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Improved PSO Algorithm based Optimal Operation in Power Systems Integrating Solar and Wind Energy Sources

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Abstract

This paper proposes an improved particle swarm optimization (PSO) algorithm for optimal operation of a power system including the solar and wind energy sources. The algorithm is to minimize operating costs of the hybrid power system. The proposed PSO algorithm is one of the standard PSO algorithm variants, which modifies the acceleration coefficients of the cognitive and social components in the velocity update equation of the PSO algorithm as linear time-varying parameters. The acceleration coefficients are varied during the evolution process of the PSO algorithm to improve the global search capability of particles in the early stage of the optimization process and direct the global optima at the end stage. Additionally, the inertia weight which is considered as a trade-off factor for the local and global search abilities of the PSO algorithm is also linearly decreased instead of a fixed constant value to improve its performance. The improved PSO algorithm based optimal operation of the hybrid power system with and without solar and wind powers is considered on a standard IEEE 30-bus 6-generator 41-transmission line test power system. The numerical results demonstrate the capabilities of the proposed algorithm to generate optimal solutions of a hybrid power system considering the solar and wind energy resources. The comparison with the standard PSO algorithm demonstrates the superiority of the proposed algorithm and confirms its potential to optimize the operating costs of the hybrid power system.

Keywords: *Optimal operation, hybrid power systems, particle swarm optimization algorithm*

1. Introduction

Energy crisis and climate change is recently interested by many countries in the world. The research moving towards renewable energy can solve these problems. Compared to conventional fossil fuel energy sources, renewable energy sources have the following major advantages: they are sustainable, never going to run out and non-polluting. Renewable energy is energy generated from renewable natural resources such as solar irradiation, wind, tide, wave, *etc*. Amongst these sources, solar and wind energy sources have received the considerable attention and are widely used. The two power sources are connected with the traditional power system to form a hybrid solar wind power system to meet the total load demand and to ease the supply burden of the traditional power system. Then, the operation strategy will be modified in the power system. The optimal operation is one of the important problems which is to decide the amount of generation so that the total cost of generation is minimal without violating system constrains.

However, the hybrid power system obviously depends on the climate conditions such as the solar irradiation, temperature and wind speed. The uncertainty and variation of the renewable energy sources create challenges in the optimal operation problem. This paper presents a methodology to treat powers of the renewable sources as negative loads.

There have been researches using various methodologies and algorithms to solve the optimal operation problem [1]-[12]. Chakraborty *et al.*, introduced an advanced quantum

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evolutionary algorithm to perform the intelligent operation problem [2]. Arriagada *et al.*, proposed a methodology to model and solve this problem incorporating renewable energies through Normal, Weibull, Beta and Uniform distributions for demand, wind speed, solar irradiation and unavailability respectively. In order to define the optimal power allocation for each generator, the Group SO orthogonal matrices, the marginal costs of the generators, the customer damage cost and Monte-Carlo trials are also presented [3]. Hoke *et al.*, applied a fast and reliable linear programming approach to the problem of grid-tied micro-grids containing conventional generators, energy storage, demand response resources and renewable energy resources [4]. Kumar *et al.*, and Bhuvaneswari presented various evolution programming techniques for solving the problem in a power system along with uncertainties in the renewable energy resources [5-6]. Additionally, a genetic algorithm, a dynamic programming technique, a reduced gradient method, a cuckoo search algorithm and an improved hopfield neural network have been proposed to solve this problem [7-12].

This paper proposes an improved PSO algorithm for the optimal operation problem of a hybrid power system including the solar and wind energy sources. The algorithm is to minimize the operating costs of the standard IEEE 30-bus 6-generator 41-transmission line test power system.

The remainder of this paper is organized as follows. The objective function and constraints of the optimal operation problem of the hybrid power system including the solar and wind energy sources are described in Section 2. A novel proposal using an improved PSO algorithm for the problem is presented in Section 3. The numerical results on the standard IEEE power system then follow to confirm the validity of the proposed application in Section 4. Eventually, the advantages of the novel application are summarized through comparison with another existing approach.

2. Optimal Operation of Hybrid Power Systems

This optimal operation problem is to minimize the fuel cost. The solar and wind energy resources depend on the atmospheric conditions such as the solar irradiation, temperature and wind speed. Their uncertainty and variation form difficulties in the problem including these resources.

