Oqimni optimallashtirish algoritmi asosida voltaj barqararligini ta’minlash uchun statik kuch kompensatorlarini ko‘p maqsadli joylash

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Dolzarblik: Oqimni optimallashtirish (PSO) algoritmi katta quvvat tizimida statik o'zgaruvchan kompensatorlarni (SVC) joylashtirishni rejalashtirish uchun ishlatiladi. SVC ning asosiy vazifasi - uzatish tizimining kuchlanishini yaxshilash va shu bilan maksimal quvvat uzatish chegarasini oshirish. Voltaj barqarorligini yaxshilash uchun muammo loyqa ishlash indeksini maksimal darajada oshirish uchun bir nechta maqsadlarga ega optimallashtirish muammosi sifatida ko'rib chiqiladi. Katta energiya tizimida ko'p maqsadli reaktiv quvvatni rejalashtirish muammosi loyqa PSO yordamida hal qilinishi mumkin.

Maqsad: Sun'iy intellekt usullari, xususan, sun'iy neyron tarmoq usullari, shu jumladan uzoq muddatli va qisqa muddatli xotira (LSTM) yondashuvidan foydalangan holda sanoat energiya iste'molini prognozlashning aniqligini oshirish.

Usullari: Uzoq qisqa muddatli xotira (LSTM) usuliga alohida e'tibor berib, bashorat qilish modelini ishlab chiqishda sun'iy neyron tarmoq texnikasi qo'llanildi. Birlamchi ma'lumotlarni qayta ishlash uchun Gauss taqsimlash tamoyillari va normalizatsiya / masshtablash usullari ishlatilgan.

Natijalar: sanoat korxonalari tomonidan elektr energiyasini iste'mol qilishni bashorat qilish uchun sun'iy neyron tarmoqlar usuliga asoslangan taklif qilingan modeldan foydalangan holda hisoblash asosli. Ushbu usulning muhim afzalligi uning o'rganish qobiliyati va prognoz qilishga moslashuvidir. Haqiqiy vaqtda hisob-kitoblar uning muvaffaqiyatli amalga oshirilishini, birinchi navbatda, kirish qatlamlarini to'g'ri tanlash va tasodifiy o'zgaruvchilarni yumshatish tufayli ko'rsatadi.

Kalit so'zlar: prognozlash, energiya sarfi, prognozlash xatosi, model adekvatligi, bir qatlamli neyron tarmoq, faollashtirish funktsiyasi, neyronlar, trening, test, tekshirish, algoritm, xato, kirish qatlami, chiqish qatlami, tortish koeffitsientlari, o'rtacha kvadrat xatosi.

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Многоцелевое размещение статических компенсаторов мощности для обеспечения стабильности напряжения на основе алгоритма оптимизации потока

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Актуальность: алгоритм оптимизации потоков (PSO) используется для планирования размещения статических компенсаторов реактивной мощности (SVC) в крупной энергосистеме. Основная функция SVC-улучшить напряжение системы передачи, тем самым повысив максимальный предел передачи мощности. Для повышения стабильности напряжения проблема рассматривается как задача оптимизации с несколькими целями для максимизации нечеткого индекса производительности. Многоцелевая задача планирования реактивной мощности в крупной энергосистеме может быть решена с помощью нечеткого PSO.

Цель: повысить точность прогнозирования потребления электроэнергии на промышленных предприятиях с использованием методов искусственного интеллекта, в частности, методов искусственных нейронных сетей, включая подход с долгосрочным и краткосрочным запоминающим устройством (LSTM).

Методы: при разработке модели прогнозирования были приняты методы искусственных нейронных сетей с особым акцентом на методе долгосрочного и краткосрочного запоминающего устройства (LSTM). Для первичной обработки данных применялись принципы гауссовского распределения и методы нормализации/масштабирования.

Результаты: обосновано вычислительным путем применения предлагаемой модели на основе метода искусственных нейронных сетей для прогнозирования потребления электроэнергии промышленными предприятиями. Существенным преимуществом этого метода является его обучаемость и адаптивность к прогнозированию. Вычисления в реальном времени демонстрируют его успешную реализацию, обусловленную прежде всего правильным выбором входных слоев и смягчением случайных величин.

