PSO BASED POOL STRATEGIES FOR DEREGULATED POWER MARKET

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Abstract: *with the deregulation of electric power systems, market participants are facing an important task of bidding the energy in a pool operation. This paper essentially aims to propose a new optimal bidding solution methodology for both power suppliers and for the system, with the impact of line limits and the transmission losses. The model of the producer surplus maximization is a bi-level maximization problem and the model of social welfare function (SWF) with elastic demand is a maximization problem. In this paper a novel hybrid optimization technique based on PSO-SQP is developed to solve the problem. In this hybrid algorithm, Canonical PSO (CPSO) with constriction factor is used as a global optimizer and SQP as the local optimizer. Simulations have been carried out on a 3-bus system and modified IEEE 30-bus system, to show the robustness and the effectiveness of the proposed hybrid algorithm.*

Index Terms - Bi-level optimization, optimal bidding strategy, pool dispatch, particle swarm optimization, Sequential Quadratic Programming

1. Introduction

In the recent past, many countries around the globe have been undergoing massive changes to introduce competition in power industry. Various models have been proposed and tested in different countries [1]. Two market models; power pool model and bilateral model are widely used throughout the world. In the pool model, the Independent System Operator (ISO) in the power pool acts, effectively, like a broker for managing energy suppliers' bids and large customers' offers, to establish a market-clearing price (MCP). MCP is the bid price of the most expensive supplier that is needed to completely meet the demand, and is used as the basis for the settlement of market commitments. Regardless of the bidding prices from suppliers, all selected bidders are paid the MCP. This approach is adopted to encourage suppliers in a competitive market to price energy close to their marginal costs. In bilateral transaction bulk of energy transactions are carried out through contracts between suppliers and customers.

Most of the pool markets in United States are operated by ISO, those who are responsible for energy settlement process in the power pool. The sealed bid auction is widely used in the pool market. The bids are generally in the form of price and quantity quotations and specify how much the seller or buyer is willing to sell or buy, and at what price. Each supplier submits a sealed bid to the pool to compete for the supply of the forecast load that is broadcast by the pool. Theoretically, in perfectly competitive market, suppliers should bid at, or very close to, their marginal production costs to maximize returns. However, the electricity market is not perfectly competitive, and power suppliers may seek to benefit by bidding a price higher than marginal production cost. Each supplier's objective is to maximize benefit, therefore, given its own costs and constraints and its anticipation of rival and market behavior, a supplier faces the problem of how best to construct its offer (bid) price. This is called the optimal bidding strategy problem. On the other side, the pool operator will use a dispatch strategy that minimizes customers' payments given the supply costs represented in the suppliers' bids, which is similar to pool operations in United Kingdom.

In recent years, some research has been done on building optimal bidding strategies for competitive generators. This problem was addressed for the first time by David [2]. He discussed a conceptual optimal bidding model and a dynamic programming based approach for England-Wales electricity markets, in which each supplier is required to bid a constant price for each block of generation. System demand variations and unit commitment costs were considered in the model. In [3], a brief literature survey about strategic bidding in competitive electricity market was presented. In general there are two methods for developing bidding strategies in competitive electricity market: game and non game based methods. In [4] & [5], the competition among participants is modeled as a non-cooperative game with incomplete information, and the imperfect information of the suppliers is solved using Nash equilibrium.

