IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

IJARSCT
Impact Factor: 6.252

Volume 2, Issue 2, July 2022

PSO Technique Based Low Carbon Economic Load Dispatching

Parveen[1] and Rohit Kumar Gupta[2]
M.Tech Scholar, Department of Electrical Engineering[1]
Assistant Professor, Department of Electrical Engineering[2]
School of Engineering & Technology, Soldha, Bahadurgarh, Haryana, India

Abstract: *Carbon emission characteristics of all kinds of power units are analyzed against the background of the low carbon economy. This paper introduces carbon trading in the dispatching model, gives full consideration to the benefit or cost of carbon emission and introduces carbon emission in the dispatching model as a decision variable so as to achieve the unity of the economy and the environmental protection of the dispatching model. A low carbon economic dispatching model is established based on multiple objectives, such as the lowest thermal power generation cost, the lowest carbon trading cost and the lowest carbon capture power plant operation cost. Load equalization, output constraint of power unit, ramping constraint, spinning reserve constraint and carbon capture efficiency constraint should be taken into account in terms of constraint conditions. The model is solved by the particle swarm optimization based on dynamic exchange and density distance. The fact that the introduction of carbon trading can effectively reduce the level of carbon emission and increase the acceptance level of wind power is highlighted through the comparison of the results of three models' computational examples. With the carbon trading mechanism, carbon capture power plants with new technologies are able to give full play to the advantage of reducing carbon emission and wind curtailment so as to promote the development of the energy conservation and emission reduction technology and reduce the total cost of the dispatching system. The dispatching unit contains a carbon capture power plant, a thermal power unit and a wind power plant. The establishment of the model takes fully into account the unity of the economy and the environmental protection of the dispatching model. The multi-objective model is solved with the particle swarm optimization based on dynamic exchange and density distance. It can be concluded from the comparison of three dispatching models that the introduction of carbon trading and carbon capture power plant can effectively reduce carbon emission of the dispatching model. The carbon capture power plant can effectively reduce carbon emission and wind curtailment of wind power and increase the level of wind power acceptance.*

Keywords: Economic Dispatching, Load Equalization, Particle Swarm Optimization

I. INTRODUCTION

[1] The author gives the idea about Carbon emission characteristics of all kinds of power units are analyzed against the background of the low carbon economy. This paper introduces carbon trading in the dispatching model, gives full consideration to the benefit or cost of carbon emission and introduces carbon emission in the dispatching model as a decision variable so as to achieve the unity of the economy and the environmental protection of the dispatching model.

A low carbon economic dispatching model is established based on multiple objectives, such as the lowest thermal power generation cost, the lowest carbon trading cost and the lowest carbon capture power plant operation cost. Load equalization, output constraint of power unit, ramping constraint, spinning reserve constraint and carbon capture efficiency constraint should be taken into account in terms of constraint conditions. The model is solved by the particle swarm optimization based on dynamic exchange and density distance. The fact that the introduction of carbon trading can effectively reduce the level of carbon emission and increase the acceptance level of wind power is highlighted through the comparison of the results of three models' computational examples. With the carbon trading mechanism, carbon capture power plants with new technologies are able to give full play to the advantage of reducing carbon emission and wind curtailment so as to promote the development of the energy conservation and emission reduction technology and reduce the total cost of the dispatching system. [2] The author tells about Dynamic load Problem. Dynamic load economic dispatch problem (DLED) is important in power systems operation, which is a complicated nonlinear constrained optimization problem. It has non smooth and non convex characteristics when generator valve-point effects are taken into account. This paper proposes an improved particle swarm optimization (IPSO) to solve DLED with valve-point effects. In the proposed IPSO method, feasibility-based rules and heuristic strategies with priority list based on probability are devised to handle constraints effectively. In contrast to the penalty function method, the constraint- handling method does not require penalty factors or any extra parameters and can guide the population to the feasible region quickly. Especially, equality constraints of DLED can be satisfied precisely. Furthermore, the effects of two crucial parameters on the performance of the IPSO for DLED are also studied. The feasibility and the effectiveness of the proposed method are demonstrated applying it to some examples and the test results are compared with those of other methods reported in the literature. It is shown that the proposed method is capable of yielding higher-quality solutions. [3] The author presents a novel heuristic optimization approach to constrained economic load dispatch (ELD) problems using the adaptive variable population PSO technique. The proposed methodology easily takes care of different constraints like transmission losses, dynamic operation constraints (ramp rate limits) and prohibited operating zones and also accounts for non-smoothness of cost functions arising due to the use of multiple fuels. Simulations were performed over various systems with different numbers of generating units, and comparisons are performed with other existing relevant approaches. The findings affirmed the robustness, fast convergence and proficiency of the proposed methodology over other existing techniques. The paper has employed the adaptive particle swarm optimization (APSO) algorithm on constrained economic load dispatch problems. Practical generator operation is modelled using several non-linear characteristics like ramp rate limits, prohibited operating zones and multiple fuels. The proposed approach is also tested with a dynamic load dispatch problem. The proposed approach has produced results comparable to or better than those generated by other algorithms, and the solutions obtained have superior solution quality and good convergence characteristics. The results obtained for non-smooth cost functions were also better, thus empirically validating its applicability for non-smooth functions, while those obtained considering ramp rate limits and prohibited operating zones were, nonetheless, comparatively better than the earlier best reported results. From this limited comparative study, it can be concluded that the APSO can be effectively used to solve smooth as well as non-smooth constrained ELD problems. In the future, efforts will be made to incorporate more realistic constraints to the problem structure, and practical large sized problems will be attempted by the proposed methodology. [4] Economic Load Dispatch (ELD) problem is one of the most important problems to be solved in the operation and planning of a power system. The main objective of the economic load dispatch problem is to determine the optimal schedule of output powers of all generating units so as to meet the required load demand at minimum operating cost while satisfying system equality and inequality constraints. This paper presents an application of Genetic Algorithm (GA) for solving the ELD problem to find the global or near global optimum dispatch solution. The proposed approach has been evaluated on 26 bus, 6-unit system with considering the generator constraints, ramp rate limits and transmission line losses. The obtained results of the proposed method are compared with those obtained from the conventional lambda iteration method and Particle Swarm Optimization (PSO) Technique. The results show that the proposed approach is feasible and efficient.

