A PSO Based Control Strategy for Combined Emission Economic Dispatch with Integrated Renewables

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***Abstract* – Combined emission economic dispatch with the effective integration of renewable energy sources for a power system is a unique problem with various challenges. The increasing integration into the power grid of renewable energy sources (RES), such as wind and solar, is becoming more prevalent and this trend is expected to continue. However, the intermittent behaviour of these renewable energy sources poses a significant challenge for power systems in terms of dispatchability and the ability to maintain stable grid operation. We propose and implement a particle swarm optimization (PSO) based technique to control each independent region of a power system. The PSO control strategy will coordinate and schedule the renewable energy resources (wind and solar) and conventional generators for each region. A cost function is optimized, and the operating cost for the power system is calculated based on the fitness of each particle. All proposed strategies and algorithms are implemented using MATLAB and validated using the IEEE-39 bus system model.**

Index Terms – Wind and solar integration in grid, Particle swarm Optimization, Renewable energy sources, optimized cost function.

I. INTRODUCTION

In today's modern world the maximum reliability is still on fossil fuel resources such as coal, natural gas, and petroleum fuels, with these resources being the majority of the electrical energy production. Electrical energy has played a positive role in global change, but it also has a negative impact since it is the dominant source for local air pollution. The usage of these fossil fuel resources is causing a threat to the environment by increasing carbon dioxide emissions. The emissions from the fossil resources in the generation of electrical energy, which accounts for 63% of the total U.S electrical generation, have been held responsible for 99% of CO2 emission in 2018 [2]. The adverse effects of fossil fuel resources and scarcity have driven the need for renewable energy resources such as wind and solar, which are the best available resources. Solar contributed about 13.3% and wind about 36.8% of the total renewable production [5]. These two renewable resources play a vital role in reducing the dependency of fossil fuel resources for the generation of electrical energy. Wind plants are clean and cost-effective sources of renewable energy by reducing the greenhouse gases by 14% [4].

The integration of renewable energy sources into the system results in variability in active and reactive power support, which can result in instability in the power grid and requires a high ramp rate backup system [6-8]. The high penetration of renewable energy resources also impacts the adequate scheduling of generators [16]. In the past few years, the use of particle swarm optimization has evolved considerably after it was proposed by Kennedy and Eberhart [9] in 1995. Optimization algorithms using a random search space algorithm like ant colony optimization, artificial fish swarm algorithm, free search algorithm, and particle swarm optimization has been used by researchers. Researchers have started using particle swarm intelligence in many of the engineering applications [10] of complex problems because of its advantages [13-14] such as fast convergence, limited parameter inputs and simple principle. Wind and solar plants provide the limited capability of reactive power support, results in less voltage stability support in comparison to conventional plants [15]. However, adequate reactive power support is needed for wind power with long transmission lines which is often available far from load centers for reliable power transfer [1]. The problem of reliable power supply from wind power plants has been explained using a game-theoretic approach in [18]. An artificial bee colony approach has been proposed to minimize the cost of the system on two test cases with the addition of thermal units [19]. PSO has been used in different real time application scenarios like for vehicle collision [21] and design of water supply systems [20].

The main contribution of this paper is to develop a new approach for combined emission economic dispatch using a PSO based control of the power generators for the purpose of reducing intermittency of the variable wind and solar plants without a battery energy storage system and reactive power compensation. We analyse the cases in which the conventional and renewable energy sources are in a random search space where the strategy is to minimize the usage of fossil resources and maximize the use of renewable energy. With different combinations of voltage set points between the sources, the swarm with the best candidate solutions, which reduces the real power losses and maintains the voltage of the load buses is selected. We assume that wind and solar power are supplied in the system instantaneously as produced, and the rest of the demand is met by the conventional energy plants. In this work, we introduce variable wind and solar penetration from three different months for creating different load conditions in the PSO based algorithm.

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The outline of the paper is as follows: Section II presents the problem formulation. In section III, the solution approach based on Particle swarm optimization is explained. Simulation results are presented in Section IV, and Section V concludes the paper with a discussion.

II. Problem Formulation

The problem addressed in this paper is a combined emission economic dispatch optimization problem to minimize the total cost of the power system with integrating renewable energy sources in the system while maintaining system stability, load bus voltage and power flow constraints. The CEEDS optimization problem is as follows,

$$\begin{aligned} &\boldsymbol{min}\{F_n(K),\ E_n(K)\} \\ &\boldsymbol{max}\{P_w^J(K), P_S^J(K)\} \end{aligned} \tag{1}$$

where $F_n(K),\ E_n(K)$ are the fuel and emission cost for the generator n and $P_w^J(K), P_S^J(K)$ are the power input from the wind and solar, respectively, for area J.