In order to solve these difficulties, this paper treats the solar and wind powers as a negative load and formulates the actual load demand on the total load demand. Then, the objective function and constraints of the optimal operation problem are described as follows.

2.1. Objective Function

The objective function of the optimal operation problem is the fuel cost function given by:

$$F_f\left(P_{Gi}\right) = \sum_{i=1}^{N_G}\left(a_i + b_i P_{Gi} + c_i P_{Gi}^2\right) \tag{1}$$

where

$F_f\,(P_{Gi})$: the fuel cost function (\$/h);

a_i, b_i and c_i: the appropriate cost coefficients for individual generating units;

P_{Gi}: the real power of the i^{th} generator (p.u);

N_G: the total number of generators.

2.2. Constraints

The main constraints of the optimal operation problem are described as follows:

- The total power generation must cover the actual load demand and the power loss in transmission lines to ensure the power balance.

$$P_D^a + P_L - \sum_{i=1}^{N_G} P_{Gi} = 0 \tag{2}$$

where

P_{Da}: the actual load demand (p.u);

P_L: the transmission power loss (p.u).

The actual load demand is given by:

$$P_D^a = P_D^t - (P_s + P_w) \tag{3}$$

where

P_{Dt}: the total load demand (p.u);

P_s: the solar power (p.u);

P_w: the wind power (p.u).

The transmission power loss is given as follows:

$$P_L = \sum_{m=1}^{N_b} \sum_{n=1}^{N_b} \begin{bmatrix} \left(\dfrac{r_{mn}}{V_m V_n}\right) \cos(\delta_m - \delta_n)(P_m P_n + Q_m Q_n) + \\ \left(\dfrac{r_{mn}}{V_m V_n}\right) \sin(\delta_m - \delta_n)(Q_m P_n - P_m Q_n) \end{bmatrix} \tag{4}$$

where

r_{mn}: the series resistance connecting between buses m and n (p.u);

V_m and V_n: the voltage magnitudes at buses m and n (p.u);

δ_m and δ_n: the voltage angles at buses m and n (p.u);

P_m and Q_m: the active and reactive powers at bus m (p.u);

P_n and Q_n: the active and reactive powers at bus n (p.u);

N_b: the total number of buses.

- The dispatched amount of the solar and wind powers is limited to a part, η of the actual load demand.

$$(P_s + P_w) \le \eta \times P_D^a \tag{5}$$

- The generated real power of i^{th} unit is restricted by the lower limit, P_{Gimin} (p.u) and the upper limit, P_{Gimax} (p.u).

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, \; i = 1, 2, \ldots, N_G \tag{6}$$

- The active power loss of transmission lines is positive.

$$P_L > 0 \tag{7}$$

In order to confirm the effectiveness of the solar and wind energy sources in the hybrid power system, the reduction percentage in the fuel cost with and without the renewable energy sources is given by:

$$\Delta C = \left(1 - \frac{F_{fR}}{F_{fN}}\right) \times 100 \tag{8}$$

where

ΔC: the reduction percentage in the fuel cost (%);

F_{fR} and F_{fN}: the fuel cost with and without the renewable energy sources ($/h).

3. Improved PSO Algorithm based Optimal Operation Problem

The PSO algorithm is reviewed in the section 3.1 followed by a description of the improved PSO algorithm.

3.1. PSO Algorithm

The particle swarm optimization (PSO) algorithm is a population-based stochastic optimization method which was developed by Eberhart and Kennedy in 1995 [13]. The algorithm was inspired by the social behaviors of bird flocks, colonies of insects, schools of fishes and herds of animals. The algorithm starts by initializing a population of random solutions called particles and searches for optima by updating generations through the following velocity and position update equations.