II. METHODOLOGY

2.1 Particle Swarm Optimization

Function optimization is the process of finding an optimal solution to an objective function describing a problem. Optimization can be either a minimization or maximization task. Optimization problems can be broadly categorized into unimodal and multi-modal problems. Unimodal problems have a single global optimum, x^*, subject to (assuming minimization)

$$f(x^*) \leq f(x) \forall_x \in \mathbb{R}^n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where $f(x): \mathbb{R}^n \rightarrow \mathbb{R}$ the objective function and n is is the dimension of the search space. Multi-modal problems, on the other hand, have more than one optimum. These optima may all be global optima, or a mixture of global and local optima. A local optimum, x_L^*, is subject to (assuming minimization)

$$f(x_L^*) \leq f(x) \forall_x \in L \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where $L \subset \mathbb{R}^n$

Many scientific and engineering optimization problems have convoluted search spaces with large numbers of optima. In the case of more than one global optimum, algorithms are needed to obtain all these solutions. It may also be beneficial to locate all, or as many as possible, local optima.

Function optimization has received extensive research attention, and several machine learning techniques such as neural networks, evolutionary algorithms and swarm intelligence-based algorithms have been developed and applied successfully to solve a wide range of complex optimization problems. By far the largest part of this research concentrated on developing algorithms that can locate only a single solution. However, evolutionary algorithms research has produced a number of approaches to find multiple solutions These evolutionary algorithms are generally referred to as niching or speciation algorithms. Each possible solution, known as a is represented by a grouping of homogeneous GA individuals.

Eberhart and Kennedy recently introduced the particle swarm optimization (PSO) approach It is similar to evolutionary algorithms in that it evolves a group of candidate solutions. PSO, however, allows each individual to maintain a memory of the best solution that it has found and the best solution found in the individual's neighborhood. Each individual's traversal of the search space is then influenced by its own memory of best positions, with the individual moving towards a stochastically weighted average of these best positions The PSO algorithm has been shown to successfully solve a variety of unimodal optimization problems. Several techniques have been proposed to improve the PSO algorithm's traversal of the search space

2.2 The Standard PSO

Particle swarm optimizers are optimization algorithms modeled after the social behavior of birds in a flock PSO is a population based search process where individuals, referred to as particles, are grouped into a swarm. Each particle in a swarm represents a candidate solution to the optimization problem. In a PSO system, each particle is flown through the multidimensional search space, adjusting its position in search space according to its own experience and that of neighboring particles. A particle therefore makes use of the best position encountered by itself and that of its neighbors to position itself toward an optimal solution. The effect is that particles fly toward a minimum, while still searching a wide area around the best solution. The performance of each particle (i.e. the closeness of a particle to the global optimum) is measured using a predefined fitness function which encapsulates the characteristics of the optimization problem.