The objective cost function:

$$\min_{\{V_n^j\}_{n\in\{1,\dots,N_j\}}^{j\in A}\{W^j\}^{j\in A}\{S^j\}^{j\in A}} C = \sum_{j\in A}\left\{\sum_{n\in N_j}\left(F_n^j(P_n^j(t)) + E_n^j(P_n^j(t))\right) + W\left(P_w^j(t)\right) + S(P_s^j(t)) + PF_j(t) * P_{j,L}(t)\right\} \tag{2}$$

Where: P_n^j, P_w^j, P_s^j is output from conventional generator, wind and solar respectively and F_n^j, E_n^j, are the fuel and emission cost function, $PF_j, P_{j,L}$ are penalty factor and power line losses respectively.

Equality constraints: The active power flow P_k and reactive power flow Q_k in all branches of the network must satisfy equations (2) and (3), for power balance.

$$P_k = \sum_{n=1}^{m} V_k V_n (G_{kn}\cos\theta_{kn} + B_{kn}\sin\theta_{kn}) \tag{3}$$
$$Q_k = \sum_{n=1}^{m} V_k V_n (G_{kn}\sin\theta_{kn} - B_{kn}\cos\theta_{kn}) \tag{4}$$

where, $k = 1,2,\dots,m.$ G_{kn} and B_{kn} are conductance and susceptance of (k,n) element of the bus admittance matrix. θ_{kn} is the bus voltage angle difference between k and n.

Inequality constraints: The inequalities that all power system components must operate within are their minimum and maximum limits are as follows:

$$V_k^{min} \le V_k \le V_k^{max} \tag{5}$$
$$P_{G,k}^{min} \le P_{G,k} \le P_{G,k}^{max} \tag{6}$$

where, $k = 1,2,\dots,m.$ .The superscripts min and max above denote the minimum and maximum limits of the variables.

The real power loss in a distribution line connecting two neighbouring buses n and $n+1$ can be computed as,

$$P_{Loss}(n,n+1) = R_n \frac{(P_n^2+Q_n^2)}{|R_n|^2} \tag{7}$$

Where, R_n is the resistance of line and P_n is the power flowing through that line.

The total real power loss of a system, $P_{o,Loss}$, can then be calculated by taking the sum of losses of all distribution line using,

$$P_{o,Loss} = \sum_{n=1}^{m} P_{Loss}(n,n+1) \tag{8}$$

III. Solution approach

A. Background of Particle Swarm Optimization

Particle Swarm optimization is the concept of mutual behavior of social animals such as birds, ants, and bees, which is developed to study the distributive behavior of the multi-players of intelligence in a system. It was introduced in the area of artificial intelligence for solving problems using swarm intelligence which mainly overcomes the barrier of centralized control. In PSO, the problem is solved by passing information within the swarm to reach the optimization goal [16]. It is also regarded as a computational algorithm that iteratively solves the problem by moving the particles of a population (i.e. Swarm) in a random but bounded search space with some initial information.

A PSO algorithm consists of a population P with x number of particles. Population P is also known as a set of candidate solutions. In PSO, each particle is called a candidate solution.

$$P=[p_1,p_2,p_3,\ \dots\dots,p_x] \tag{9}$$

where p_1, p_2 are different particles in the population.

These particles move around a search space D with an initial position $p_o(t)$.

$$p_x= [p_o,p_{o1},p_{o2}\ ,\ \dots\dots\ ,p_{mD}] \tag{10}$$

Each particle in the swarm moves from its initial position with a particular velocity $v_o(t)$ in the search space in a particular direction (space trajectory). The motion of the particle is based on the equation below:

$$p_x(t+1)=\{p_x(t)+v_x(t+1)\} \tag{11}$$

where p_x, v_x defines the position and velocity of particle respectively for two successive time iterations defined by t and t+1.

The velocity of the particle is defined by the following equation:

$$v_x(t+1)=v_o(t) + w_1(PB_x-p_x(t))*A_1 + w_2(GB-p_x(t))*A_2 \tag{12}$$

Where PB_x is the personal best of particle n and GB is the global best of the swarm. w_1 and w_2 are defined as acceleration coefficients which controls the steps taken by the particles in the space usually ranging between 0 to 4. A_1 and A_2 are the diagonal matrix of random generated numbers, which are known as weight inertia.

B. Simulation Setup

The test system is decentralized into three individual areas. Power flow data for these areas is obtained from the MATPOWER [17] program. Depending on the flow between areas, tie line buses are defined as either load bus or generator bus. The highest capacity generator bus is considered the slack bus. Each decentralized area has a slack bus.

