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Implementing Particle Swarm Optimization in Wind Farm to Place Wind Turbines

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Abstract: In this paper, particle swarm optimization is utilized to optimize the placement of wind turbines in a wind farm. Since wind is one of the sustainable energy sources, it is important to build the wind parks as efficient as possible to extract the largest possible amount of electrical power. Here, the location of each wind turbine is adjusted within a predefined square field considered as a wind farm. The output power of the farm and the total cost of construction are the parameters considered to create an objective function. The simulated results are shown in graphs and tables. Also comparisons are carried out with previous presented optimizations. The results prove that in present study, the efficiency and electrical power extraction of the wind farm are increased regarding the total cost of construction.

Key words: Particle Swarm Optimization, wind farm, optimization, wind turbine, wake effect

INTRODUCTION

WIND ENERGY has been accepted as good and efficient energy source with large industry manufacturing and thousands of Mega Watts is being installed as new capacity each year. Among the renewable energy sources, wind energy and solar energy are known as the less harmful sources to the environment (Mekhilef, Saidur *et al*. 2011, Rahmani, Fard *et al*. 2011, Safari and Mekhilef 2011, Mahmodian, Rahmani *et al*. 2012). A considerable knowledge containing the technology and science of wind turbines and wind farms has been established. However, there are still exciting novel developments in wind issue, particularly in wind turbines (Burton, Sharpe *et al*. 2001, Muller, Deicke *et al*. 2002, Hau 2006).

Wind farms or as they are occasionally called wind parks, are locally concerned of tied groups of wind turbines which are connected electrically and commercially. There are several merits to this structure in respect of electrical and commercial (Manwell, McGowan *et al*. 2002, Mathew 2006). For installing wind turbines in a wind farm, some studies related to place the turbines must be undertaken to determine the optimum place of each turbine. In 1994 an estimation of the global wind energy resource was gave by the World Energy Council. In that estimation about 27 percent of the earth's land surface annually experiences mean wind speed of higher than 5.1 meter per second above it. Because of the suitability issue, containing urban areas, being crop cultivation and other land uses, just 4% of mentioned area might be usable for generating electricity through wind farms (Ackermann and Söder 2000). The last issue substantiates the necessity of paying attention to optimize the placing of wind turbines in a wind farm.

Some interesting concepts were proposed in the past. Among them some of them were based on the AI and mathematic models. Mosetti *et al*. (Mosetti, Poloni *et al*. 1994) has proposed an optimization based on genetic algorithms for placing wind turbines in a wind park. In (Grady, Hussaini *et al*. 2005) same work is done by improving some parameters and getting better results. After them Marmidis *et al*. (Marmidis, Lazarou *et al*. 2008) proposed new optimization utilizing the Monte Carlo method. In current study binary PSO has been utilized to have an easier comparison with the previous works. The optimization is developed through a C code programming, based on the PSO method.

Mathematical Models:

2.1. Wake effect in a wind farm:

Wind turbine is known as a device which extracts electrical power from kinetic energy of wind. At each wind turbine some of the kinetic energy of the wind is being removed and it must slow down but it is only true for the mass of air that passes through the rotor diameter (rotor disc). Figure 1 shows the cross sectional area of the stream air through a wind turbine. It can be seen that the air crossing through the rotor disc will be expanded to accommodate slower moving air. The reason is that there is no air flowing across the boundary then the mass flow rate of the wind along stream tube is constant and is the same for all wise conditions along the stream tube (Burton, Sharpe *et al*. 2001).

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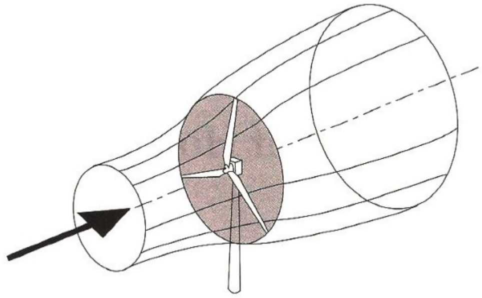

Fig. 1: The expansion of stream tube along a wind turbine.

There exists a drop in static pressure for the air passing through the rotor disc, so the air pressure is below the atmosphere pressure level on the leaving. This phenomenon forces the air proceeding downstream with lower speed and static pressure. this region of stream is called *wake* (Burton, Sharpe *et al*. 2001).