Each particle i maintain a current position, x_i, current velocity, v_i, and personal best position, y_i. For the purposes of this paper, x_i represents a position in an unconstrained, continuous search space. The personal best position associated with a particle i is the best position that the particle has visited thus far, i.e. a position that yielded the highest fitness value for that particle. If f denotes the objective function to be minimized, then the personal best of a particle at a time step t is updated as

$$y_i(t+1) = \begin{cases} y_i(t) \ if\ f(x_i(t+1) \geq f(y_i(t)) \\ x_i(t+1) \ if\ f(x_i(t+1) < f(y_i(t)) \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Different PSO models have been developed based on the neighborhood topology particles use to exchange information about the search space In the g best model, which is used in this paper, the best particle is determined from the entire swarm and all other particles flock towards this particle. If the position of the best particle is denoted by the vector$\hat{y}$, then

$$\hat{y}(t) \in \{y_0, y_1, \ldots\ldots, y_s\} \big| f(\hat{y}(t)) = min\{f(y_0(t), f(y_1(t), \ldots., f(y_s(t))\} \ldots\ldots\ldots\ldots (4)$$

Where s is the total number of particles in the swarm. For each iteration of a g best PSO, the jth-dimension of particle i's velocity vector, v_i, and its position vector, x_i, is updated as follows:

$$v_{i,j}(t+1) = wv_{i,j}(t) + c_1 r_{1,j}(t)(y_{i,j}(t) - x_{i,j}(t) + c_2 r_{2,j}(t)(\hat{y}_{i,j}(t) - x_{i,j}(t)) \ldots\ldots\ldots (5)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \ldots\ldots\ldots\ldots (6)$$

Where w is the inertia weight, c_1 and c_2 are the acceleration constants and $r_{1,j}(t)$, $r_{2,j}(t) \sim U(0,1)$. Upper and lower bounds are usually specified on vi to avoid too rapid movement of particles in the search space; that is, $v_{i,j}$ is clamped to the range The inertia weight, w, was introduced by Shi and Eberhart to control the influence of the velocity vector on a particle's position. Decreasing w from a relatively large value to a small value over time, results in rapid initial exploration of the search space, and facilitates later exploration. Small w-values result in small adaptations to particle positions, effectively yielding a local search.

The PSO algorithm performs repeated applications of the update equations until a specified number of iterations has been exceeded, or until velocity updates are close to zero. The reader is referred to for a study of the relationship between the inertia weight and the acceleration constants in order to select values that will ensure convergent behavior.

The guaranteed convergence particle swarm optimizer

The best algorithm exhibits an unwanted property: when $x_i = y_i = \hat{y}$ (for any particle i), the velocity update in Eq 4.7 depends only on the $wv_i(t)$ term. When a particle approaches the global best solution, its velocity approaches zero, implying that eventually all particles will stop moving. This behavior does not guarantee convergence to a global best solution, or even a local best, only to a best position found thus far Van den Bergh et al. introduced a new algorithm, called the Guaranteed Convergence PSO (GCPSO) to pro-actively counteract this behavior in a particle swarm. Let τ be the index of the global best particle. The velocity and position updates for the global best particle are then redefined to be

$$v_{\tau,j}(t+1) = x_{\tau,j}(t) + \hat{y}_j(t) + wv_{\tau j}(t) + \rho(t)(1 - 2r_{2,j}) \quad \ldots\ldots\ldots (7)$$

$$x_{\tau,j}(t+1) = \hat{y}_j(t) + \hat{y}_j(t) + wv_{\tau j}(t) + \rho(t)(1 - 2r_{2,j}) \quad \ldots\ldots\ldots (8)$$

The term $-x_\tau$'resets' the particle's position to the global best position$\hat{y}$, wv_τsignifies a search direction, and $\rho(t)(1 - 2r_2(t))$adds a random search term to the equation. The parameter $\rho(t)$ is dynamically adapted to control the size of the bounding box around $\hat{y}$ within which a local search is conducted to force a change in the value of $\hat{y}$, thereby preventing the above problem.

