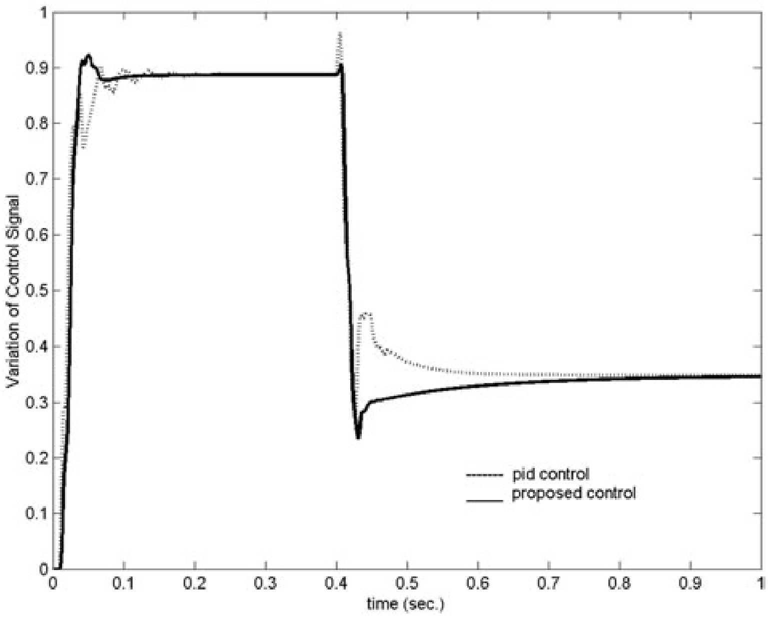

Fig. 17 *Variation of the control signal with proposed controller* (—) *and PID controller* (······).

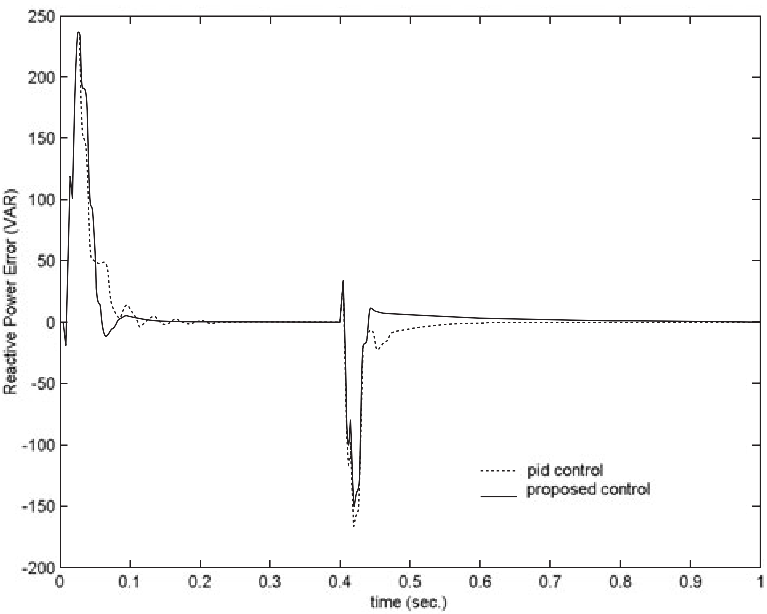

Fig. 18 *Variation of the reactive power error (VAR) with proposed controller* (—) *and PID controller* (······).