Ключевые слова: прогнозирование, энергопотребление, ошибка прогнозирования, адекватность модели, однослойная нейронная сеть, функция активации, нейроны, обучение, тестирование, валидация, алгоритм, ошибка, входной слой, выходной слой, весовые коэффициенты, среднеквадратическая ошибка.

Multiple placement of static power compensators to ensure voltage stability based on flow optimization algorithm

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Relevance: Particle Swarm Optimization (PSO) Algorithm is used for Static VAr Compensators (SVCs) planning in a large power system. The primary function of a SVC is to improve transmission system voltage, thereby enhancing the maximum power transfer limit. To enhance voltage stability, the problem is considered as a multiple goals optimization problem for maximizing a fuzzy performance index. The multi-objective VAr planning problem in large-scale power system can be solved by the fuzzified PSO.
Aim: To elevate the accuracy of electricity consumption forecasting at industrial enterprises by using artificial intelligence methods, specifically, artificial neural network techniques, including the Long-Short Term Memory (LSTM) approach.
Methods: When developing the forecasting model, artificial neural network techniques were adopted, with a particular emphasis on the Long-Short Term Memory (LSTM) method. For primary data processing, Gaussian distribution principles and normalization/scaling techniques were applied.
Results: Substantiated computationally by applying the proposed model based on the artificial neural network technique for forecasting electricity consumption of industrial enterprises. A significant advantage of this method is its capability for learning and adaptability to forecasting. Real-time computations demonstrate its successful implementation, attributed primarily to appropriate selection of input layers and mitigation of random variables.
Keywords: forecasting, power consumption, forecasting error, model adequacy, single-layer neural network, activation function, neurons, training, testing, validation, algorithm, error, input layer, output layer, weighting coefficients, root mean square error.

1. Introduction

In the last decades, efforts have been made to find the ways to assure the security of the system in terms of voltage stability. It is found that flexible AC transmission system (FACTS) devices are good choices to improve the voltage profile in power systems that operate near their steady-state stability limits and may result in voltage instability. Taking advantages of the FACTS devices depends greatly on how these devices are placed in the power system, namely on their location and size.

A great deal of work has been carried out to develop analytical and control synthesis tools to detect and avoid voltage instability. In the literature a tool has been reported based on the determination of critical modes known as modal analysis. Modal analysis has been used to locate SVC and other shunt compensators to avoid voltage instability [1],[15]. Obviously, this method meets difficulties in placement of SVC optimally. Over the last decades there has been a growing interest in algorithms inspired from the observation of natural phenomenon. It has been shown that these algorithms are good replacement as tools to solve complex computational problems. Various heuristic approaches have been adopted by researches including genetic algorithm, tabu search, simulated annealing, ant colony and particle swarm optimization. Planning of FACTS devices has been a major concern of power industries and many researches around the world [2]-[11]. Recently, Kennedy and Eberhart introduced the Particle Swarm Optimization (PSO) method as an evolutionary computation technique [12]. The original version of the PSO operates in continuous space [12] was extended to operate on discrete binary variables [13]. The PSO has been proven to be very effective for static and dynamic optimization problems. For the first time, the PSO is applied in power systems in 1999 [14], and has been successfully applied to various problems such as power system stabilizer design, reactive power and voltage control, and dynamic security border identification. In spite of the importance of FACTS devices in power system stability, however, the only application of PSO on FACTS devices can be found in [15]. Where a fuzzy controller is designed by the hybrid of GA and PSO to enhance the damping of electromechanical modes of the Thyristor Controlled Series Compensator (TCSC).

In view of this, this paper considers the problem of planning of SVC in a large power system to maintain the nodal voltage magnitudes. The problem is formulated into a multi-objective optimization problem for maximizing a fuzzy performance index, which represents maximizing the system VAr margin, minimizing voltage deviation and RI2 losses.

Particle swarm optimization PSO is as an optimization tool that provides a population-based search procedure in which individuals, called particles, change their positions with time. In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience, and the experience of neighboring particles, making use of the best position encountered by itself and its neighbors. Particles in the PSO are defined by two variables: x and v in which x is the position of the particle representing a candidate solution to the problem and v describes the velocity. In the PSO, two different definitions are used as: the individual best and the global best. As a particle moves through the search space, it compares its fitness value at the current position to the best fitness value it has ever attained previously. The best position that is associated with the best fitness encountered so far is called the individual best or *p*best. The global best, or *g*best, is the best position among all of the individual's best positions achieved so far.