III. RESULTS

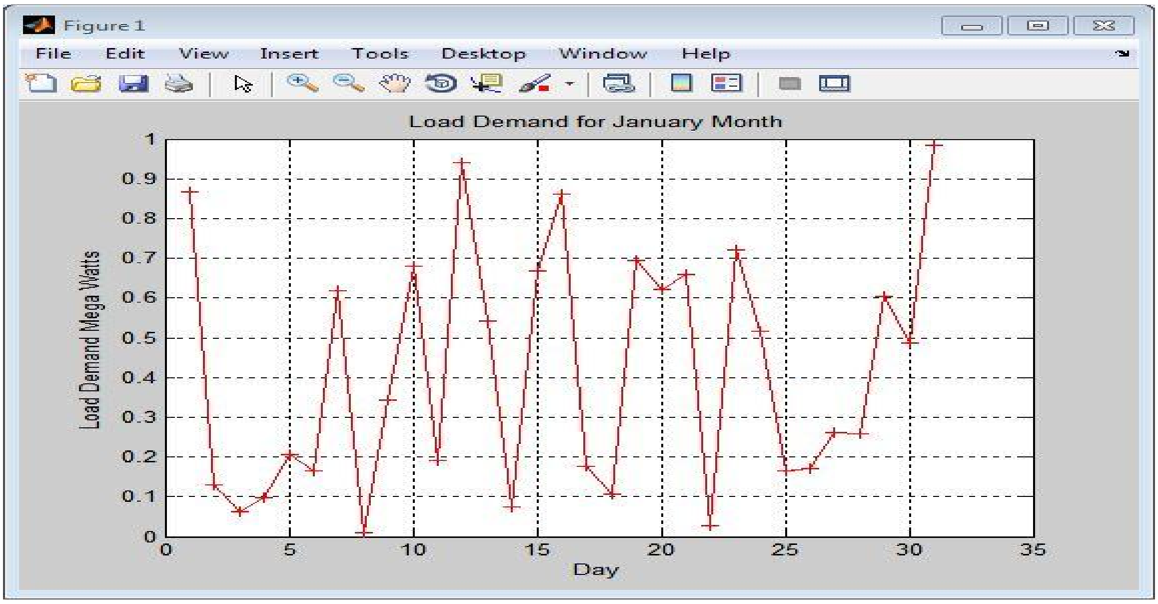

Fig 1 Load Demand for Jan Month

Fig 1 shows load demand for Jan Month. In our research, we calculate load demand in Mega Watts. The graph shows that load demand vary with day.