The velocity update equation:

$$\boldsymbol{v}_i(k+1) = w\boldsymbol{v}_i(k) + c_1 r_1(\boldsymbol{pbest}_i(k) - \boldsymbol{x}_i(k)) + c_2 r_2(\boldsymbol{gbest}(k) - \boldsymbol{x}_i(k)) \tag{9}$$

The position update equation:

$$\boldsymbol{x}_i(k+1) = \boldsymbol{x}_i(k) + \boldsymbol{v}_i(k+1) \tag{10}$$

where

$\boldsymbol{v}_i(k)$: the k^{th} current velocity of the i^{th} particle;

$\boldsymbol{x}_i(k)$: the k^{th} current position of the i^{th} particle;

k: the k^{th} current iteration of the algorithm, $1 \le k \le n$;

n: the maximum iteration number;

i: the i^{th} particle of the swarm, $1 \le i \le N$;

N: the particle number of the swarm.

Usually, v_i is clamped in the range [$-v_{max}$, v_{max}] to reduce the likelihood that a particle might leave the search space. In case of this, if the search space is defined by the bounds [$-x_{max}$, x_{max}] then the v_{max} value will be typically set so that $v_{max} = mx_{max}$, where $0.1 \le m \le 1.0$ [14].

$pbest_i$(k): the best position found by the i^{th} particle (personal best).

$gbest(k)$: the best position found by a swarm (global best, best of the personal bests).

c_1 and c_2: the acceleration coefficients called cognitive and social parameters respectively; the c_2 regulates the step size in the direction of the global best particle and the c_1 regulates the step size in the direction of the personal best position of that particle; c_1 and $c_2 \in [0, 2]$.

With large cognitive and small social parameters at the beginning, particles are allowed to move around a wider search space instead of moving towards a population best. Additionally, with small cognitive and large social parameters, particles are allowed to converge to the global optima in the latter part of optimization [14].

r_1 and r_2: the two independent random sequences which are used to effect the stochastic nature of the algorithm, r_1 and $r_2 \in$ U(0, 1) [14].

w: the inertia weight [14]. This value was set to 1 in the original PSO algorithm [13]. Shi and Eberhart investigated the effect of w values in the range [0, 1.4] [15], as well as in a linear time-varying domain. Their results indicated that choosing $w \in$ [0.9, 1.2] results in a faster convergence. A larger inertia weight facilitates a global exploration and a smaller inertia weight tends to facilitate a local exploration [16]. Thus, the balance of the inertia weight, w during the evolution process of the PSO algorithm is necessary. This improves the convergence capability and search performance of the algorithm.

Applying the PSO algorithm for the optimal operation problem, the i^{th} particle is represented as the optimal real power, P_{Gi} generated from the hybrid power system. The best position found for the i^{th} particle is represented as $\{pbestP_{Gi}\}$. The rate of the position change, which is the velocity for the i^{th} particle, is represented as $\{v_{PGi}\}$. The best position found by the swarm is represented as $\{gbestP_G\}$. The objective function (1) plays the important role in searching the best position for the i^{th} particle and the best position of the swarm. The position and velocity of the i^{th} particle are updated using (9)-(10). In this application, the initial positions and velocities of the i^{th} particle are random sequences; the inertia weight, w is set to 0.9; the cognitive and social parameters, c_1 and c_2 are set to 2; the two independent random sequences, r_1 and r_2 are uniformly distributed in U(0, 1).

It is obvious that the PSO algorithm is one of the simplest and most efficient global optimization algorithms, especially in solving discontinuous, multimodal and non-convex problems. However, for local optima problems, the particles sometimes become trapped in undesired states during the evolution process which leads to the loss of the exploration abilities. Because of this disadvantage, premature convergence can happen in the PSO algorithm which affects the performance of the evolution process. This is one of the major drawbacks of the PSO algorithm. In order to improve the performance of the PSO algorithm, the variant of the PSO algorithm, known as the improved PSO algorithm is presented in the next section.