Figure 2 illustrates a scheme of a flow field which consists of a wake with a uniform velocity that decreases with distance downstream. U_0 is the initial free velocity and D is the turbine diameter. U_x indicates the velocity at distance X downstream in the wake where the diameter is D_x. the constant k is the wake decay constant which determines the rate of increasing the diameter in the direction of downstream (Mathew 2006).

The wake decay constant, k, is totally related to the parameters of wind turbines. Equation (1) shows the relation between k and the turbine parameters, where Z is the hub height and Z_0 is the roughness coefficient for the surface.

$$k = \frac{0.5}{\ln\left(\frac{Z}{Z_0}\right)} \tag{1}$$

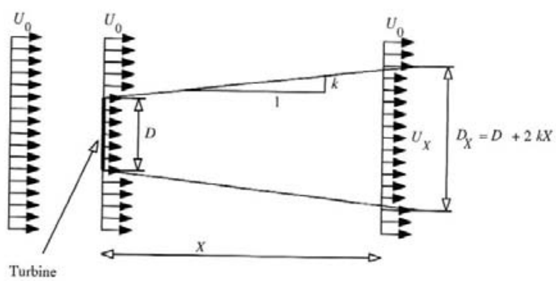

Fig. 2: Schematic view of wake description.

In this model, the same as most of semi-empirical models, the initial non-dimensional velocity deficit (the axial induction factor), α, is a function of the turbine thrust coefficient (CT). Equation (2) demonstrates the ideal Betz model (Mathew 2006):

$$\alpha = 0.5\left(1 - \sqrt{1 - C_T}\right) \tag{2}$$

The velocity deficit at the distance X downstream can be obtained from following equation:

$$1 - \frac{U_X}{U_0} = \frac{\left(1 - \sqrt{1 - C_T}\right)}{\left(1 + 2k\frac{X}{D}\right)^2} \tag{3}$$

Considering the wake effect of all the front turbines for the i^{th} turbine inside a wind park, leads to following equation:

$$U_i = U_0 \left[1 - \sum_{j=1}^{N_j} \left(1 - \frac{U_j}{U_0} \right)^2 \right] \tag{4}$$

In equation (4), N_j indicates the number of turbines standing in front of the i^{th} turbine, and the U_j is wind speed of related turbine.

Power Output And Cost Modeling:

The power output from a wind turbine is given by the famous expression below:

$$P = 0.5 C_P \rho A U^3 \tag{5}$$

Where ρ is the density of air (1.225 kg/m^3), C_P is the power coefficient, A is the rotor swept area, while U is the wind speed. Based on equation (5), the output power of the wind turbine is proportional to the cube of the wind speed. However, mentioned equation is true for a specific interval of wind speed. Figure 3 demonstrates the ideal power curve of a specific 1 MW wind turbine (Mathew 2006).

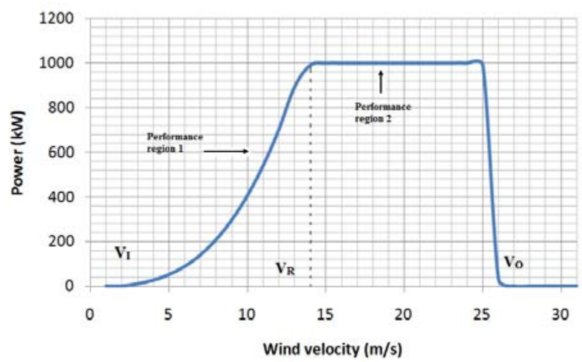

Fig. 3: Ideal power curve of the chosen wind turbine.

There are three points in the characteristic which make important speeds of turbine, cut in velocity (V_I), rated velocity (V_R) and the cut out velocity (V_O). The minimum wind velocity, at which the producing of power starts to begin for the system, is called cut in velocity. Obviously it is different with the start up speed at which the rotation of rotor starts. Although the cut in velocity varies from turbine to turbine, most of commercial wind turbines have the V_I of 3 to 5 *m/s*. Rated velocity is the lowest wind velocity corresponding to the P_R which is rated power for the wind turbine. The system efficiency usually reaches its maximum at V_R. From V_I, to V_R, the generating power increases with the velocity of wind while between V_R and V_O, the producing power is restricted to constant power P_R, which is corresponding to V_R and irrespective of changes in velocity. Hence the theoretical maximum expected power from the turbine is P_R which will be determined by V_R. To protect the rotor and drive trains from serious damages due to excessive, the machine is completely shut down at velocities higher than V_O (Mathew 2006).

