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Particle Swarm Optimization Technique for Equalization of EV Load with Variable Wind Power Generation

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Abstract

Objectives: An Electric Vehicle (EV) charging station supplies electrical energy for the charging of Electric Vehicles. As the plug-in hybrid electric vehicle is expanding, there is a growing need for widely distributed publicly accessible charging stations. This paper defines Optimization method for equalize/match charging schedule of Electric vehicle with dynamic wind power availability. **Methods/Statistical Analysis**: Optimal charging cost and average running time are the major considerable constraints at equalization of dynamic wind power with EV load. Depending upon the remaining parking time, the EVs are aggregated to reduce the size of the problem. The proposed model innovatively incorporates the degree of equalization between EV charging load and Wind power into the objective function. Estimation of EV parking time affects the charging schedule, so it is a considerable factor for optimization. **Findings:** Particle Swarm Optimization (PSO) technique can optimize/reduce the scheduling problems and it can equalize dynamic behavior of wind power generation with respect to EV loads. **Applications/Improvements:** Computational efficiency and the average running time show the validation of the proposed technique.

Keywords: Electric vehicle, Particle Swarm Optimization (PSO), Smart Grid, Wind Power Generation (WPG)

1. Introduction

Now a day's world power utilization increases rapidly, to meet this growing power utilization the consumption of fossil fuel is increases. To preserve fossil fuels for future generations renewable power generation is the best alternative. Due to this the research was increasing in this area to maximize power generation from available sources. Among all renewable power generations wind power generation plays an important role due to its cleanness and high power generation capability[1]. Due to the dynamic behavior of wind the power generation is not in steady case, to make wind generation satisfactory different types of generators and turbine control methods are utilizing. And another way is load dispatching and load scheduling based on availability of generation. For this the analysis of wind power generation and availability of Battery Energy Storage System[2] (BESS), the generated power is fed to BESS than load is applied on it. Here the rating of battery required to build BESS system is high due to this it is not economical. Another way is making utility as a smart grid; in this the Management of loads[3] based on supply attributes is done.

Among all types of controllable loads EV is one of the most considerable loads due to its greater variableness in terms of charging. The proposed method can defines reduces the deviation in between load and wind generation in the sense of charging cost minimization. From past few years research have been done to reduce the cost of EV charging[4]. But till now some problems are facing in coordination of renewable energy sources with EV load. The problems can be raised due to dynamic behavior of wind at its source side and variable loading of EV, i.e., EV loading profile changes due to lack of information about

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vehicles[5] arriving, departure, parking time and no. of vehicles that are coming so on. To minimize uncertainties in EV scheduling, PSO can used. The PSO is a global optimization approach[6] for the management of energy which leads to the minimization of energy cost. To get a result for the direct application of the method in real-time control PSO is used. The main contributions are:

- To inventively join the coordinating degree amongst demand and supply into the objective function to get adaptable adjusting.
- The PSO methodology is proposed to upgrade the normal running time for every decision phase of the method and expand the limit of EV.

2. System Design

2.1 Basic System Analysis

Basically source consist of conventional and non-conventional energy sources, these are in grid connected mode. Due to this let us consider source consist wind and non-renewable power sources, system schedule controller (PSO controller), time aggregator and Electrical vehicles these can be shown in Figure 1[7].

The time aggregator is said to be the virtual agent for the EVs parked at that instant. The EVs with a similar remaining parking time are grouped into a similar set. As a result of the completely diversified driving nature of the EVs, the quantity of the aggregators is dependent on time. We consider the unconstrained matching problem on the basis of phases which are divided into 24. Every phase is 1 hour. Similarly this method can be applied for all type of phases. To overcome this problem PSO technique s used. PSO is an effective tool for solving unconstrained optimization problem. The details of this method and the respective elements of the technique PSO, e.g., fitness function, modeling of constraints and objective function are detailed in this section.