Using the g best and $p$best, the i^{th}particle velocity in the d^{th} dimension is updated according to the following equation:

$$v_{id}(t+1) = w \cdot v_{(id)}(t) + c_1 \cdot rand(pbest_{id} - x_{id}(t) + c_2 \cdot Rand(gbest_{id} - x_{id}(t)) \quad (1)$$

where , w is inertia weight factor, c_1 and c_2, are acceleration constant, rand() and Rand () are random number between 0 and 1.

Based on the updated velocities, each particle changes its position according to the following equation:

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (2)$$

The principle PSO is shown by Fig. 1.

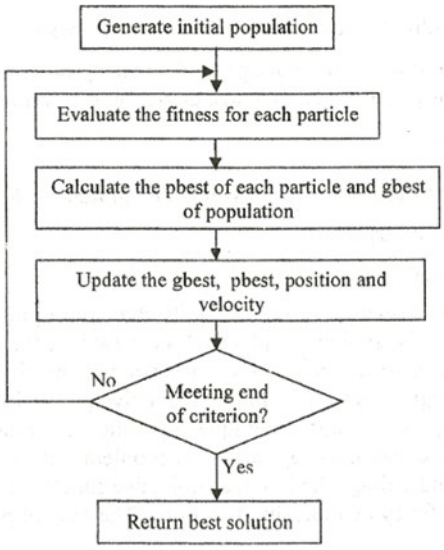

Fig. 1. General principle of PSO algorithm.

2. Methods and materials

The VAr planning problem using the SVC is formulated by considering a number of different objective functions, i.e., multi-objective functions. They include in this paper the objectives of increasing the system VAr margin, reduction of the active power loss and reduction of voltage deviation.

Multi-objective Functions

l) *The system VAr margin.* The system VAr margin can be evaluated by stressing the system gradually from an initial operating state until the state of critical voltage stability is reached. This can be done by increasing all loads, gradually, near to the point of voltage collapse. The system VAr margin Q can be increased as follows:

Subject to $\boldsymbol{Q} = \sum \Delta Q_i$ (3)

where, ΔQ_i , is the VAr demand imposed on each bus for stressing the system towards the critical point.

2) *Active power loss.* The total power loss is minimized as follows

$$P_{i \cdot} \sum [V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j)] Y_{ij} \cos \varphi_{ij} \quad (4)$$

where v, and are the magnitude and angle of voltage at bus i, and are the magnitude and angle of the admittance of the line from bus *i* to bus *j*.

3) *Voltage deviation*. To have a good voltage performance, the voltage deviation at each load bus must be made as small as possible. The voltage deviation is minimized as follows:

$$f = \max_{k \in \Omega} \left| V_k - V_{ref\ k} \right| \quad (5)$$

where Ω is the set of all load buses, V_k is the voltage magnitude at load buses k and $V_{ref\ k}$ is the nominal or reference voltage at bus k .

Multi-objective Optimization

There are a number of approaches to solve the multi-objective optimization problem. In this paper, a fuzzy logic technique is applied. To place a SVC based on the above objective functions, first the system is pushed near to the point of voltage collapse by increasing all loads. Then to increase the system VAr margin, a trade-off among the active power losses and voltage deviation must be achieved. For this, fuzzy logic technique is applied to transform the multi-objective optimization problem into a constrained optimization problem with a single objective function, where active power losses and voltage deviation as objective functions are quantified into a set of fuzzy objectives selected by fuzzy membership functions. The overall problem can be as follows:

$$obj = min\{P_{l\cdot}, f\} \tag{6}$$

Table I shows the fuzzy rules for solving the problems.

Table 1. Fuzzy rules Input 1 (*f*)

			G	M	B
	G		VVG	G	VB
Input 2 (P_l)	M		VG	M	VB
	B		M	B	VB

To achieve a trade-off between two objective functions, the fuzzy membership function shown in Figs. 2-3 is considered. Also, Fig. 4 shows the flow chart for SVC placement.