Back to equation (5), Although for each type of wind turbine we have a different coefficient multiplying to U, we consider the situation that wind turbine is being placed in a wind farm with U_0=12 *m/s* to have an output near the rated power and also being able to have a comparison with previous works. In this type the equation (5) will be rewritten to following shape:

$$P_i = 0.3 U_i^3 \tag{6}$$

$$P_{total} = \sum_{i=1}^{N} 0.3 U_i^3 \tag{7}$$

In equation (6) P_i and U_i are the power output and wind speed of i^{th} turbine, and in (7) P_{total} is the total output power of the wind park considering that N is the total number of wind turbines which has been placed in it.

Reference (Mosetti, Poloni *et al*. 1994) had an assumption for the total cost of the wind turbines. Based on that, in large scale, the cost per year of a single turbine is one with a maximum cost reduction in of 1/3 for each additional wind turbine. Following equation demonstrates the cost function considered by them:

$$Cost = N\left(\frac{2}{3} + \frac{1}{3}e^{-0.00174 \times N^2}\right) \tag{8}$$

Where the *Cost* is total costs of wind turbines and the *N* is number of wind turbines have been installed in a wind park.

Having an optimization procedure Objective function has been assumed in equation (9), where the minimum value of this function leads us to the optimized point.

$$Objective = \frac{Cost}{P_{total}} \tag{9}$$

Where, *Cost* is as described above, and P_{total} is the total power extracted by all of the *N* turbines in the wind farm. This objective function which is sometimes called fitness function will minimize the cost per unit energy produced.

Particle Swarm Optimization:

Besides Genetic Algorithm (GA), Dynamic Programming (DP) and other methods of Artificial Intelligence, Particle Swarm Optimization (PSO) is another evolutionary computation technique developed by Eberhart and Kennedy, in 1995, based on the social behaviors of a school of fish or bird flock (Kennedy and Eberhart 1995, Poli, Kennedy *et al*. 2007). This optimization algorithm utilizes a swarm of particles flying in a determined search space while any particle proposes a solution to the problem at each step. PSO has some parameters and different ideas and improvements for modeling. The location and velocity of i^{th} particle are as follow:

$$X_i^{k+1} = X_i^k + V_i^k \tag{10}$$

$$V_i^{k+1} = W \times V_i^k + c_1 \times r_1\left(Gbest^k - X_i^k\right) + c_2 \times r_2\left(Pbest_i^k - X_i^k\right) \tag{11}$$

Where, X_i^k and V_i^k are the location and velocity of i^{th} particle at k^{th} iteration and *W* is the Inertia weight of velocity. "*Pbest*" and "*Gbest*" are known as global best and personal best which derived based on a user defined objective function. Indeed, *Pbest* is the best location in the search space experienced by each particle while *Gbest* is the best ever experienced location. The *c1* and *c2* are the acceleration coefficients that are normally equal to 2. The *r1* and *r2* are random numbers between 0 and 1. Based on the above equation, Figure 4 shows the scheme of movement of a particle in a swarm, based upon the model proposed by (Chen and Li 2006).

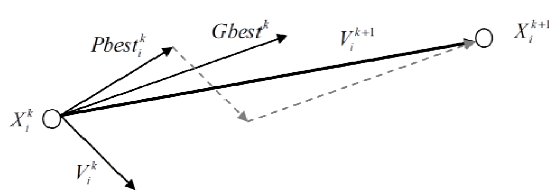

Fig. 4: The scheme of movement of a particle in PSO algorithm.

Since PSO is a stochastic intelligence based algorithm, it is not largely dependent on the size of the problem space. This method showed itself so powerful in solving extremely non-linear and non-differentiable mathematic problems and also demonstrated a good convergence profile (Engelbrecht 2005, Clerc 2006). Therefore, it can also be used for solving different optimization problems of power system. Several articles are published in last few years focusing on this issue (Yoshida, Kawata *et al*. 2000, Eberhart 2001, Gaing 2004, Rahmani, Khairuddin *et al*. 2010). PSO brings in several advantages over the other optimization techniques such as GA, some of them are as following (del Valle, Venayagamoorthy *et al*. 2008):

1) Having fewer parameters to adjust makes the PSO easier to implement.