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

Impact Factor: 6.252

Volume 2, Issue 2, July 2022

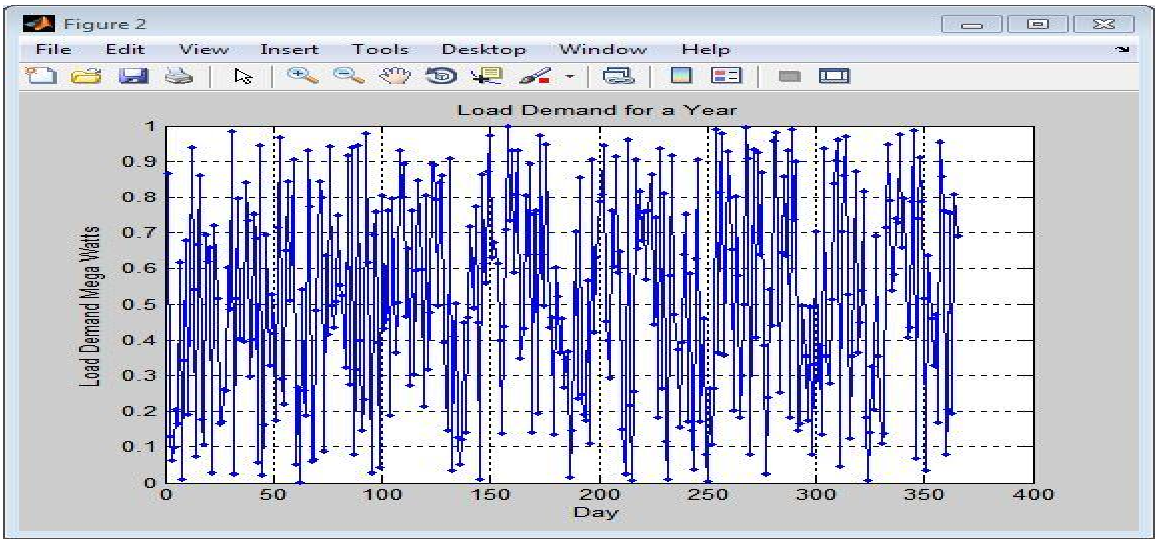

Fig 2 Load Demand for Complete Year

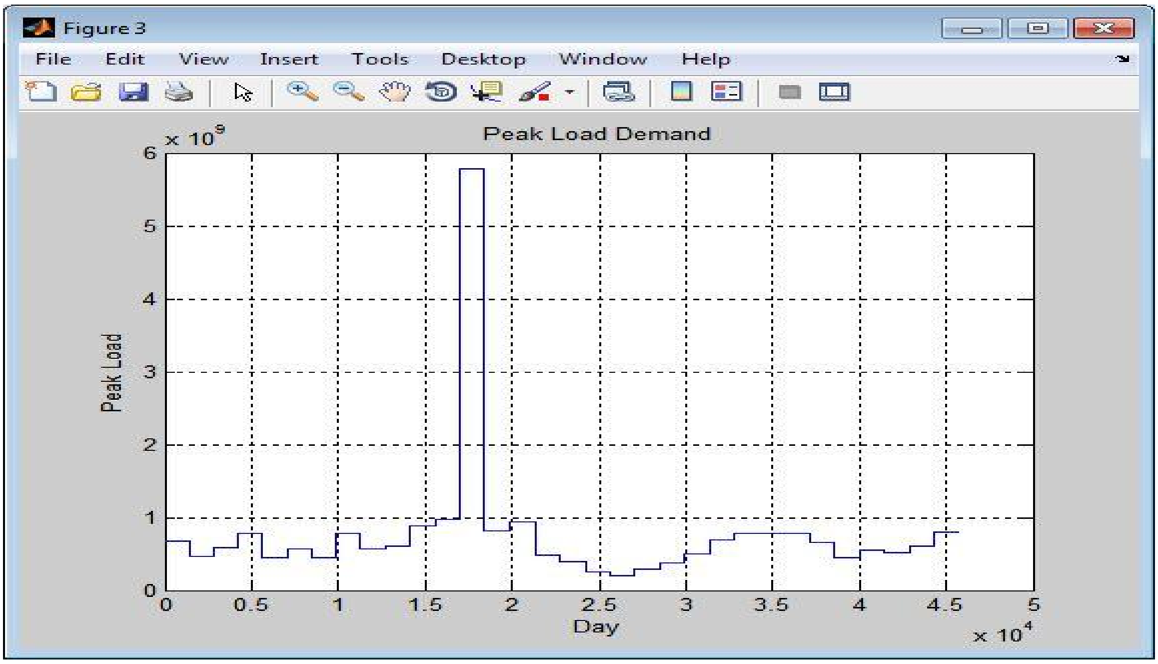

Fig 3 Peak Load Demand for Complete Day

Fig 2 shows load demand for Complete Year. In our research, we calculate load demand in Mega Watts. The graph shows that load demand vary with day.

Fig 3 shows load demand for one day. In our research, we calculate load demand in Mega Watts. The graph shows that load demand vary with time. It will be maximum for 1.5 h to 2 h.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
Impact Factor: 6.252
Volume 2, Issue 2, July 2022

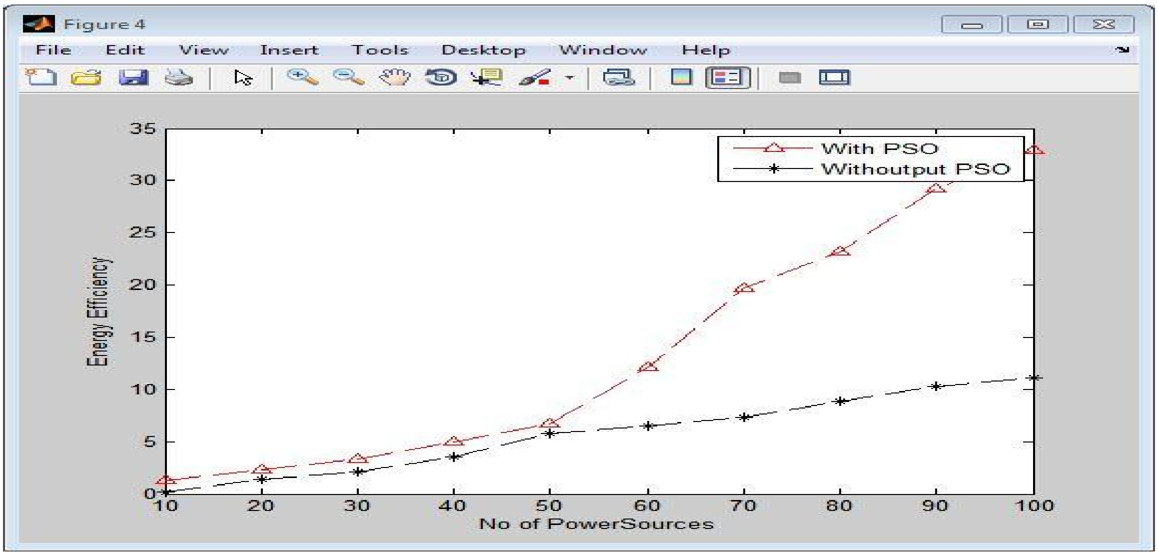

Fig 4 Energy Efficiency with PSO and without PSO.