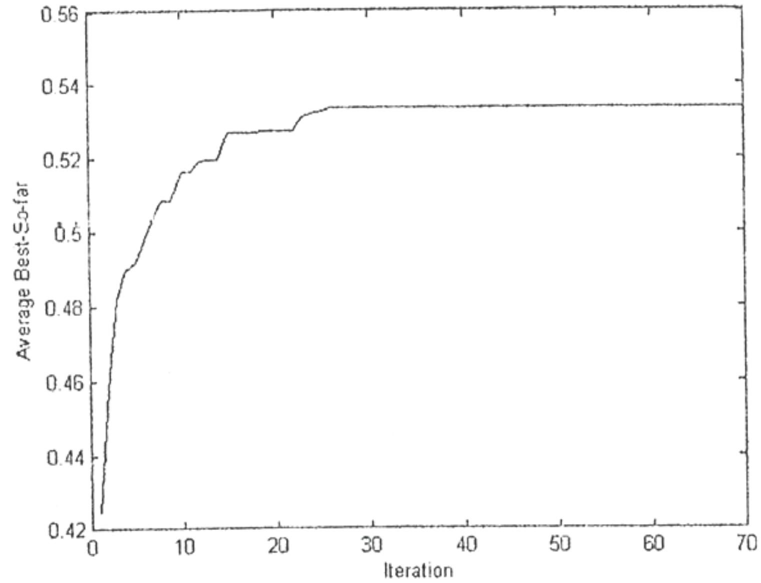

Fig. 2. Membership function related to voltage (*f*) for the study system.

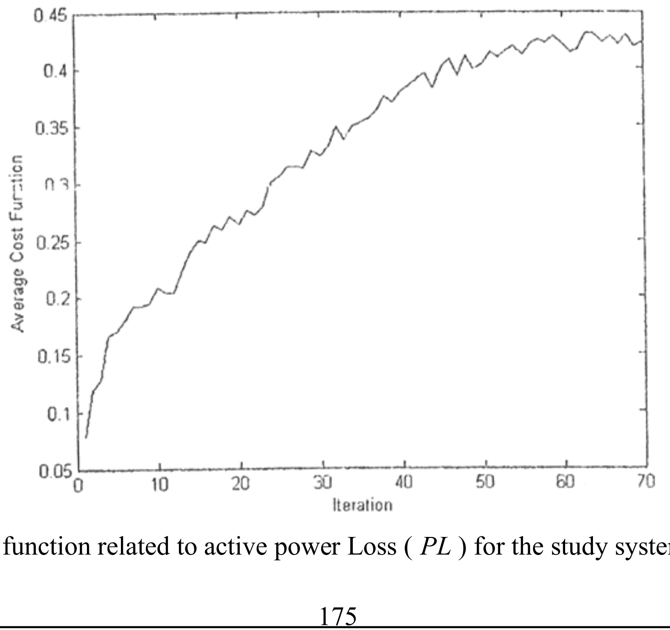

Fig 3. Membership function related to active power Loss (*PL*) for the study system.

3. Results and Disscussion

A 5-area-16-machine system: The study system, consisting of 16 machines and 68 buses. This is a reduced order model of the New England (NE) New York (NY) interconnected system. The first nine machines are the simple representation of the New England system generation. Machines 10 to 13 represent the New York power system. The last three machines are the dynamic equivalents of the three large neighboring areas interconnected to the New York power system.

PSO incorporating with fuzzy objective function is used to locate SVC in the power system shown in Fig. 5. The implementation is presented below:

Placing of SVC using PSO starts from an initial load. All loads are increased gradually near to the point of voltage collapse, all at once. In the PSO algorithm, n particles are generated randomly where n is selected to be 50. The goal of the optimization is to find the best location of SVC where the optimization is made on two parameters: its location and size. , therefore, each particle is a *d*-dimensional vector in which $d = 2$. The initialization is made on the position randomly for each particle. The number of iteration is considered to be 70, which is the stopping criteria. The parameter in (1) must be tuned. These parameters control the impact of the previous velocities on the current velocity where, in this paper, $c1 = c2 = 2$ and w is decreasing linearly from 0.9 to 0.1. Each particle in the population is evaluated using the objective function defined by (7), searching for the particle associated with. The best previous position of the $i^{th}I$ particle is recorded and represented as: $pbest_{i,1}, pbest_{i,2}$ and the index of the best particle among all of the particles in the group is for the gbest.