2) In PSO, each single particle has two units of memory containing its own previous best value and its neighborhood best, so it makes this method have more effective memory ability than the GA method.

3) In this algorithm, all the particles improve their locations by using the data from the most successful particle. Therefore; it can be more efficient in maintaining the diversity of swarm. On the other hand in GA the worse solutions are removed and just the good parents are saved for next iteration, this solution makes the population revolve around a set of best individuals.

Implementing Pso In Wind Farm:

In current study, a 2km in 2km square field has been considered for planting the wind turbines. That is the same case study that the previous mentioned works. Each wind turbine needs an especial room to be put equal to 5 times of the rotor diameter which means 5 times 200m (See Figure 5). Table 1 shows the properties of modeled wind turbine.

Table 1: The wind turbines properties.

Wind turbine parameters	value
Hub height	60 m
Rotor diameter	40 m
Thrust coefficient	0.88

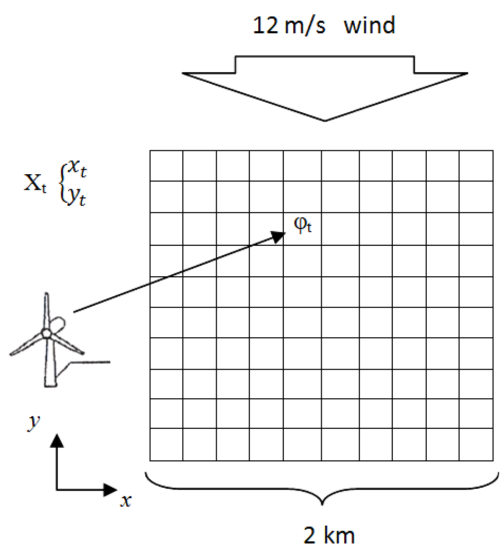

Fig. 5: The square field which is considered as case study.

Hence, 100 possible wind turbine places can be considered in current study. Figure 4 shows the field and the possible places for planting the wind turbines. As it is discussed in (Grady, Hussaini *et al*. 2005), by such a consideration, the wake effect of each turbine does not effect on the adjacent cell so just the wake effect on the behind turbines will be considered.

Equations (12) and (13) show the relations between the different parameters of PSO in this modeling, where V_t is the velocity at time step *t*, X_t is the position of particle at time step *t*, $p_{i,t}$ shows the best previous position at time step t, while $p_{g,t}$ is the best neighbor's previous best at time step *t*. c_1 and c_2 are the cognitive/social confidence coefficients.

$$v_{t+1} = w \cdot v_t + c_1\left(p_{g,t} - X_t\right) + c_2\left(p_{i,t} - X_t\right) \tag{12}$$

$$X_{t+1} = X_t + v_{t+1} \tag{13}$$

In current simulation each wind turbine is considered as a particle while the whole complex of wind turbines is modeling the swarm. In the other words the wind turbines are moving in a wind park as the particles of a swarm to achieve different possible answers for the problem. It means that the number of wind turbines is equal to the number of particles of the swarm. The flowchart of the simulation is depicted in Figure 6.

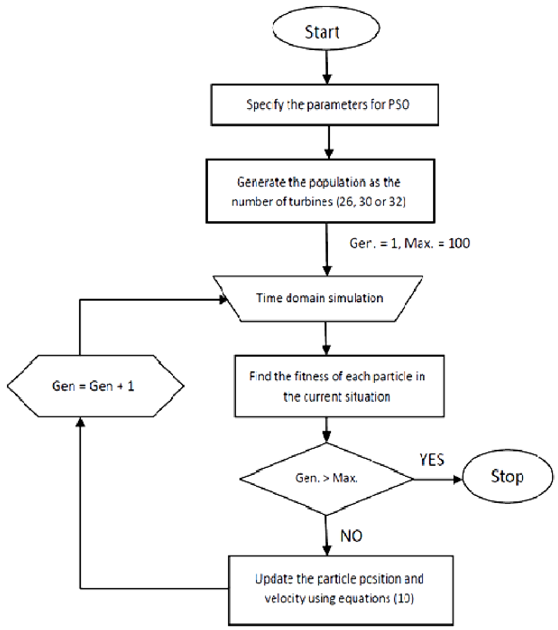

Fig. 6: Flowchart of particle swarm optimization algorithm.