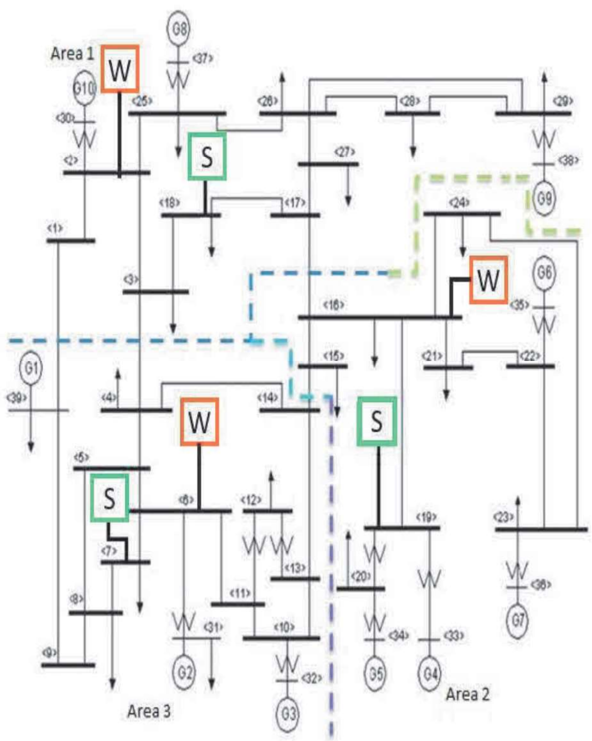

Figure 1: IEEE 39 bus system decentralized into three areas.

Each of the individual areas consist of conventional sources, solar plants, wind plants, and variable loads. For the integration of renewables, the most sensitive bus is selected using Q-V sensitivity analysis. The conventional generators and renewable generators are scheduled to meet the load demand.

C. *PSO Control Strategy Formulation*

The PSO algorithm is developed in each of the decentralized control regions in the system. The conventional and renewable generator sources are considered as particles, and the voltage set points been considered as velocity. Each particle initial position is set based on the minimum generator supply rating. A PSO algorithm is applied to find the best solution set points which would reduce the overall cost of the decentralized system and also minimize the real power loss. The flow chart of the PSO algorithm is shown in Figure 2.

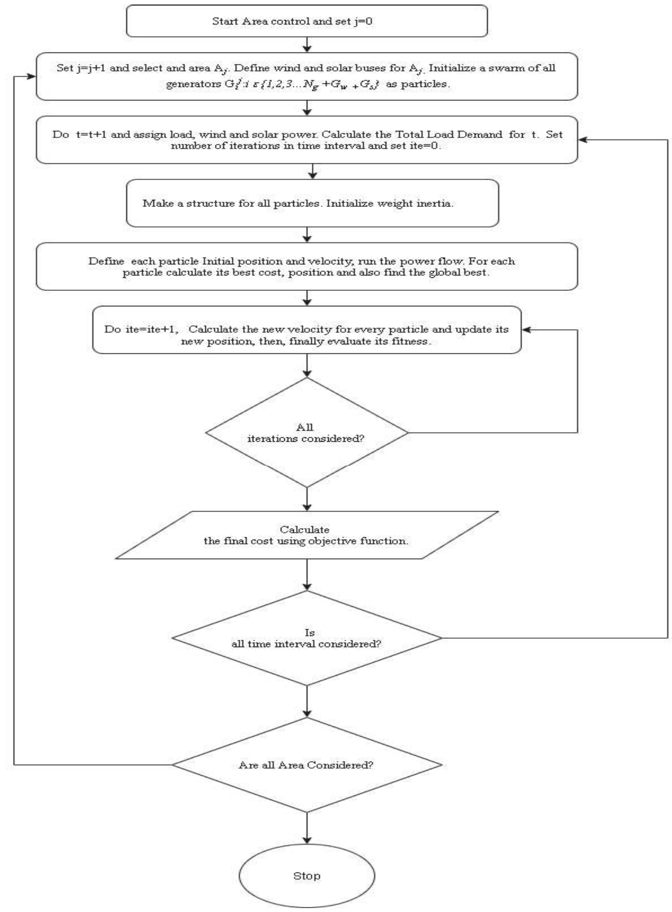

Figure 2: Flow chart PSO based control algorithm

Particles: In each area, conventional $\{p_x^j : x \in 1,2, \ldots, p_g^j\}$, wind generators $\{p_x^j : x \in 1,2, \ldots, p_w^j\}$ and solar generators $\{p_x^j : x \in 1,2, \ldots, p_s^j\}$ are considered as particles.