Using the gbest and pbest, particle velocity and position is updated according to (1) and (2). Also, in each iteration, the gbest and pbest are updated.

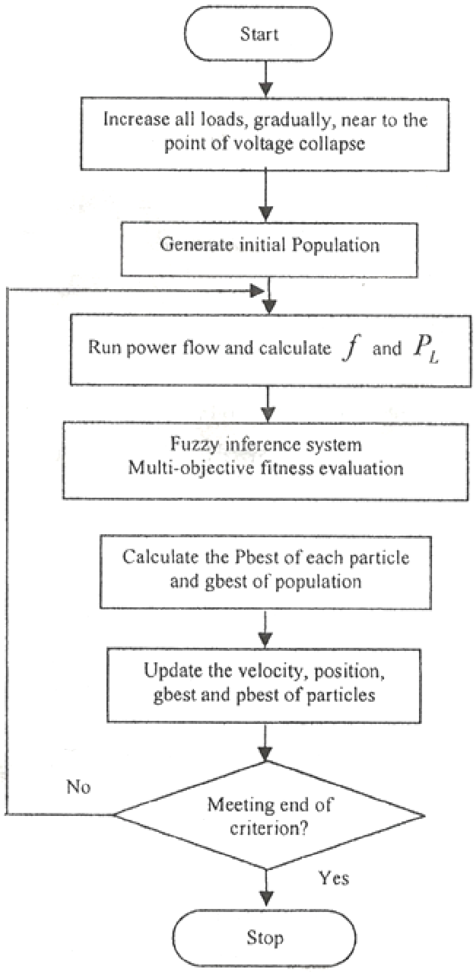

Fig. 4. Flow chart for SVC placement

To locate SVC by PSO, suitable bus is selected based on 20 independent runs, under different random seeds. At the end of the 20 independent runs, the following results are identified by the algorithm: 45% of results show that the SVC should be placed at bus 1 with 650 MVAr size; 30% of results show that the SVC should be placed at bus 47 with 363 MVAr size and 25% result showed different buses. The results are summarized in Table II.

Table 2. The results obtained by PSO with fuzzified objective function

SVC Placemtn	MVAr Size	Maximum Voltage deviation	losses
bus 1	650	0.070	398
…			
bus 47	363	0.0630	428

The results obtained by PSO are averaged over independent runs. The average best-so-far and mean cost function of each run is recorded and averaged over 20 independent runs. To have a better clarity, the convergence characteristics in finding the location and size of a SVC is given in Figs. 6-7.

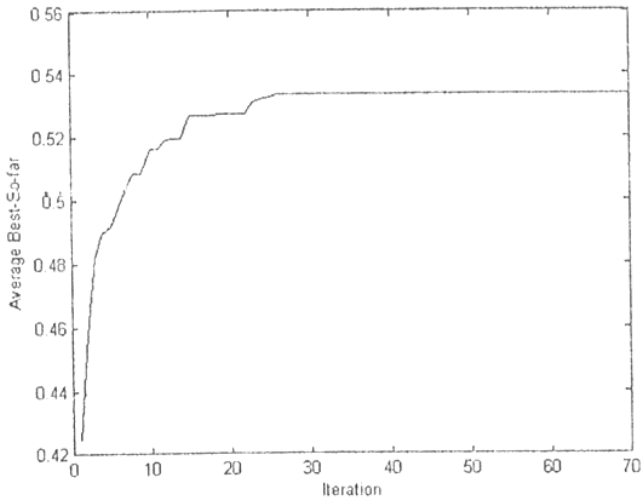

Fig. 6. Convergence characteristic of PSO on the average best-so- far in finding the solution, 650 MVar SVC at bus 1 with 50 particle