In [6], a dynamic model of strategic bidding for the situation with three power suppliers was proposed by utilizing the historical and current market clearing prices. This model is heuristic in principle, and is not directly applicable to the general case with more than three suppliers. In [7], the bidding behavior model of the suppliers is developed, and how a supplier would construct his bid as a function of his private cost and cost distributions of other bidders are also discussed. In [8], a model and a method for optimization-based bidding and self-scheduling are discussed with respect to New England market based on lagrangian relaxation method. In [9], an optimal bidding strategy for the power suppliers are framed as a stochastic optimization problem and it is solved by Monte Carlo based and optimization based methods. An interior - point optimal power flow model was proposed in [10] for the sensitivity based optimal bidding strategy for the suppliers. The impact of congestion on the profit of the suppliers and clear problem formulation with the solution by using Nash equilibrium is discussed by Peng [11]. In [12], the bidding strategy problem is modeled as a two level optimization problem. In the first level the suppliers are maximizing their own profit and in the second stage ISO dispatching the power subject to minimization of total system cost. The bidding strategy model for risk averse and risk seeker suppliers are discussed in [13]. Recently, a global optimization technique known as Particle Swarm Optimization (PSO) has become a candidate for solving the optimization problem in power system. PSO is a stochastic search algorithm and it searches randomly from point to point to reach the optimum. In [14], the maximization of the producer surplus is modeled as a bi-level optimization problem and using PSO solves it. The rate of solution convergence is very fast at the beginning with PSO. Thereafter, it is very slow up to the end of convergence. This results in large computation time. In contrast the deterministic Sequential Quadratic Programming (SQP) method is accurate and fast when the variations in the control variables are small and is very effective in correcting the moderate constraint violations. The above fact suggests that a hybrid method with PSO algorithm for initial solution and SQP method for getting the final solution be an effective and fast method. In [15], the effect of demand elasticity on the strategic bidding behavior of the producers is discussed. A model to address generation companies' medium-term strategic analysis based on a conjectured-price-response market is discussed in ref [16]. The problem of the development of optimal offering strategies by electricity producers in day-ahead energy auctions with step-wise energy offer format is discussed in ref [17]. In [18], the transmission enhancement in a competitive electricity market is analyzed in terms of its impact on the social welfare function.

Given this background, this paper proposes a dispatch algorithm based on Canonical PSO (CPSO), which is combined with SQP. In this CPSO-SQP based hybrid algorithm CPSO used as a base search algorithm and SQP used as a fine tuner. This paper considers the impact of transmission line limits and transmission line losses on the dispatch cost of the pool.

The first part of this paper focuses on the application of the proposed hybrid algorithm to develop the bidding strategy for power suppliers to maximize their profit (maximization of surplus), the second part describe the strategy followed by ISO for settling the market to minimize the system operating cost (Social Welfare Function (SWF) Maximization). The effectiveness of this hybrid algorithm is checked with simple 3-bus system and the modified IEEE 30-bus system and the results are tabulated.

2. Problem formulation

In this paper two pool strategies for deregulated power market are developed. In the first strategy the maximization of the producer surplus is discussed and in the second strategy the maximization of social welfare function is discussed. The problem formulations of both are given below,

Strategy I: *Producer Surplus Maximization*

It is a bi-level optimization problem. In the first level market settlement problem is solved to find the value of the MCP, then in the next level suppliers are trying to increase their profit by finding the suitable value of bidding constant. For simplicity it is assumed that consumer side bidding is constant.

A bid consists of price offers and the amount of load to be satisfied by the market for each hour. Price offers specify a stack of MW levels. By integrating a staircase price offer curve, the bidding cost function is piecewise linear. To reduce the number of parameters associated with a bid, the piece-wise linear bidding cost function is approximated by a quadratic function, then the marginal cost curve of i^{th} producer can be expressed as,

$$C_{mci}(P_{gi}) = \alpha_i + \beta_i P_{gi}\ ;\ i = 1.........n_g \qquad (1)$$

Where, α_i and β_i are the intercept $(\$/MWh)$ and slope $(\$/MWh^2)$ of the cost curve, P_{gi} is the power output (MW) for the i^{th} generator, n_g is the no of suppliers.

For the i^{th} supplier, the strategic supply function is formulated as,

$$C_i(P_{gi}) = k_i(\alpha_i + \beta_i P_{gi}) \qquad (2)$$

This can be reformulated as,

$$C_i(P_{gi}) = a_i + b_i P_g \qquad (3)$$

The customers benefit function $B_j(P_{dj})$ is modeled with a linear demand curve and it expressed as,

$$B_j(P_{dj}) = d_j + e_j P_{dj}\ ;\ j = 1....n_d \qquad (4)$$

Where, d_j and e_j are, respectively, the intercept $(\$/MWh)$ and slope $(\$/MWh^2)$, P_{dj} is the demand (MW) of the j^{th} customer. n_d, is the no of customers.