3.2. Improved PSO Algorithm

An improved PSO is one of the PSO algorithm variants which was introduced in [17] with the time-varying acceleration coefficients of the cognitive and social components as well as the time-varying inertia weight. For most of the population-based optimization techniques, it is desirable to encourage the individuals to wander through the entire search space without clustering around local optima during the early stages of the optimization, as well as being important to enhance convergence towards the global optima during the latter stages [17]. The acceleration coefficients of the cognitive and social components in the velocity update equation are one of the parameters which help the algorithm to satisfy the requirements above in the early and latter stages. The modification of the acceleration coefficients is to improve the global search capability of the particles in the early stage of the optimization process. The algorithm then directs particles to the global optima at the end stage so that the convergence capability of the search process is enhanced. To achieve this, large cognitive and small social parameters are used at the beginning and small cognitive and large social parameters are used at the latter stage. The mathematical representation of this modification is given as follows [17]:

$$\boldsymbol{v}_i(k+1) = w(k)\boldsymbol{v}_i(k) + c_1(k)r_1(\boldsymbol{pbest}_i(k) - \boldsymbol{x}_i(k)) + c_2(k)r_2(\boldsymbol{gbest}(k) - \boldsymbol{x}_i(k)) \tag{11}$$

where

$$c_1(k) = \left(c_{1final} - c_{1initial}\right) \times \frac{k}{n} + c_{1initial} \tag{12}$$

$$c_2(k) = \left(c_{2final} - c_{2initial}\right) \times \frac{k}{n} + c_{2initial} \tag{13}$$

$c_1(k)$ and $c_2(k)$: the time-varying acceleration coefficients of the cognitive and social parameters;

$c_{1initial}$ and c_{1final}: the initial and final values respectively of the cognitive parameter;

$c_{2initial}$ and c_{2final}: the initial and final values respectively of the social parameter.

Additionally, the inertia weight is also linearly decreased instead of a fixed constant value given by:

$$w(k) = \left(w_{final} - w_{initial}\right) \times \frac{k}{n} + w_{initial} \tag{14}$$

$w(k)$: the time-varying inertia weight;

$w_{initial}$ and w_{final}: the initial and final values respectively of the inertia weight.

The improved PSO algorithm is applied for the optimal operation problem of hybrid power systems. The position and velocity of the i^{th} particle are updated using (10) and (11) respectively. The velocity update equation uses the time-varying acceleration coefficients. The coefficient, $c_1(k)$ is set to decrease linearly during a run with $c_{1initial}$ = 2.5 and c_{1final} = 0.5 whereas the coefficient, $c_2(k)$ is set to increase linearly with $c_{2initial}$ = 0.5 and c_{2final} = 2.5. Thus, the cognitive parameter is large and the social parameter is small at the beginning. This enhances the global search capability in the early part of the optimization process. Then, the cognitive parameter is decreased linearly and the social parameter is increased linearly until at the end of the search, the particles are encouraged to converge towards the global optima with small cognitive and large social parameters. Furthermore, the inertia weight is started with a large value of 0.9 and linearly decreased to 0.4 that will lead to a better performance. When the inertia weight is small, the PSO algorithm behaves like a local search algorithm. Conversely, when the inertia weight is large, the PSO algorithm behaves like a global search algorithm. This also means that a larger inertia weight facilitates a global exploration and a smaller inertia weight tends to facilitate a local exploration [18].

These modifications improve the evolution process performance and overcome the premature convergence of the PSO algorithm. The initial positions and velocities of the i^{th} particle are initialized as random sequences which are the optimal real powers, P_{Gi} generated from the hybrid power system. These parameters are updated using (10) and (11) with the velocity vector, $\{v_{PGi}\}$. In this application, the two independent random sequences, r_1 and r_2 are uniformly distributed in U(0, 1).

The flow chart of the improved PSO algorithm in the optimal operation problem of the hybrid power system integrating the solar and wind energy sources is described in Figure 1.