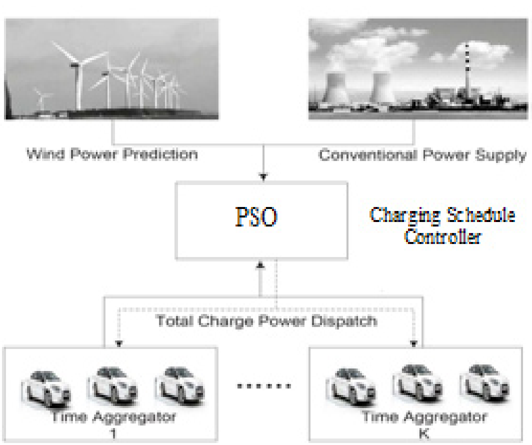

Figure 1. Basic structure of the system.

2.2 PSO based Schedule Control

The main intention is to present a PSO global optimization approach for management of energy which leads to the minimization of energy cost and to obtain minimum average running time in real-time control. Since the PSO optimization variables are parameters[8,9] of the rule-based method. This scheme can be used online also as the scheme no longer relies on a priori driving cycles after the offline optimization process is completed. The best ideal control execution which is used to conduct the PSO algorithm[10] will be achieved by the scheme of Energy Management.

3. Methodology Implementation

3.1 Fitness Function

In this theory, the performance of each particle is estimated by using the fitness function which is considered to be the objective function, through which a PSO can be assigned to the control variables of EV. However, as PSO is directly applicable only to unconstrained optimization problem, the driving performance requirements[11] are considered as constant.

3.2 Modelling of Constraints

Here, the system state is stated as $S_t = [W_t, P_t^i, C_t^i]$, where t = 1,2…T denotes phases with T=24, i=1,2…N indicates the EV number, P_t^i denotes the remaining parking time, C_t^i is the required energy to be charged for the i_{th} number of EV at the initial phase t, W_t is the wind power generated at phase t is calculated using the Equation (10). P_t^i and C_t^i are stated as follows:

$$(P_t^i, C_t^i) = \begin{cases} (P_t^i > 0, C_t^i \geq 0), & \text{if } J_i(t) = 1 \\ (P_t^i = 0, C_t^i = 0), & \text{if } J_i(t) = 0 \end{cases} \quad (1)$$

Where $J_i(t) = 1$ if the i_{th} EV is parking at phase t, otherwise $J_i(t) = 0$

3.3 Charging Energy Constraints:

$$0 \le C_t^i \le B_{cap}$$
$$0 \le C_t^i \le P \cdot P_t^i \quad (2)$$

Where Equation (2) indicates the required energy to be charged for every EV must not be more than the capacity of battery B_{cap} (60KWh). Equation (2) indicates the required energy to be charged must not be more than the maximum energy at the remaining parking times. P indicates the constant charging power (3 KW)

3.4 EV Charging Load Constraint

$$P_t^{EV} = P \cdot \sum_{i=1}^{N} Z_t^i \quad (3)$$

Where P_t^{EV} indicates the entire EV charging power at phase t, it is scheduled to meet the uncertain wind energy. Z_t^i is the binary variable that indicates whether the EV is at the charging point or not.

3.5 Thermal Power Supply Constraint

$$P_t^{Gen} = max(P_t^{EV} - W_t, \quad 0)$$
$$0 \le P_t^{Gen} \le \overline{P}_t^{Gen} \quad (4)$$

Where P_t^{Gen} indicates the power generated by the thermal station, it is used when the wind energy is insufficient for the charging of EV. $\overline{P}_t^{Gen}$ is the maximum power generated by the thermal power plant.

3.6 Objective Function

EV charging load is to be scheduled to equalize the availability of wind energy, a factor is introduced to provide the equalization between supply and demand

$$M_t = 1 - \frac{|W_t - P_t^{EV}|}{max(W_t - P_t^{EV})} \quad (5)$$

The above factor is included into the objective function to get the optimal equalization between wind power and charging load of EV[12].