RESULTS AND DISCUSSION

In this part, the obtained results utilizing PSO is compared with the previous works including Genetic Algorithm in both (Mosetti, Poloni *et al*. 1994, Grady, Hussaini *et al*. 2005), and the Monte Carlo simulation which was manipulated in (Marmidis, Lazarou *et al*. 2008). The case has been considered in all the existing studies, is a square shape 2km in 2km ground for turbines to be sat. In this study the same condition and even the same turbine type has been chosen to have a fair comparison.

After programming and simulating the wind farms in three situations (26 turbines, 30 turbines and 32 turbines), the results are illustrated in Table 2. The previous works in this field are brought to have a comparison between different plantings of turbines. In the table, part *i*, *iii* and *v* are related to current study, part *ii* shows the simulation result of (Mosetti, Poloni *et al*. 1994), *iv* is the result of (Grady, Hussaini *et al*. 2005) while *vi* belongs to (Marmidis, Lazarou *et al*. 2008).

Table 2: Comparative results.

simulation number	Number of turbines	Total power (KW per year)	Efficiency (%)	Objective value
i	26	12 819	95.11	0.001539
ii	26	12 352	91.645	0.001619
iii	30	14 601	93.88	0.001489
iv	30	14 310	92.015	0.001543
v	32	16 445	93.05	0.001396
vi	32	16 395	-------	0.001410

The obtained results of present study have been compared with the three previous works in this field. Row *ii* shows the result which has been achieved by (Mosetti, Poloni *et al*. 1994) for the first time. After them (Grady, Hussaini *et al*. 2005) compared their result (which is in row *iv*) with *ii*, but they did not reach the same number of wind turbines. Meanwhile, it would be better to compare the results with the same number of turbines. Having the same number of wind turbines will give a better sight about output power to judge. Rows *i* and *iii* are the results of present study for comparing with *ii* and *iv*, it can be observed that the results are precisely better with the same number of wind turbines. Modeling is done with 32 wind turbines too, and the result in row *v* is better than (Marmidis, Lazarou *et al*. 2008) in row *vi*.

Figure 7 demonstrates the convergence of objective function for PSO-based method used for various numbers of turbines. 26 turbines, 30 turbines and 32 turbines are chosen to compare with (Mosetti, Poloni *et al*. 1994), (Grady, Hussaini *et al*. 2005) and (Marmidis, Lazarou *et al*. 2008) respectively.

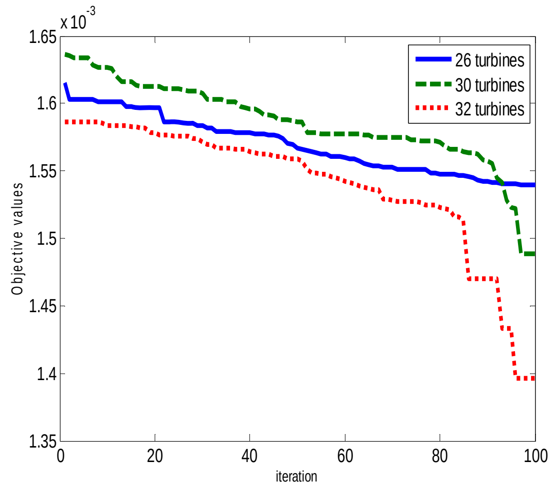

Fig. 7: The convergence of the objective values.

The results of the present study demonstrate that PSO algorithm can be utilized in optimization of a wind park beside its various applications in power system analysis. As far as the renewable energies and especially wind energies are getting more attraction nowadays, the optimization of wind farms must be done with applying progressive methods. In present case, the PSO-based method is manipulated to optimize the placing of wind turbines in a wind farm. The results are precisely improved comparing with the other AI-based methods have been utilized before.

Conclusions:

In conclusion, this project optimizes a wind farm by implementing a PSO-based method. The algorithm shows multiple advantages over the other algorithms applied to the current optimization problem. That is due to easier implementing parameters and keeping all the particles, unlike GA as an AI method which loses half of its population in each generation and needs to regenerate. The comparative study between current work and the previous cases clearly shows that, PSO can be utilized in optimizing a wind farm beside its various usages in engineering.