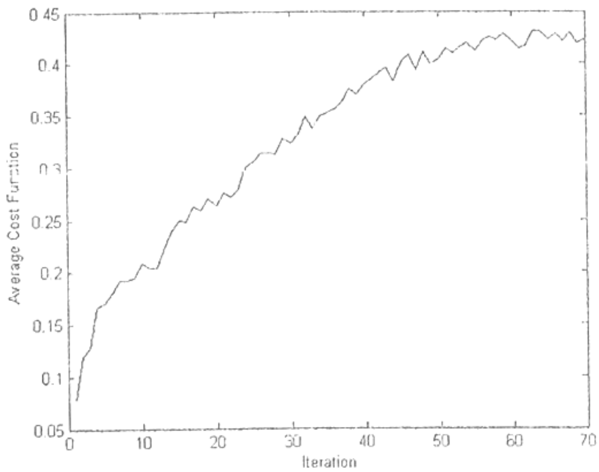

Fig. 7. Convergence characteristic of PSO on the average cost function in finding the solution, 650 MVar SVC at bus 1 with 50 particle

4. Discussion

As the results obtained show, the algorithms didn't converge to a specific solution and the results obtained are different. Any of buses 1 and 47 could be a solution to the problem. Although Table Il, may identify the optimal and suboptimal solution, but lets the algorithm leads us to the optimal solution. To find the optimal solution, as the first try, the number of particles is increased to 100.
Suitable buses are selected based on 20 independent runs, under different random seeds. The results obtained are as follows: 80% of results obtained by fuzzy PSO show that the SVC should be placed at bus 1 with 650 MVAr size.
Once again the number of particles is increased to 150. Suitable buses are selected based on 20 independent runs, under different random seeds. The results obtained are as follows: 100% of results obtained by fuzzy PSO show that the SVC should be placed at bus 1 with 650 MVAr size.

The obtained results by PSO are averaged over independent runs. The average best-so-far and mean cost function of each run are recorded and averaged over 20 independent runs for 100 and 150 particles. The results are given in Figs. 8-9 that show the results obtained for 50 and 100 particles are the same but for 150 particles are different. That shows the algorithm is finding the optimal solution. Also, the voltage profile when system is heavily stressed, before and after placing of SVC shown in Figs. 10-11. These Figs. show that the voltage profile is improved.

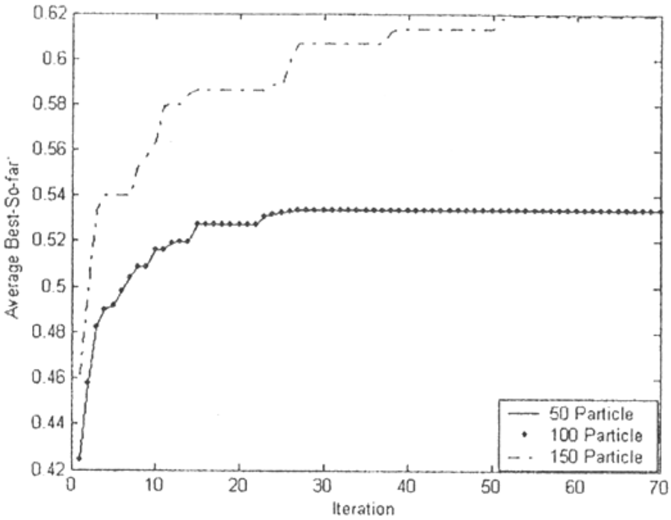

Fig. 8. Convergence characteristic of PSO on the average best-so- far in finding the solution, 650 MVar SVC at bus 1 for different particles.

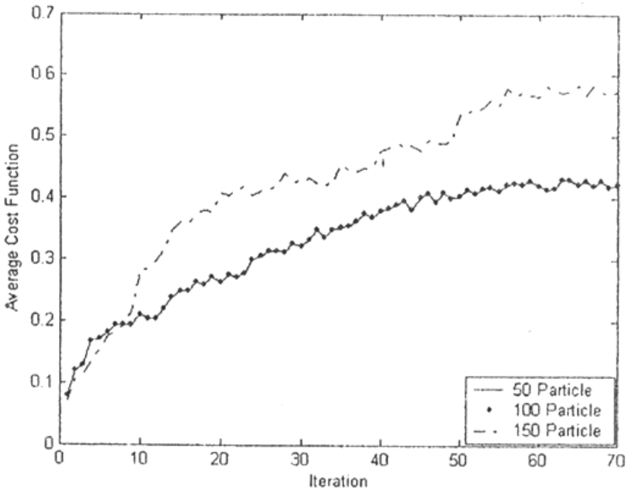

Fig. 9. Convergence characteristic of PSO on the average cost function in finding the solution, 650 MVar SVC at bus I for different particles.