To find the profitable value of k_i for the i^{th} supplier, it is assumed that the bidding strategies of other suppliers are known. With the same assumption, the profitable value of k for all the suppliers are found with out violating any system constraints.

In the first level the value of MCP is calculated by using the bidding equations submitted by the suppliers and the demand. The objective function and the constraint for the next level to maximize the supplier profit is given below,

$$\text{Max profit} = MCP * (P_{gi}) - C_{mci}(P_{gi}) \qquad (5)$$

Subject to,

Energy balance constraint,

$$\sum_{i=1}^{n_g} P_{gi} = \sum_{j=1}^{n_d} P_{dj} + P_{Loss} \qquad (6)$$

Where, P_{Loss} is the total system transmission loss.

Individual generation constraint,

$$P_{gi,min} \le P_{gi} \le P_{gi,max} \qquad (7)$$

Strategy II: *Maximization of social welfare function*

In this problem both the suppliers and the customers get the benefit from the pool, otherwise it can be the profit to the ISO.

The objective function and the set of equality and inequality constraints are listed below,

$$MAX\left\{\sum_{j=1}^{n_d} B_j(P_{dj}) - \sum_{i=1}^{n_g} C_i(P_{gi})\right\} \qquad (8)$$

Subject to,

Power balance constraint,

$$\sum_{i=1}^{n_g} P_{gi} = \sum_{j=1}^{n_d} P_{dj} + P_{Loss} \qquad (9)$$

Individual generation constraint,

$$P_{gi,min} \le P_{gi} \le P_{gi,max}\ ;\ i = 1.......n_g \qquad (10)$$

Individual demand constraint,

$$P_{dj,min} \le P_{dj} \le P_{dj,max}\ ;\ j = 1.......n_d \qquad (11)$$

Line flow constraints

$$L_j \le L_{j,max}\ ;\ j = 1.......NL \qquad (12)$$

Where, NL is the total number of lines in the given network. L_j is the MVA power flow in j^{th} line. AC load flow model is used to check the violations in line limits as well as to compute the losses.

3. PSO Based Bidding Strategies

A. Overview of PSO

PSO is one of the modern heuristic algorithms developed by Kennedy and Eberhart [20]. It has been developed through simulation of simplified social models. Compared to other evolutionary methods, the advantages of PSO are ease of implementation and only few parameters to adjust.

Similar to other evolutionary algorithms, PSO must also have a fitness function that takes the agents position and assigns to it a fitness value. For consistency, the fitness function is the same as for other evolutionary algorithms. The position with maximum fitness value in the entire run is called the global best (G_{best}), each agent also keeps track of its maximum fitness value, called its local best (P_{Lbest}), and each agent is initialized with a random position and random velocity. The velocity V_j of the j[th] agent, each of n dimensions, is accelerated toward the global best and its own personal best.

Agent's velocities on each dimension are clamped to maximum allowable velocity V_{max} if the sum of accelerations exceeds this limit. V_{max} is an important parameter that determines the resolution with which regions between the present position and the target positions are searched. If V_{max} is too high, agents may fly past good regions. If it is low, agents may not explore sufficiently beyond locally good regions. To enhance the performance of the PSO V_{max} is set to the value of the dynamic range of each control variable in the problem. After performing sufficient experiments on various types of test cases, it has been concluded that a better approach is to use a "rule of thumb" to limit V_{max} to the maximum limit of the control variable of the problem.

PSO also has a well-balanced mechanism with flexibility to enhance and adapt to both global and local exploration abilities. This is realized by using an inertia weight ω and is usually calculated using the following expression:

$$\omega = \omega_{max} - (\omega_{max} - \omega_{min}) \frac{iter}{iter_{max}} \qquad (13)$$

Where $\omega_{max}/\omega_{min}$ is the initial/final weight, $iter_{max}$ is the maximum iteration count, and iter is the current iteration number. For largest values of inertia weight, PSO has global exploration feature and vice versa. Even then, there is a need for a trade-off between the quality of solution and fine-tuning of the PSO while selecting its simulation parameters.