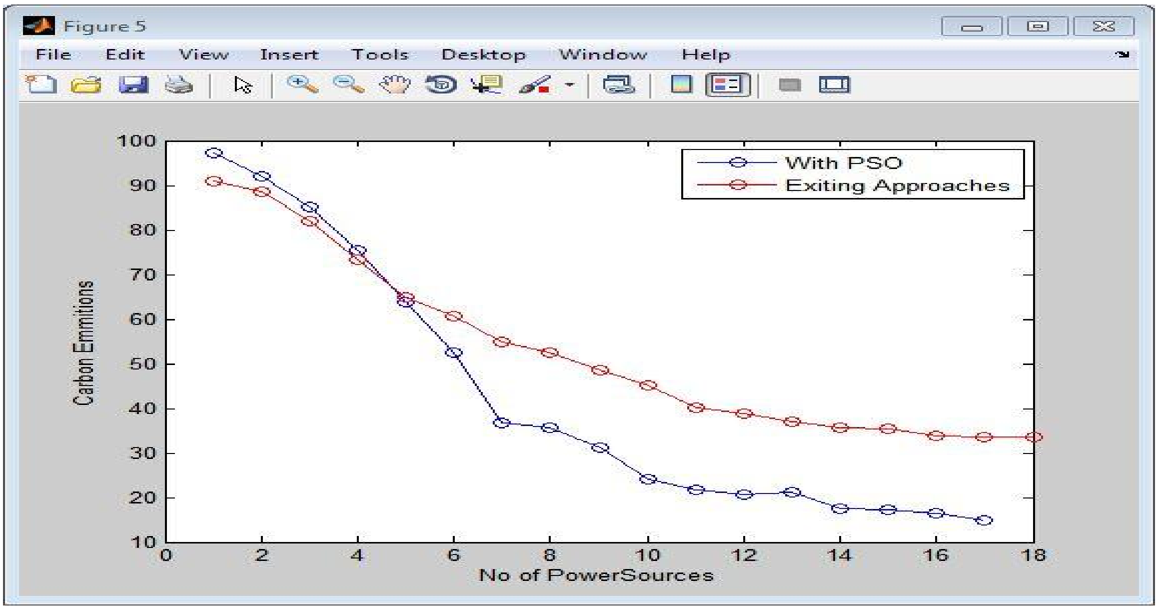

Fig 5 Carbon Estimation with PSO Approach

Fig 4 shows Energy Efficiency with PSO and without PSO. It shows that as no. of sources increases, Energy Efficiency also increases. For same no. sources , Energy efficiency is more with PSO technique as compare to without PSO technique.