Optimization objective considered is defined as follows:

$$C_t(S_t, A_t) = (1 - \lambda)\frac{W_t - P_t^{EV}}{max(W_t - P_t^{EV})} + \lambda . \beta_t . max(P_t^{EV} - W_t, 0) \quad (6)$$

Where λ the weighting factor is at all phases *t*. The impact of the high wind power is reduced with small λ. The cost of the charging is reduced with large λ when the wind power is less.

3.7 PSO Algorithm

Particle Swarm Optimization (PSO) was developed by James Kennedy and Russell Eberhart. In the PSO algorithm, position and speed of every particle are the two variables. Here in this case, the particles i.e., Electric Vehicles will move to the next position from the current position with respect to their current speed. The speed of the particle is decided with respect to the positions of the particle swarm i.e., best position of this particle and the best position of the entire possible particles of the system. Here, every particle speed is expressed as V = [v1, v2, v3, v4] T. At every iteration time, w is linearly changed from w_{max} (here, is 1.2) to w_{min} (here, is 0.1) in keeping with the constant factor k and repetitive method of every particle's position and speed are operated by the below Equations. After 100 iterations as mentioned, the particles are converged at the best point.

$$V_i^{k+1} = \begin{pmatrix} V_{i1}^{k+1} \\ V_{i2}^{k+1} \\ V_{i3}^{k+1} \\ V_{i4}^{k+1} \end{pmatrix} = W(k)\begin{pmatrix} V_{i1}^{k} \\ V_{i2}^{k} \\ V_{i3}^{k} \\ V_{i4}^{k} \end{pmatrix} + C_1 r_1(k) * \left(\begin{pmatrix} P_{i1}^{k} \\ P_{i2}^{k} \\ P_{i3}^{k} \\ P_{i4}^{k} \end{pmatrix} - \begin{pmatrix} X_{i1}^{k} \\ X_{i2}^{k} \\ X_{i3}^{k} \\ X_{i4}^{k} \end{pmatrix}\right) + C_2 r_2(k)\left(\begin{pmatrix} g_{i1}^{k} \\ g_{i2}^{k} \\ g_{i3}^{k} \\ g_{i4}^{k} \end{pmatrix} - \begin{pmatrix} X_{i1}^{k} \\ X_{i2}^{k} \\ X_{i3}^{k} \\ X_{i4}^{k} \end{pmatrix}\right) \quad (7)$$

$$X_i^{k+1} = \begin{pmatrix} X_{i1}^{k+1} \\ X_{i2}^{k+1} \\ X_{i3}^{k+1} \\ X_{i4}^{k+1} \end{pmatrix} = X_i^k + V_i^{k+1} = \begin{pmatrix} X_{i1}^{k} \\ X_{i2}^{k} \\ X_{i3}^{k} \\ X_{i4}^{k} \end{pmatrix} + \begin{pmatrix} V_{i1}^{k+1} \\ V_{i2}^{k+1} \\ V_{i3}^{k+1} \\ V_{i4}^{k+1} \end{pmatrix} \quad (8)$$

Step 1: Initial conditions.

The particle swarm scale is initialized to a variable M = 100 and the maximum number of iteration times is initialized to N = 100. At the given boundary intervals, the positions of particles are selected accordingly and the speed is initialized to zero.

Step 2: Fitness function calculation.

Calculate the fitness function for every particle based on the rule-based method and then note the personal best time of every particle, it is denoted as $P_1^0 \ldots\ldots P_M^0$, the best among all the possible positions are selected as the best position of the entire particles G^0.

Step 3: Assign the feasible points.

Using the above equations, the position of every particle $X_1^k, \ldots, X_M^k$ and their velocity $V_1^k \ldots V_M^k$ are calculated from the second iteration. And at every iteration time, the fitness function is calculated and the best position of the particle $P_1^k \ldots P_M^k$ and the best position of the entire particles of the system G_i^k are noted according to:

$$P_i^k = \left\{X_i^* \middle| f(X_i^*) = \min\left[f(X_i^0), f(X_i^1), \ldots, f(X_i^k)\right]\right\} \quad (9)$$

$$G_i^k = \left\{P_M^* \middle| f(P_M^*) = \min\left[f(P_M^0), f(P_M^1), \ldots, f(P_M^k)\right]\right\} \quad (10)$$

Step 4: Final improvement.