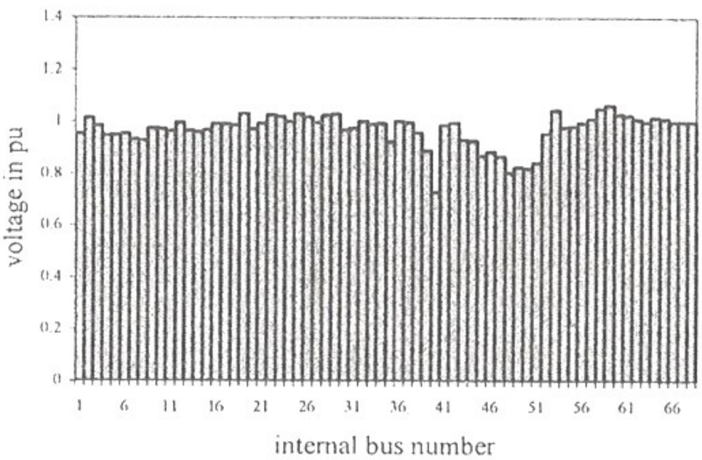

Fig. 10. Bus voltage magnitude profile when system is heavily stressed.

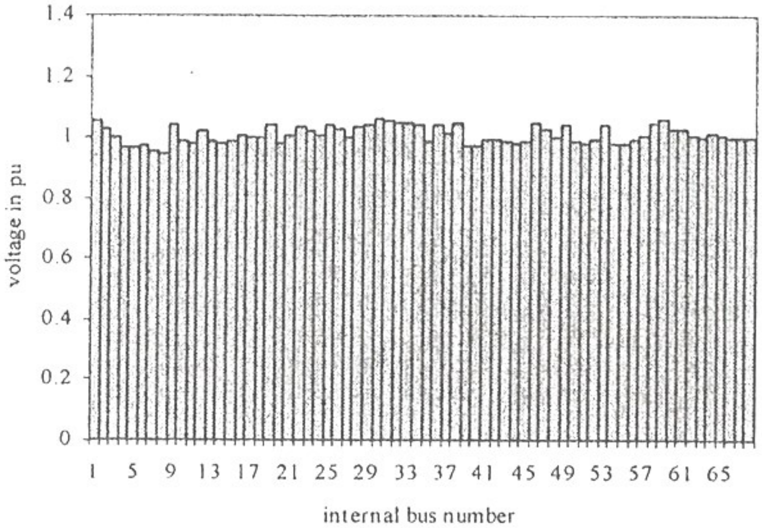

Fig. 11. Bus voltage magnitude profile of the stressed system after placing 650 MVar SVC at bus 1.

5. Conclusion

In this paper PSO with a fuzzy objective function is applied to place SVC in a power system where, VAr planning is based on increasing of the system VAr margin, reduction of the system RI^2 losses and reduction of voltage deviation. The number of populations is considered to be 50. The algorithm didn't converge to a specific solution and the obtained results were different. 45% of the results obtained by PSO identify bus 1 for SVC placement while 35% of results identify bus 47 for placement of SVC and 25% of the results identify different buses which are not a good placement for SVC. It seems that some particles had trouble jumping out of local optima and it was resulted identifying different buses.

Different obtained solution to the problem by PSO leaded us to increase the populations to 100 to have enough sample from the search space. 80% of the obtained results by PSO identify bus I for placement of SVC. Once again the populations increased to 150. 100% of the obtained results by PSO identify bus 1 for placement of SVC. The results show that by increasing the number of particles the algorithm found the optimal solution.

Although the PSO seems to be sensitive to the tuning of some weights or parameters in the algorithm and the number of particles, it has a great potential in solving complex power system problems.

To have an optimal VAr planning from an economic viewpoint, the investment cost for SVC must be considered where the authors are working on it. Also, the guaranteed version of PSO will be tried.

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