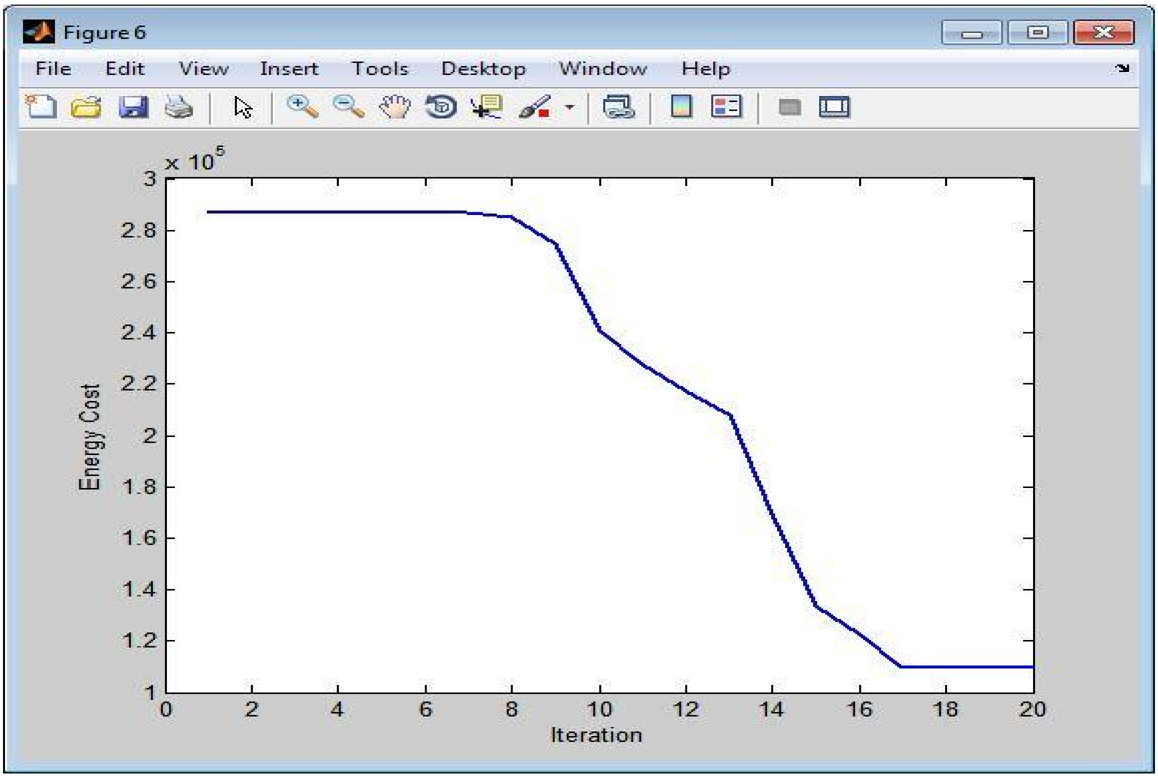

Fig 6 Energy Cost of different iteration of load

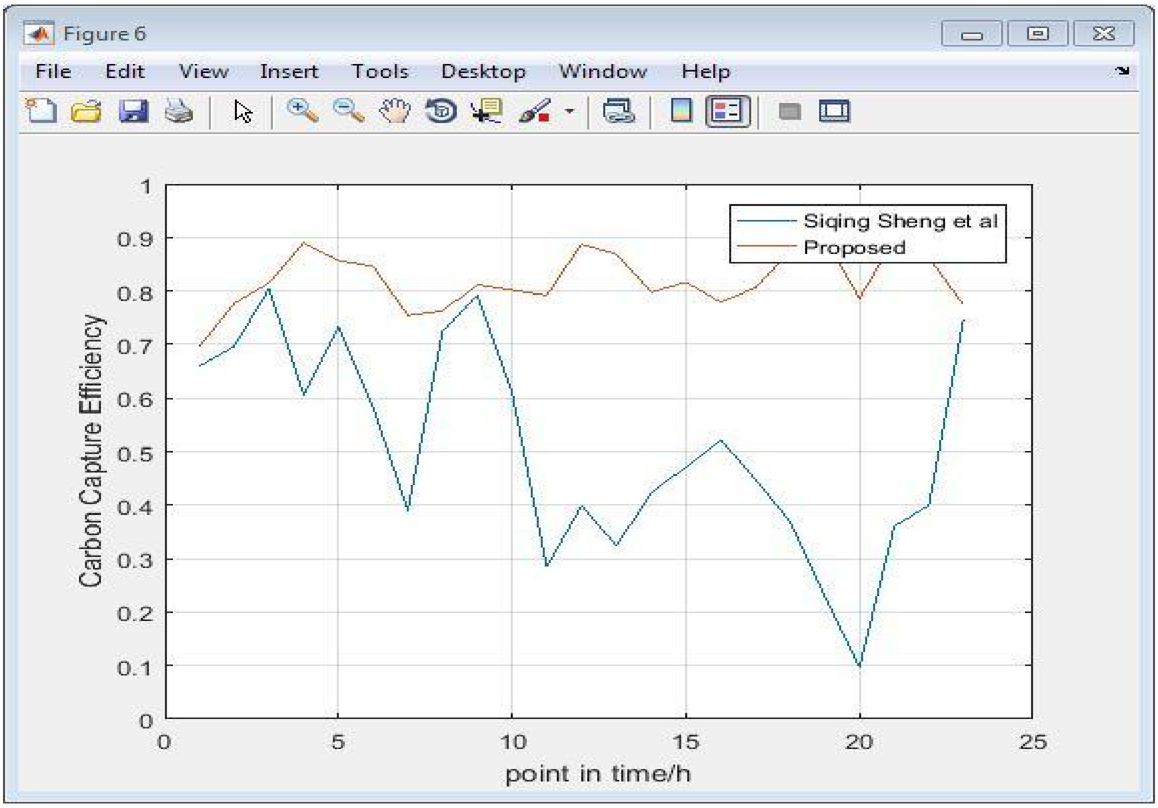

Fig 7 Carbon Capture Efficiency

Fig 5 shows Carbon Estimation with PSO Approach. Carbon estimation is more appropriately as compare to without PSO .

Fig 6 shows Energy Cost of different iteration of load. As iteration of load increase energy cost decreases.

Fig 7 shows carbon capture efficiency with base paper. Carbon capture efficiency is increases as compare previous technique.