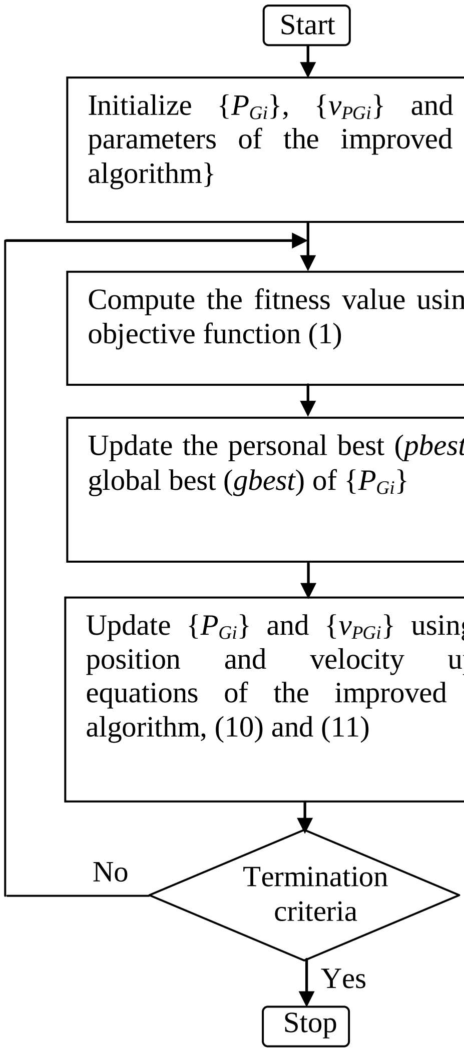

Figure 1. Flow Chart of the Improved PSO Algorithm in the Optimal Operation Problem of the Hybrid Power System

4. Numerical Results

The numerical results of the optimal operation problem are performed on the standard IEEE 30-bus 6-generator 41-transmission line test power system, Figure 2 using the proposed PSO algorithm. The fuel cost coefficients of the 6 generators in this power system are given in Table 1 [19].

Table 2 is the total load demand, the solar power and the wind power generated in day and night of 24 hours of the hybrid power system. Figure 3 shows the actual load demand of the hybrid power system.

Table 3 presents the result of the best fuel cost obtained by the PSO and improved PSO algorithms. It can be realized that the fuel cost of the power system with the renewable energy sources, F_{fR} is always less than that without the renewable energy sources, F_{fN} as in Figures 4-5. This confirms the advantages of the power systems with the renewable energy sources such the solar and wind energy sources. In the periods of 8-12 hours and 12-18 hours, the total power of the solar and wind energy generators is 0.3 (p.u) which is a largest value in day and night of 24 hours. Thus, the reduction percentages in the fuel cost with and without the renewable energy sources are high, 29.15% by using the PSO algorithm and 33.50% by using the improved PSO algorithm at the total load demand of 2.8 (p.u); and 24.15% by using the PSO algorithm and 27.90% by using the improved

PSO algorithm at the total load demand of 1.7 (p.u), Figure 6. These results show that the generation burden of the traditional fossil energy sources is significantly reduced through using the renewable energy sources such as the solar and wind energy sources. Basically, the total generation cost of the hybrid power systems including the solar and wind energy sources is always less than the traditional power systems of the fossil energy sources. The minimum and maximum reduction percentages are 9.73% and 29.15% with the PSO algorithm while these values are 13.80% and 33.50% with the improved PSO algorithm.

Furthermore, the results obtained show that the improved PSO algorithm is always better than the PSO algorithm in the optimal operation problem of the hybrid power system, Table 3 and Figure 6. The improvement percentages are 4.07%, 3.50%, 4.35%, 3.76% and 4.66% at the actual load demand, 0.5 (p.u), 0.9 (p.u), 2.5 (p.u), 1.4 (p.u) and 0.95 (p.u), respectively by using the improved PSO algorithm. This means that the proposed algorithm overcomes the premature convergence disadvantage of the PSO algorithm which becomes stuck in a local optimum during the search process.

Table 1. Fuel Cost Coefficients

G_i	a_i	b_i	c_i	P_{Gi}^{min} (p.u)	P_{Gi}^{max} (p.u)
1	10	200	100	0.05	0.50
2	10	150	120	0.05	0.60
3	20	180	40	0.05	1.00
4	10	100	60	0.05	1.20
5	20	180	40	0.05	1.00
6	10	150	100	0.05	0.60

Table 2. Total and Actual Load Demands in Day and Night of 24 Hours

t (h)	P_D^t (p.u)	P_s (p.u)	P_w (p.u)	$P_s + P_w$ (p.u)	P_D^a (p.u)
0-5	0.6	0.005	0.095	0.1	0.5
5-8	1.1	0.05	0.15	0.2	0.9
8-12	2.8	0.2	0.1	0.3	2.5
12-18	1.7	0.1	0.2	0.3	1.4
18-24	1.2	0.05	0.2	0.25	0.95

Table 3. Best Fuel Cost using the PSO and improved PSO Algorithms without and with the Solar and Wind Energy Sources