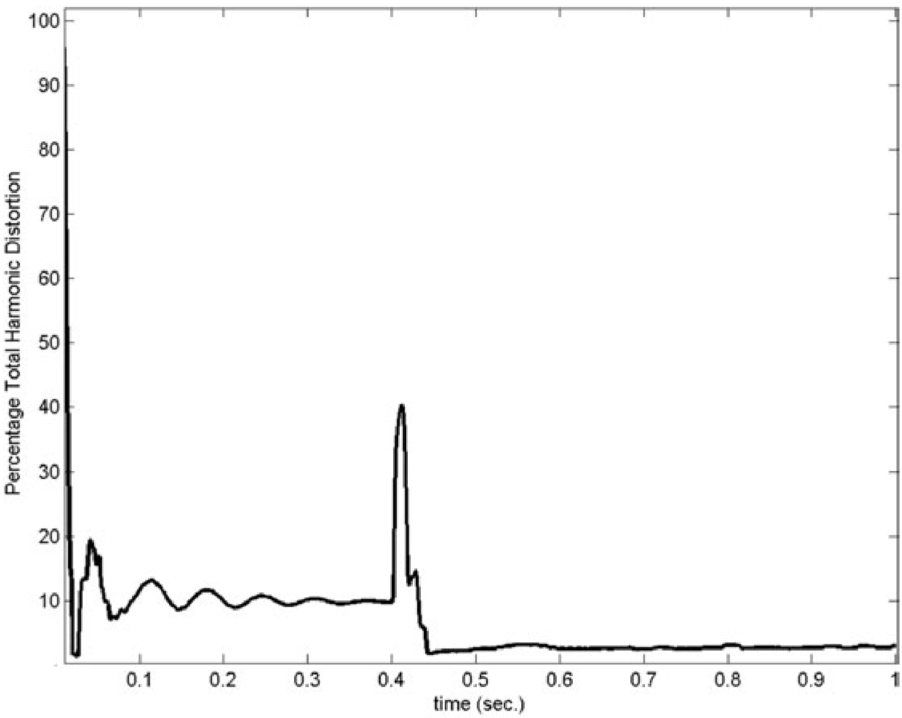

Fig. 19 *Percentage total harmonic distortion variation with respect to time.*

of adaptive control is to maintain consistent performance of a system in the presence of these uncertainties. Therefore an advanced fuzzy control mechanism should include adaptive characteristics. To cope with these nonlinear loads, a nonlinear adaptive mechanism is constructed. The proposed architecture includes a basis PI controller that is tuned on-line by an FLC mechanism depending on the process behaviour. The adaptation mechanism depends only on the error value of the reactive power and its rate. On the other hand, it is well known that it is a crucial job to tune the controller parameters like scaling factor membership functions and construction of the rule base. Among the design variables, much more attention must be paid to scaling factor adjustment since the scaling factors in an FLC act like proportional gains in a conventional controller. The rule base of an FLC at first seems to be at the heart of the FLC but their structures are generally similar for a specific process. On the other hand, membership functions are generally chosen as triangular forms in order to minimise the time spent during the computation. The parameters of the fuzzy controllers are mostly determined by a trial and error approach; but this may be a time-consuming procedure and it may be a hard task to find out the optimal parameter in a complex FLC. To tackle this problem, a GA based optimisation method is proposed. The proposed method depends on the transient and steady-state performance of the controller. Experimental results show that better performances are achieved with the proposed method, optimised with Gas, when it is compared with a conventional PID controller.

References

1 R. S. Kemerer and L. E. Berkebile, ‘Directly Connected Static VAR Compensation in Distribution System Applications, *IEEE Trans Industry Appl.*, **35** (1999), 11.
2 M. Z. EL-Sadek, G. EL-Saady and M. Abo-EL-Saud, ‘A variable structure adaptive neural network static VAR controller,’ *Electric Power Systems Res.*, **45** (1998).
3 G. EI-Saady, M. Z. EL-Sadek and M. Abo-El-Saud; ‘Fuzzy adaptive model reference approach-based power system static VAR stabilizer’, *Electric Power Syst. Res.*, **45** (1998).
4 S. Y. Lee, C. Wu and W. N. Chang, ‘A compact control algorithm for reactive power compensation and load balancing with static VAR compensator’, *Electrical Power Energy Syst.*, **58** (2001).
5 S. M. AL-Alawi and K. A. Ellithy, ‘Tuning of SVC damping controllers over a wide range of load models using an artificial neural network, *Electrical Power Energy Syst.*, **22** (2000).
6 Z. Y. Zhao, M. Tomizuka and S. Isaka, ‘Fuzzy Gain Scheduling of PID Controllers’, *IEEE Trans. Syst. Man. Cybern.*, **23** (1993), 5.
7 W. Li, ‘Design of a Hybrid Fuzzy Logic Proportional Plus Conventional Integral-Derivative Controller’, *IEEE Trans. Fuzzy Syst.*, **6** (1998), 4.
8 M. Sugeno, *Industrial Applications of Fuzzy Control* (Elsevier, Amsterdam, 1985).
9 R. H. Lasseter and S. Y. Lee, ‘Digital Simulation of Static VAR System Transients’; *IEEE Trans. PAS* **101** (1982), 10.
10 L. J. Bohmann and R. H. Lasseter, ‘Equivalent Circuit for Frequency Response of a Static VAR Compensator’, *IEEE Trans. PWRS*, **1** (1986), 4.
11 T. J. E. Miller, *Reactive Power Control in Electric Systems* (John Wiley and Sons, New York, 1982), pp.640–649.
12 W. Xu, J. R. Marti and H. W. Dommel, ‘Harmonic Analysis of Systems with Static Compensators’, *IEEE Tran. Power Syst.*, **6** (1991), 1.
13 B. C. Kuo, *Automatic Control Systems*, 5th edn (Prentice-Hall, Englewood Cliffs, 1987).
14 K. J. Aström and B. Wittenmark, *Adaptive Control* (Prentice Hall, Englewood Cliffs, 1989).
15 T. H. S. Li and M. Y. Shieh, ‘Design of a GA-based fuzzy PID Controller for Non-minimum Phase Systems’, *Fuzzy Sets Sys.*, **111** (2000).
16 K. F. Man, K. S. Tang and S. Kwang, ‘Genetic Algorithms: Concepts and Applications’, *IEEE Trans. Indust. Electr.*, **43** (1996), 5.
17 C. I. Karr and E. J. Gentry, ‘Fuzzy Control of pH Using Genetic Algorithms’, *IEEE Trans. Fuzzy Syst.*, **1** (1993), 1.
18 Y. S. Zhou and Y. L. Lai, ‘Optimal Design for Fuzzy Controllers by Genetic Algorithms’, *IEEE Trans. Industry Appl.*, **36** (2000), 1.
19 K. F. Man, K. S. Tang and S. Kwang, ‘Genetic Algorithms: Concepts and Applications’, *IEEE Trans. Indust. Electr.*, **43** (1996), 5.
20 Y. S. Zhou and Y. L. Lai, ‘Optimal Design for Fuzzy Controllers by Genetic Algortihms’, *IEEE Trans. Industry Appl.*, **86** (2000), 1.