When the iteration time reaches the maximum number of iteration times N, the PSO algorithm is stopped.

3.8 CRN and EV Aggregation

To reduce the average running time, the Common Random Number can be used for every activity. The CRN is utilized to think about the execution difference of various designs[13]. The fundamental thought is to produce a typical arrangement of test paths for all the activity assessment.

At every phase t, watching the present state St, the rollout technique would assess all the possible activities to get the ideal activity. At the point of N stopped EVs holding up to be charged, there will be 2^N activities to be assessed. The activity space 2^N will increment exponentially with the size of the Electric Vehicle number. The large activity space will make it unmanageable to execute PSO technique to the stochastic coordinating issue. To defeat these challenges, EV aggregation[14] is utilized. Here, we group the EVs by the parking time remained as in Figure 1. On grouping the EVs the activity space gets reduced. The choice of charging EV is ensured at the point when the aggregator gets the required power to be charged.

4. Results Analysis

In this section, the wind power generation data and the electric vehicle parking schedules are considered for further analysis. To verify the effectiveness of the computation of the PSO algorithm a numerical case is considered.

4.1 Statistical Data Analysis

The wind power generation purely depends on wind speed availability[15]. Figure 2 shows the histogram and

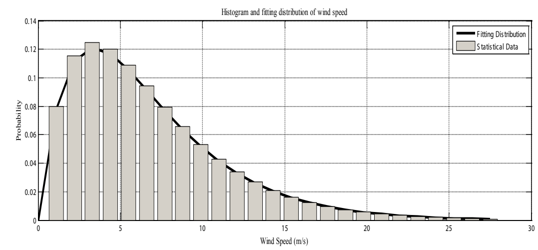

Figure 2. Histogram and fitting distribution of wind speed.

fitting distribution of the wind speed. Speed of the wind[16] is measured on hourly basis and it is used as an input to PSO. The probability distribution of the wind speed is set using Weibull distribution[17]. Here, the wind speed data is considered from the Wind Technology Centre from 2016 January to March on hourly basis. Figure 3 Shows Histogram and fitting distribution of trip driving distance is used to analyze EV parking time and running status. i.e., arriving time and departure time of the vehicle details respectively.

Every parking event is noted by its arriving time and duration of parking. This parking duration depends on the arriving time of the parking vehicle. It is assumed that the duration of parking for every parking vehicle follows the Gaussian distribution. The probability (Pt_{PK}) for the EV to park at time tand the mean (Micro(t)) and variance (Sigma(t)) value of Gaussian distribution analyzed are shown in Table 1.

4.2 Numerical Case

In order to show the performance of the applied strategies, we perform an experiment where the number of EVs is increased in ten replications from 100 to 1000. To solve the problem using PSO technique we select sample paths as 100 denoted as M_a. So that the randomness of the performance comparison is reduced.

EV charging policies

The base method used as:

$$\pi_1(1) = Z_t^i = \begin{cases} 1, & if\, E_t^i > 0 \\ 0, & otherwise. \end{cases} \quad (11)$$

$\pi_1(2)$: By using CRN and EV aggregation the method is enhanced and budget limits are not considered. Base method is compared with the enhanced method $\pi_1(2)$. All the EVs are considered where the average and standard deviation values are calculated[5]. M_{avg} indicates the matching factor and F represents the total charging cost of the EV. The matching factors of the both policies are

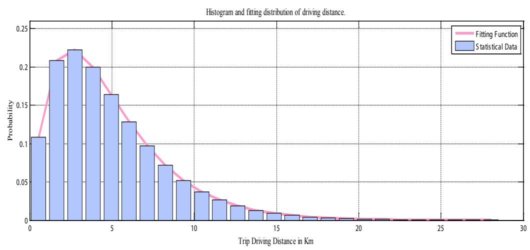

Figure 3. Histogram and fitting distribution of driving distance.