Experimental results indicate that it is preferable to initialize the inertia weight to a large value, in order to promote global exploration of the search space, and gradually decrease it to get more refined solutions. Thus an initial value around '1' and a gradual decline towards '0' is considered as a proper choice for ω . If ω_{max} is the maximum value of the inertia weight, two real valued parameters, ω_{scale} and $\omega_{iterscale} \in [0,1]$ are determined, such that ω is linearly decreased from ω_{max} to $\omega_{max}\omega_{scale}$, over $iter_{max}\omega_{iterscale}$ iterations. Then for the last $iter_{max}(1 - \omega_{iterscale})$ iterations, it has a constant value, equal to $\omega_{max}\omega_{scale}$. Proper fine-tuning of the parameter may results in faster convergence and alleviation of local minima.

This paper deals with maximization with using constriction model [21] to find the velocity of the particles, which is much suitable for maximization problems. The equation for velocity of the particle by using this is give below,

$$v_j = \chi[\omega * v_j(t-1) + C_1 * rand_1(X_{L,best} - X_{j-1}) + C_2 * rand_2(X_{best}, X_{j-1})] \qquad (14)$$

Where, X is the control variable of the objective function $f(X)$.

χ , is the constriction factor and it is derived analytically through the formula

$$\chi = \frac{2w}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \qquad (15)$$

$\varphi = C_1 + C_2$ And w = 1

The CPSO model is used for this problem, where the value of $C_1 = C_2$.

The design of the CPSO constriction factor variant was tuned in a similar manner as the inertia weight variant.

B. Producer surplus maximization using PSO

The steps involved in producer surplus maximization is as follows,

1) Generation of Initial Conditions: *The initial conditions of all the 'M' agents (m = 1,2,3.....M) have to be generated randomly within the limits. For this problem it is assumed that the bidding of the other suppliers is known, and then random numbers has to be generated for the bidding constant* 'k' *for the ith supplier. Find the value of* P_{gi} *by using the following equation,*

$$P_{gi} = (MCP - k_i\beta_i)/k_i\,\alpha_i \quad (16)$$

Check for violations in individual generator power limits and the energy balance equation. Set the iteration count t = 1.

2) Evaluation of Agents: Each agent is evaluated using the fitness function of the problem to maximize the bidding constant 'k' of the supplier 'i'. The real power limit of the generator is constrained by adding them as the exact penalty terms to the objective function to form a generalized fitness function F_m, and is given below,

$$F_m = MCP * P_{gi} - C_{ai}(P_{gi}) + \sum_{i=1}^{n_g} \mu_1 (P_{gi} - P_{gi,limit}) \quad (17)$$

Where μ_1 is the penalty parameter, and

$$P_{gi,limitt} = \begin{cases} P_{gi,min}, \text{if } P_{gi} < P_{gi,min} \\ P_{gi,max}, \text{if } P_{gi} > P_{gi,max} \\ P_{gi}, \text{otherwise} \end{cases} \quad (18)$$

Search for the best fitness function value $F_{i,best}$ among the M agents. Set the agent associated with $F_{m,best}$ as the global best (G_{best}) of all the agents. The best fitness value of each agent up to the current iteration is set to that if the local best of that agent $(P_{L,best})$.

3) Modification of Each Searching Point: Using the global best and the local best of each agent up to the current iteration, the searching point of each agent has to be modified according to the following expression:

$$k_i = v_i + k_i(t-1) \quad (19)$$

Where,

$$v_i = \chi[\omega * v_i(t-1) + C_1 * rand_1(k_{PL,best} - k_{t-1}) + C_2 * rand_2(k_{G,best} - k_{t-1})] \quad (20)$$

where, $rand_1$ and $rand_2$ are random numbers between 0 and 1, C_1 and C_2 are positive constants called as the cognitive and social parameters (acceleration parameters) respectively. Similar to inertia weight, this factor also controls the exploration of the PSO. This acceleration factors are pull the solution towards P_{best} and G_{best} positions. After fixing the value of C_1 and C_2, find the value of constriction factor [χ], select the Proper values of ω_{max}, ω_{scale} and $\omega_{iterscale}$.