Velocity: The voltage set points of generators including the renewables in each area j, v_x^j is defined by generator voltage set points $\{V_{x1}^j, V_{x2}^j, \ldots, V_{xm}^j\}$. The voltage set points is assigned to each particle randomly by PSO within the range of $0.98 \leq V_{xm}^j \leq 1.02$.

Fitness Evaluation: The constraints have been set for conventional generators, wind, and solar generators. Thus, if the constraints are violated then a penalty is applied to the cost function.

$$C(i_n) = \left(\left(\sum_{n=1}^{j} G_n \right) - (T_k) \right) \quad (12)$$

$$Pen(k) = M\left(F_{p.u}\right) * C(i_n) \quad (13)$$

$$Fitness(k) = (C(k) + Pen(k)) \quad (14)$$

where $C(i_n)$ is the constraints for each conventional, wind and solar generator. Pen(k) and Fitness(k) are penalty and fitness at k-th time-interval.

$[M(F_{p.u}), (T_k)]$ is the max fuel cost per unit and total demand.

IV. Simulation Results

In this section, simulation results are presented with the application of the PSO algorithm concept to the IEEE 39 bus test system. The system has 10 generator buses, 29 load buses, 46 transmission lines and 12 transformers. Bus 31 is the slack bus in the centralized case. The resulting cost of operation is obtained using PSO algorithm which is implemented in MATLAB (using the MATPOWER toolbox [17]). Wind buses of three decentralized areas are 2, 16, and 6, and solar buses of the areas are 18, 19, and 7. Figure 1 demonstrates the decentralized test case with indications of wind and solar buses. Historical wind data was obtained from Bonneville Power Administration from three different months January, March and June for the three areas. Solar data was obtained from National Renewable Energy Laboratory historical data file from three months March, July and November. Figure 3 shows the wind and solar for 24-hours. Simulations were run for a 24-hour period with *t=5-minute* step.

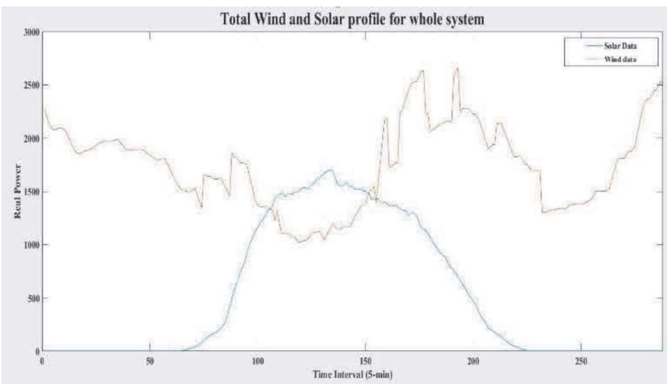

Figure 3: Wind and Solar for whole system in 5 minute interval

A comparison of real power losses in the areas is shown between the PSO algorithm and base cases in Figures 4, 5, and 6. A significant (22%) amount of real power loss was observed, which also indicates the same amount of increase in the spinning reserve of the overall system. The simulations were run for the voltage set points range . Table II illustrates that the algorithm maintaining the voltage at each load bus in the desirable range. Figure 2 demonstrates the algorithm flow to reach the optimization goal. Figure 7 shows the comparison of the cost between the PSO and base case.