Table 1. Parameter setting of the parking event

Time(t)	$P_{t\,PK}$	Micro(t)	Sigma(t)	Time(t)	$P_{t\,PK}$	Micro(t)	Sigma(t)
1	0.0077	10.4602	3.3162	13	0.0059	5.2301	3.0217
2	0.0075	10.0244	3.2849	14	0.0055	4.7943	2.9565
3	0.0076	9.5885	3.2539	15	0.0049	4.3584	2.8292
4	0.0076	9.1527	3.2415	16	0.0048	3.9226	2.9193
5	0.0076	8.7169	3.2242	17	0.0047	3.4867	2.6687
6	0.0076	8.281	3.1867	18	0.0045	3.0509	2.8199
7	0.0075	7.8452	3.0768	19	0.0043	2.6151	2.8178
8	0.0073	7.4093	3.1161	20	0.0036	2.1792	2.1391
9	0.007	6.9735	3.005	21	0.0077	1.7434	2.4435
10	0.0067	6.5376	2.9676	22	0.0075	1.3075	2.6609
11	0.0064	6.1018	2.6024	23	0.0076	0.8717	2.3739
12	0.0061	5.666	2.9275	24	0.0076	0.4358	2.000

almost same but the only difference is the running time. The average running time for the enhanced method is better when compared to the basic method. Between two decision phases the average running time interval must not exceed the limits. Table 2 shows the performance of the basic method and enhanced method with λ = 0. The matching factor of enhanced method is better compared to basic method with increased values of standard deviation in all the cases. Table 3 shows the charging cost values with λ=1. From the both tables we understand that the charging of EV schedule matches with wind power generation. The λ is selected as 0 to reduce the high wind power impact, λ as 1 to reduce the cost of charging.

Figure 4 demonstrates the wind and EV energy to be charged for various charging methods on considering one sample path of equal amount of wind supply power. On comparing base method and the enhanced method the following points are observed.

- Equalizing factor between demand and supply is improved as the EV charging power follows the wind power[18].

Table 2. Performance of the method λ=0

Case N	Mavg1 (mean)	Mavg1 (std)	F1 (mean)	F1 (std)	Mavg2 (mean)	Mavg2 (std)	F2 (mean)	F2 (std)
100	0.5	0.5	321	085.7	0.5	0.6	162	285.5
200	0.5	0.6	831.6	083.7	0.5	0.6	694.4	279.1
300	0.5	0.6	1342.1	80.1	0.6	0.5	1226.9	266.9
400	0.5	0.6	1852.7	120.8	0.8	0.8	1759.3	402.6
500	0.5	0.7	2363.2	149.1	1	1	2291.8	497.1
600	0.6	0.7	2873.8	112.7	0.8	0.8	2824.2	375.7
700	0.6	0.8	3384.3	84.7	0.5	0.6	3356.7	282.2
800	0.8	0.8	3894.9	97.8	0.6	0.7	3889.1	326
900	0.8	0.8	4405.4	109.9	0.5	0.7	4421.6	366.2
1000	1	1	4916	122.9	0.5	0.8	4954	409.5

Table 3. Performance of the method λ=1

Case N	Mavg1 (mean)	Mavg1 (std)	F1 (mean)	F1 (std)	Mavg2 (mean)	Mavg2 (std)	F2 (mean)	F2 (std)
100	0.3	0.3	270	2.9	0.5	0.4	103	599.6
200	0.3	0.3	776.1	2.8	0.6	0.4	509.1	586
300	0.3	0.3	1282.2	2.7	0.6	0.4	915.2	560.5
400	0.4	0.4	1783.3	4	0.9	0.5	1321.3	845.4
500	0.5	0.5	2294.4	5	1.1	0.7	1727.4	1044
600	0.4	0.4	2800.6	3.8	0.9	0.5	2133.6	788.9
700	0.3	0.3	3306.7	2.8	0.6	0.4	2539.7	592.7
800	0.3	0.3	3812.8	3.3	0.7	0.4	2945.8	684.5
900	0.3	0.4	4318.9	3.7	0.5	0.5	3351.9	769
1000	0.3	0.4	4825	4.1	0.6	0.5	3758	860