IV. CONCLUSION

In the background of low carbon economy development, this dissertation introduces carbon trading in objective function and establishes a low carbon economic dispatching model with such multiple objectives as the lowest thermal power generation cost, the lowest carbon trading cost and the lowest carbon capture power plant operation cost. The dispatching unit contains a carbon capture power plant, a thermal power unit and a wind power plant. The establishment of the model takes fully into account the unity of the economy and the environmental protection of the dispatching model. The multi-objective model is solved with the particle swarm optimization based on dynamic exchange and density distance. It can be concluded from the comparison of three dispatching models that the introduction of carbon trading and carbon capture power plant can effectively reduce carbon emission of the dispatching model. The carbon capture power plant can effectively reduce carbon emission and wind curtailment of wind power and increase the level of wind power acceptance. The carbon capture power plant and the carbon trading mechanism have a bright future in the development process of low-carbon electricity.

REFERENCES

[1] Siqing Sheng , Liangliang Li &Meng Liu "Low-Carbon Economic Dispatching for Power Grid Integrated with Carbon Capture Power Plants and Wind Power System" , Matec Web of Conferences , Vol 22, issue 2 , pp 1-7 , Feb 2016.

[2] Xiaohui Yuan et.al "An improved PSO for dynamic load dispatch of generators with valve-point effects" Elsevier Science Direct Vol34 ,pp 67-74 , 2009.

[3] B.K. Panigrahi et.al "Adaptive particle swarm optimization approach for static and dynamic economic load dispatch" Elsevier Science Direct Energy Conversion & Management , Vol 49 , pp 1407- 1415 , 2008.

[4] W. M. Mansour et.al "Dynamic Economic Load Dispatch of Thermal Power System Using Genetic Algorithm" IRACST – Engineering Science and Technology: An International Journal (ESTIJ), Vol. 3, No.2, April 2013.

[5] S. Ganesan and S. Subramanian "Dynamic Economic Dispatch Based on Simple Algorithm", International Journal of Computer and Electrical Engineering, Vol. 3, No. 2,pp 226-232 April, 2011.

[6] P.Sivaraman et.al "PSO Approach for Dynamic Economic Load Dispatch Problem" International Journal of Innovative Research in Science, Engineering and Technology.

[7] I. A. Farhat "Optimal Dynamic Economic Load Dispatch Using Artificial Immune System" International Journal of Computer, Electrical, Automation, Control and Information Engineering Vol:8, No:1, pp. 75- 81 , 2014.

[8] F. Benhamida et.al, "Dynamic Economic Load Dispatch Optimization with Ramp Rate Limit Using GAMS-CONOPT Solver" , International Conference on Electrical Engineering , Nov 2013.

[9] Xiamen yabtra "Special Report on Carbon Dioxide Capture and Storage" , Cambridge, UK: Cambridge UniversityPress , IPCC 2010

[10] Chen, Q.X., Kang, C.S. & Xia, Q., et al. "An analysis on key factors of the low carbonization of the power industry and the influence on power source planning" , Automation of Electric Power Systems, 33(15): 18-23., 2009.

[11] Dong, X.T., Yan, Z. &Feng, D.H., et al. "Economic dispatching of the power system involving wind power output penalty cost" , Power System Technology, (8): 76-80 , 2012.

[12] Zhou, W., Peng, Y. & Sun, H. "Economic dispatching of the power system with wind power plant", Proceedings of the CSEE, 29(25): 13-18, 2009.

[13] Zhang, X.H. & Dong, X.H. "A study on the dynamic economic dispatching of the multi-objective low-carbon electric power system with wind power plant", Power System Technology, pp. 25-31, 2013.

[14] Zhang, X.H., Yan, K.K., Lu, Z.G. &Zhong "Low-carbon economic dispatching of the electric power system based on scenario probability", Power SystemTechnology, 78(7): 1836-1841 , 2014.

[15] Kang, C.Q., Ji, Z. & Chen, Q.X. "A review and the outlook of flexible operational methods of carbon capture power plant" ,Automation of Electric Power Systems, (3): 1-9 , 2012

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
Volume 2, Issue 2, July 2022
IJARSCT
Impact Factor: 6.252

[16] Chen, Q.X., Kang, C.Q., & Xia, Q. "A study on the operational mechanism and peak-regulation efficiency of carbon capture power plant", Proceedings of the CSEE, 30(7): 22-28 , 2010

[17] Gao, Y.J., Li, R.H., Liang, H.F. & Zhang "The optimization dispatching of electric power system involving carbon capture power plant and electrical changing station in the carbon market environment" , Automationof Electric Power Systems, 38(17): 150-156 , 2014

[18] "Special Report on Carbon Dioxide Capture and Storage", Cambridge: Cambridge University Press,pp: 2-4. , 2014

[19] Wang, X. & Yuan, "Emission rights distribution and price management in carbon emissions permit trading" ,Financial Development Review, (11): 48-57 , 2010

[20] Jin, X.L. "A Study on the Multi-objective Optimization Algorithm Based on PSO and its Application", Hangzhou: Zhejiang University, 2006