P_D^a (p.u)	Algorithm	Best cost, F_{fN}($/h)	Best cost, F_{fR}($/h)	ΔC (%)	Improve-ment (%)
0.5	PSO	151.60	136.85	9.73	**4.07**
	Improved PSO	151.52	130.62	13.80	
0.9	PSO	225.05	180.22	19.92	**3.50**
	Improved PSO	219.75	168.27	23.42	
2.5	PSO	534.93	379.02	29.15	**4.35**
	Improved PSO	533.72	354.94	33.50	
1.4	PSO	320.14	242.84	24.15	**3.76**
	Improved PSO	317.59	228.97	27.90	
0.95	PSO	232.72	183.27	21.25	**4.66**
	Improved PSO	228.62	169.38	25.91	

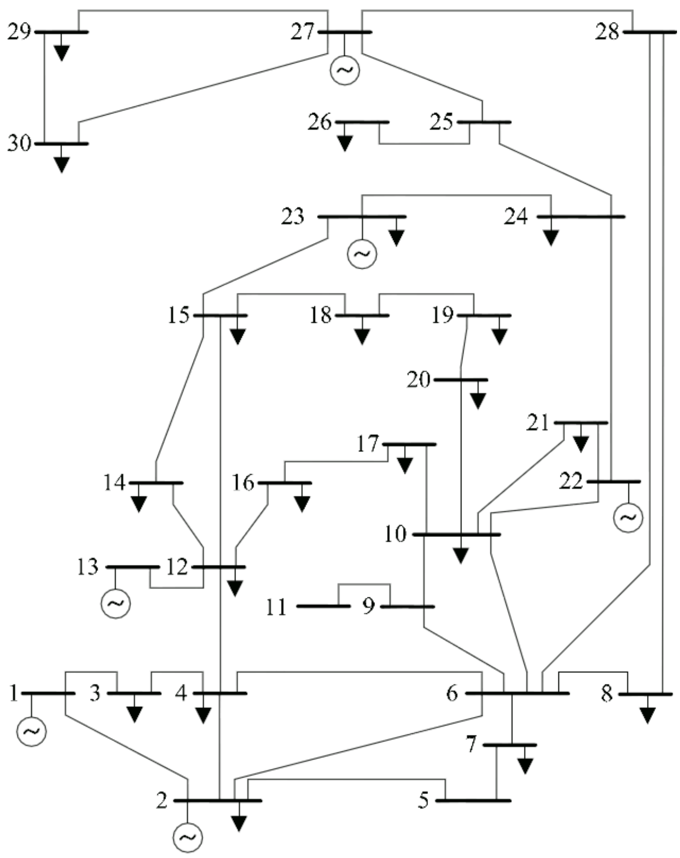

Figure 2. IEEE 30-bus 6-generator 41-transmission Line Test Power System

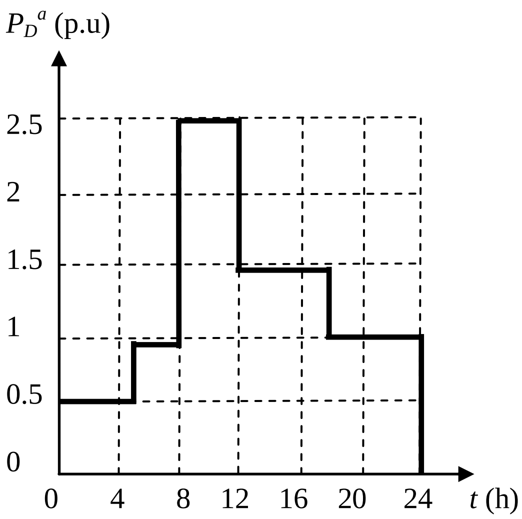

Figure 3. Actual Load Demand

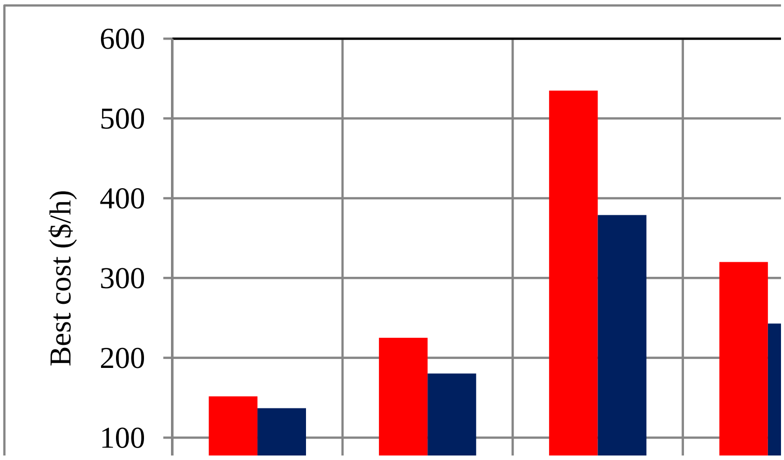

Figure 4. Variations of Fuel Cost with the PSO Algorithm

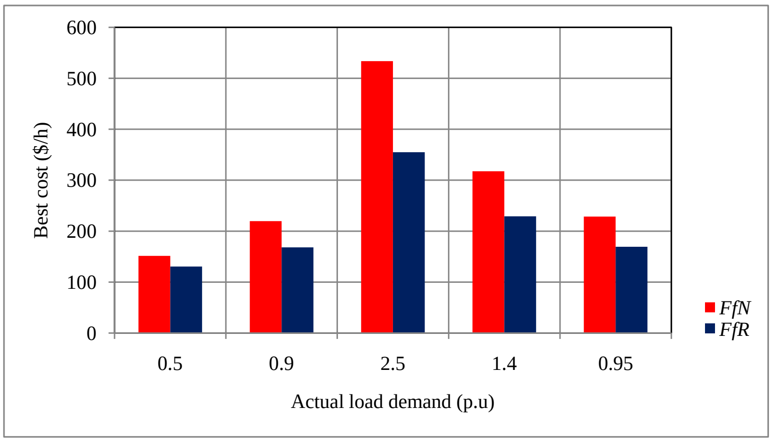

Figure 5. Variations of Fuel Cost with the Improved PSO Algorithm

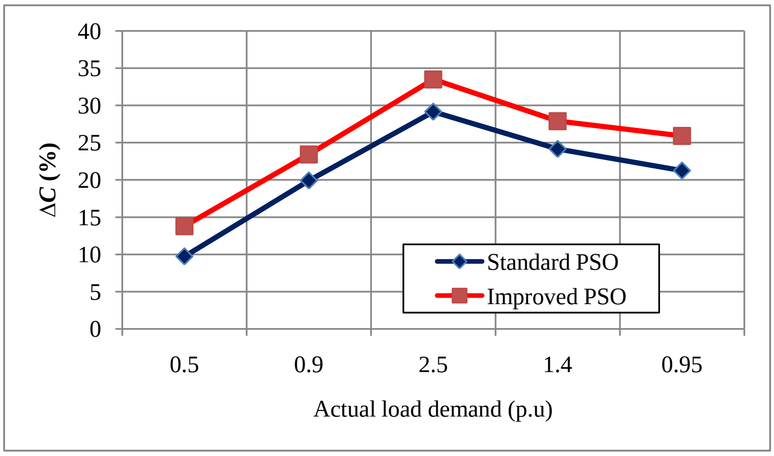

Figure 6. Variation of the Percentage Reduction with the PSO and improved PSO Algorithms

5. Conclusion

In this paper, a novel application based on the improved PSO algorithm has been proposed to solve the optimal operation problem of the hybrid power system including the solar and wind energy sources. The problem has been formulated to minimize the fuel cost. The generated powers of the solar and wind energy sources are treated as a negative load to form the actual load demand on the total load demand. The improved PSO algorithm modifies the acceleration coefficients of the cognitive and social components as well as the inertia weight in the velocity update equation of the PSO algorithm as linear time-varying parameters. The improved PSO algorithm is always better than the PSO algorithm. The proposed algorithm overcomes the premature convergence disadvantage of the PSO algorithm which becomes stuck in a local optimum during the search process. The fuel cost of the power system with the renewable energy sources is always less than that without these sources. Obviously, the efficient utilization of the renewable energy sources supports to reduce the fuel cost of the power system.

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