4) Modification of the Global and the Local Bests: The value of $P_{L,best}$ and G_{best} values are updated for each iteration by evaluating the fitness function of current iteration to find the current best value and compare it with all the previous iterations respectively.

5) Termination Criteria: Repeat from step 2 until the tolerance value is reached or maximum value of iteration is reached

C. Maximization of social welfare function using PSO

1) Generation of Initial Conditions: For this problem the 'M' agents are generated randomly for both generation (P_{gi}) and demand (P_{dj}) with in the limits. The size of matrix for generators and demands are $[m \times n_g]$ and $[m \times n_d]$ respectively. Run the AC load flow model to find the losses of the system and this loss is equally allocated to all the participants of the pool (both generators and loads) by using pro-rata method. Set the iteration count iteration count t = 1.

2) Evaluation of Each Agent: Each agent is evaluated using the fitness function of the problem to maximize the social welfare function. The real power limit of the generator and the real power limit of load is constrained by adding them as the exact penalty terms to the objective function to form a generalized fitness function F_m, and is given below,

$$F_m = \sum_{j=1}^{n_d} B_j(P_{dj}) - \sum_{i=1}^{n_g} C_i(P_{gi}) + \mu_1 \sum_{i=1}^{n_g} (V_i - V_{i,limit}) + \mu_2 \sum_{i=1}^{NL} (LF_i - LF_{i,limit}) \quad (21)$$

Where μ_1, μ_2 is the penalty parameter, and NL is the total no of transmission lines,

$$V_{i,\text{limit}} = \begin{cases} V_i^{\min} \text{ if } V_i < V_i^{\min} \\ V_i^{\max} \text{ if } V_i > V_i^{\max} \\ V_i, \text{otherwise} \end{cases} \quad (22)$$

$$LF_{i,\text{limit}} = \begin{cases} LF_i^{\max} \text{ if } LF_i > LF_i^{\max} \\ LF_i, \text{otherwise} \end{cases} \quad (23)$$

Search for the best value of all the fitness function values $F_{k,best}$ from $F_k, k = 1,2.....M$ Follow the same procedure similar to strategy 1 to find the value of (G_{best}) and $(P_{L,best})$.

3) Modification of Each Searching Point**:** The searching point of each agent has to be modified according to the following expression:

$$P_{gi}(t) = v_i + P_{gi}(t-1) \quad (24)$$

$$P_{dj}(t) = v_j + P_{dj}(t-1) \quad (25)$$

where,

$$v_i = \chi[\omega * v_i(t-1) + C_1 * rand_1 - (P_{gi_{L,best}} - P_{gi}(t-1) +$$

$$C_2 * rand_2(P_{gi,best} - P_{gi}(t-1)] \quad (26)$$

$$v_j = \chi[\omega * v_j(t-1) + C_1 * rand_1 - (P_{dj_{L,best}} - P_{dj}(t-1) +$$

$$C_2 * rand_2(P_{dj,best} - P_{dj}(t-1)] \quad (27)$$

where, v_i and v_j gives the velocities for generators P_{gi} and loads P_{dj} respectively.

4) Modification of the Global and the Local Bests: The value of $P_{L,best}$ and G_{best} values are updated similar to the strategy 1.

5) Termination Criteria**:** Repeat from step 2 until the tolerance value is reached or maximum value of iteration is reached.