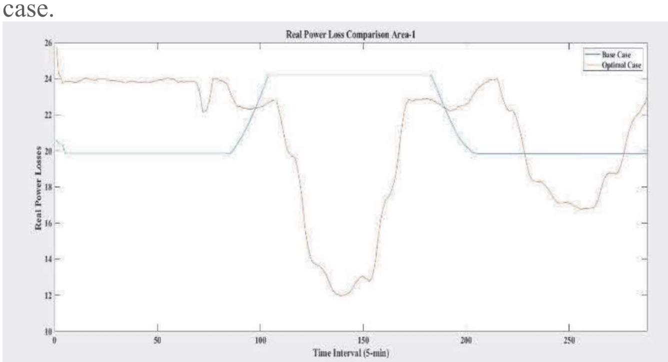

Figure 4: Comparison of real power loss with and without algorithm

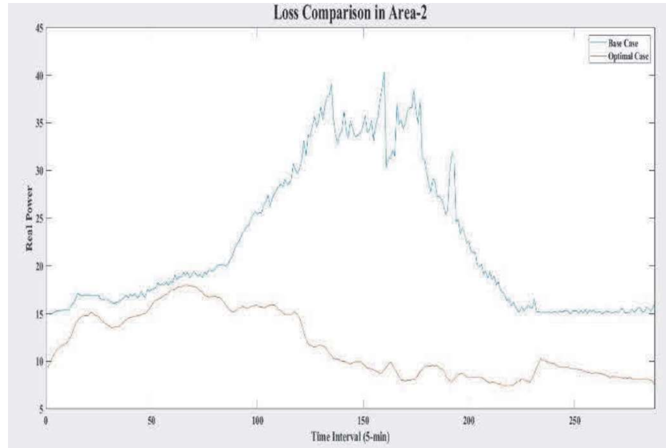

Figure 5: Comparison of real power loss in area-2 with and without algorithm

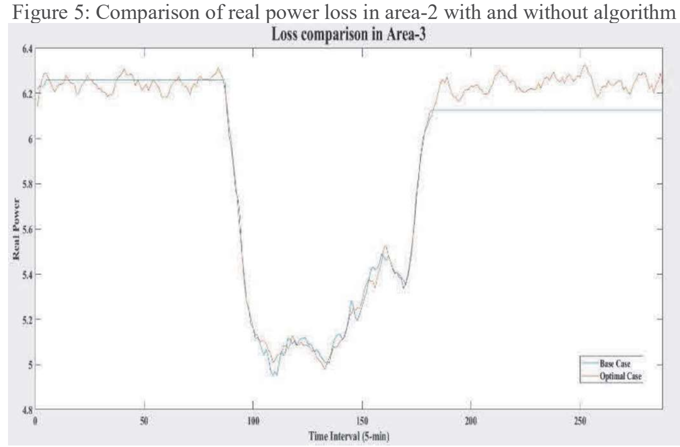

Figure 6: Comparison of real power loss in area-3 with and without algorithm

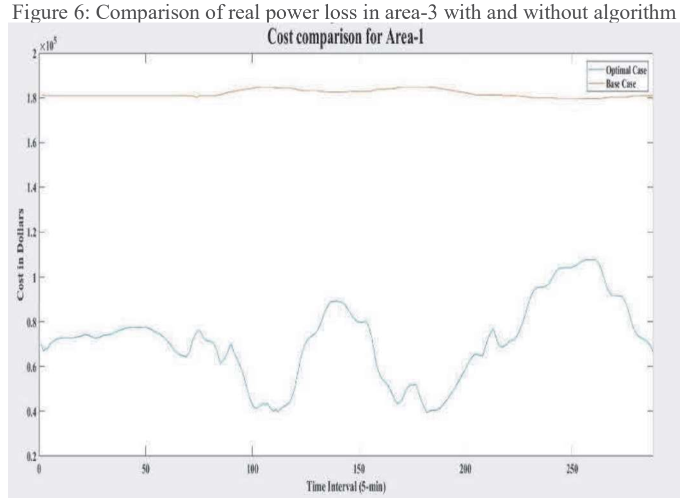

Figure 7: Comparison of Cost of Area-1 with and without algorithm

TABLE I
OBJECTIVE FUNCTIONS COMPARISON

	Base Case	PSO	Loss Reduction	%
Real loss in system	14249.7	11020.9	3228.8	22.65

TABLE II

LOAD BUS VOLTAGE COMPARISON

Load Bus number	Voltage set points Optimal Case	Voltage Set points Base Case
1	0.987746639562672	0.988548934208684
3	0.988169214402658	0.990573506435293
17	0.997492719501569	1.00385133115896
25	0.984450671053609	1.02377433822331
26	1.00289006966437	1.02766797439045
27	0.994398983830113	1.01064293021919
28	1.01476362496072	1.03749241941639
29	1.01828400688490	1.04127813623869

V. CONCLUSION

In this paper, a combined emission economic dispatch problem was solved with effective integration of intermittent renewable energy sources via a PSO based control algorithm while maintaining system constraints and stability. Simulation results were compared between before and after application of algorithm. The algorithm was able to find best solution set points to minimize the overall cost for each time period and all penetration conditions, while three different wind and solar conditions were created in the IEEE 39 bus system for validity of the algorithm. The voltage at all load buses was also maintained within a desirable range. Overall, the simulation results look significantly good for pre-scheduling bus voltage set points of the generators to reduce the fluctuations in the grid induced by variable loads and renewables. Our results imply that the PSO-based algorithm is able to minimize system cost and reduce real power losses to improve benefits. The results are limited to decentralized test scenario while better result might be obtained through distributed cooperative test case between areas with tie-line power flows and integration of battery energy storage system at different nodes.

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