Current study was based on a flat planting with same hub height for all the turbines. The model can be assumed as an offshore wind farm. However, developing the C code to be able to manipulate hub heights to achieve a better result can be the main area of work.

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REFERENCES

Ackermann, T. and L. Söder, 2000. "Wind energy technology and current status: a review." Renewable sustainable energy rev, 4(4): 315-374.

Burton, T., D. Sharpe, N. Jenkins and E. Bossanyi, 2001. Wind energy, Wiley Online Library.

Chen, X. and Y. Li, 2006. An improved stochastic PSO with high exploration ability, May.

Clerc, M., 2006. Particle swarm optimization, Wiley-ISTE.

del Valle, Y., G.K. Venayagamoorthy, S. Mohagheghi, J.C. Hernandez and R.G. Harley, 2008. "Particle swarm optimization: basic concepts, variants and applications in power systems." Evolutionary Computation, IEEE Transactions on, 12(2): 171-195.

Eberhart, R., Y. Shi, 2001. Particle swarm optimization: developments, applications and resources. Evolutionary Computation, 2001. Proceedings of the 2001 Congress on, IEEE.

Engelbrecht, A.P., 2005. Fundamentals of computational swarm intelligence, Wiley Chichester,, UK.

Gaing, Z.L., 2004. "A particle swarm optimization approach for optimum design of PID controller in AVR system." Energy Conversion, IEEE Transactions on, 19(2): 384-391.

Grady, S., M. Hussaini and M. Abdullah, 2005. "Placement of wind turbines using genetic algorithms." Renewable Energy, 30(2): 259-270.

Hau, E., 2006. Wind turbines: fundamentals, technologies, application, economics, Springer Verlag.

Kennedy, J. and R. Eberhart, 1995. Particle swarm optimization. Neural Networks, 1995. Proceedings., IEEE International Conference on, Perth, WA , Australia, IEEE.

Mahmodian, M.S., R. Rahmani, E. Taslimi and S. Mekhilef, 2012. Step By Step Analyzing, Modeling and Simulation of Single and Double Array PV system in Different Environmental Variability. International Conference on Future Environment and Energy, Singapore, IPCBEE.

Manwell, J.F., J.G. McGowan and A.L. Rogers, 2002. Wind energy explained, Wiley Online Library.

Marmidis, G., S. Lazarou and E. Pyrgioti, 2008. "Optimal placement of wind turbines in a wind park using Monte Carlo simulation." Renewable Energy, 33(7): 1455-1460.

Mathew, S., 2006. Wind energy: fundamentals, resource analysis and economics, Springer Verlag.

Mekhilef, S., R. Saidur and A. Safari, 2011. "A review on solar energy use in industries." Renewable and Sustainable Energy Reviews, 15(4): 1777-1790.

Mosetti, G., C. Poloni and B. Diviacco, 1994. "Optimization of wind turbine positioning in large windfarms by means of a genetic algorithm." Journal of Wind Engineering and Industrial Aerodynamics, 51(1): 105-116.

Muller, S., M. Deicke and R.W. De Doncker, 2002. "Doubly fed induction generator systems for wind turbines." Industry Applications Magazine, IEEE, 8(3): 26-33.

Poli, R., J. Kennedy and T. Blackwell, 2007. "Particle swarm optimization." Swarm intelligence, 1(1): 33-57.

Rahmani, R., M. Fard, A.A. Shojaei, M.F. Othman and R. Yusof, 2011. A complete model of stand-alone photovoltaic array in MATLAB-Simulink environment. Research and Development (SCOReD), 2011 IEEE Student Conference on.

Rahmani, R., A. Khairuddin, S.M. Cherati and H.A.M. Pesaran, 2010. A novel method for optimal placing wind turbines in a wind farm using particle swarm optimization (PSO). IPEC, 2010 Conference Proceedings, IEEE.

Safari, A. and S. Mekhilef, 2011. "Simulation and Hardware Implementation of Incremental Conductance MPPT With Direct Control Method Using Cuk Converter." Industrial Electronics, IEEE Transactions on 58(4): 1154-1161.

Yoshida, H., K. Kawata, Y. Fukuyama, S. Takayama and Y. Nakanishi, 2000. "A particle swarm optimization for reactive power and voltage control considering voltage security assessment." Power Systems, IEEE Transactions on, 15(4): 1232-1239.