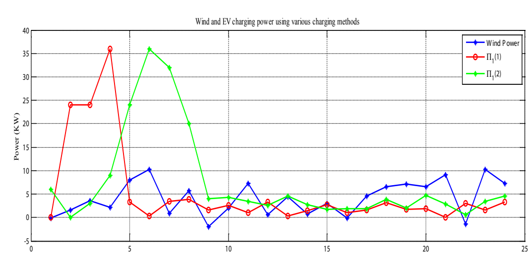

Figure 4. Wind and EV charging power using various charging methods. **(a)** Basic method $\pi_1(1)$. **(b)** Enhanced method $\pi_1(2)$.

- Wind power usage is incremented as the overall generated wind energy per day is 80KWh (approx.), where the wind per usage is 68KWh (approx.) for enhanced method and 45KWh (approx.) for basic method.

- The fluctuating effect on grid[19] is reduced as the equalizing factor between EV charging power and wind power is improved.

During the unavailability of wind energy supply, thermal power supply is utilized.

Time interval is one of essential limit in decision making. Figure 5 and 6 shows the required time for every decision phase in base and enhanced method, when making decision at a phase. It is seen that the running time increments directly with the EV number. The customary strategy may come up short in regards to running time in large scale issues due to the condemnation of dimensionality. Using PSO technique reduces the running time so it is better than the conventional method. The other factor considered in this paper is charging capacity of EV. Figure 7 depicts the fact that the PSO technique can maximize the charging capacity compared to other conventional methods. For instance, by totaling EVs (three aggregators), the quantity of activities lessens from 2^{100} to 7776 in the instance of N = 100. In this manner, our strategy spares huge average running time and enhances the efficiency.

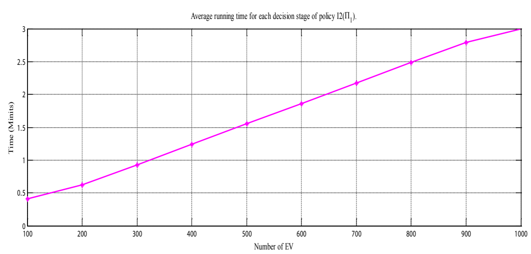

Figure 5. Required time for making decision at every phase using base method $\pi_1(1)$.

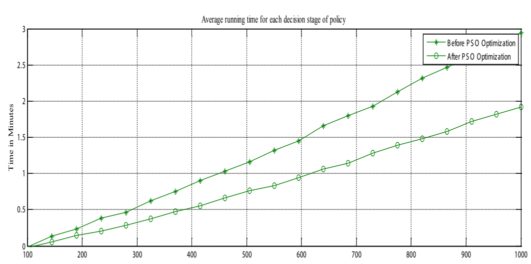

Figure 6. Required time for every decision phase of basic method and PSO technique.

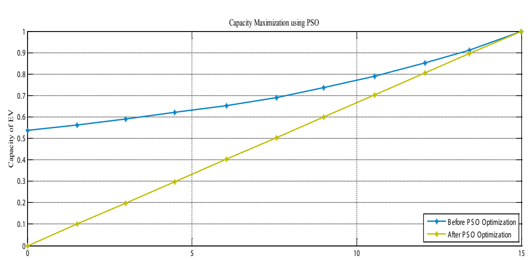

Figure 7. Charging capacity maximization using PSO.

5. Conclusion

It defines equalization/matching of EV load with stochastic wind power variations with minimized charging cost function. PSO is implementable directly only to unconstrained optimization problem. The dynamic behavior of wind source and EV load aggregation are taken to optimize scheduling. Based on the EV, Source status and cost of charging taking as a constraint, the iterative process is done to fetch optimal charging schedule (with in the required limit). The optimal charge scheduling can reduce cost of charging. Optimal charging schedule is based on size of EV load and reduced wind variations to grid. So, PSO technique is introduced to optimize load scheduling problems.

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