4. Sequential Quadratic Programming

The SQP method seems to be the best nonlinear programming method for constrained optimization [22]. It is the extension of quadratic programming, it is the non-iterative method, but SQP is an iterative method most suited for constrained non-linear problems. It outperforms every other nonlinear programming method in terms of efficiency, accuracy, and percentage of successful solutions, over a large number of test problems. The method closely resembles Newton's method for constrained optimization just as is done for unconstrained optimization. At each iteration approximation is made of the Hessian of the Lagrangian function using a Broyden–Fletcher–Goldfarb–Shanno (BFGS) quasi-Newton updating method. This is then used to generate a quadratic programming sub problem whose solution is used to form a search direction for a line search procedure. For the minimization problems, the Jacobean and Hessian is positive definite (all the eigen values having positive real parts). Since our objective function is to be maximized, it is needed to change the search direction in such a way that the Hessian matrix is negative definite (all the Eigen values having negative real parts). In this paper, SQP is used as a local optimizer to fine-tune the better region explored by the PSO algorithm in its run. Using the MATLAB optimization toolbox simulates the SQP subroutine.

5. Simulation Results

A. Optimal Selection of CPSO Parameters

Selecting the optimal range of inertia weigh ω and acceleration factors C_1 and C_2 considerably affects the performance of the PSO algorithm. Therefore, to fix an optimal range of inertia weight, to solve the two proposed strategies, experiments were conducted by varying the value agent size, cognitive parameter (C_1), social parameter (C_2), starting value of the inertia weight $(\omega_{\max})$, final value (ω_{scale}) of ω in percentage of $\omega_{\max}$ $\omega_{iterscale}$ percentage of iterations, for which $\omega_{\max}$ is reduced and maximum value of step size $(V_{\max})$.

The inertia weight varied from 2.0 to 0.1, in steps of 0.1, the agent's size is varied from 10 to 1000 in steps of 10, and the maximum number of iteration is varied from 10 to 250 in steps of 10. Different possibilities of trial runs were conducted to optimally estimate all the parameters for the proposed CPSO method.

To ensure reliability in producing quality solutions by the proposed method, the relative frequency of convergence toward a quality solution is targeted. The hybrid method has reliably produced the quality solutions for inertia weights above 0.6 for all of the cases. Similarly, the average computation time taken by the CPSO method to solve the test cases for various inertia weights is also calculated.

The optimal values for C_1 and C_2 are selected by conducting similar experiments for both the strategies. For the first strategy the value of C_1 and C_2 are found to be (1.8) because of the linear nature of the constraints, but for the second strategy with it value results in deviation of optimal point. For this case it is found the value of C_1 and C_2 is lying between (0.8) and 1.0.

B. Numerical Solutions

Two test systems are taken to demonstrate the feasibility of the proposed method. A simple 3-bus system with 2 generators and a modified IEEE 30–bus system with 6 suppliers and 21 consumers are taken as test systems. The bidding equations are known. For the producer surplus maximization problem it is assumed the bidding constant of the competitive generators are known. MATLAB is used as a front-end language and the simulations are carried out on a Pentium IV, 1-GHz, 512–MB RAM processor.

Test System 1: A 3-bus [21] system with 2 suppliers and two loads are considered. The network diagram is shown in Figure 1.

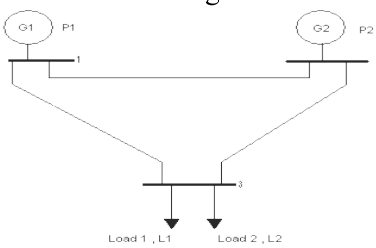

Fig. 1. Network diagram of the 3 bus test systems.

The cost functions and the unit capacity of the two suppliers are given below,

$$C_{a1} = 0.01P_1^2 + 12P_1 + 300 \text{ \$/hr}, 50 \leq P_1 \leq 500 \text{ MW}$$

$$C_{a2} = 0.015P_2^2 + 6P_2 + 400 \text{ \$/hr}, 100 \leq P_1 \leq 600 \text{ MW}$$

The demand function and their limits of the 2 loads are as follows,

$$B_1 = 0.016L_1^2 + 35L_1 \text{ \$/ hr},$$

$$0 \leq L_1 \leq 900MW$$

$$B_2 = 40L_2 \text{ \$/ hr}, \quad 0 \leq L_2 \leq 200MW$$

The total system load is 1000 MW.

Producer surplus maximization: -

The value of bidding constant of supplier 2 (K_2) is varied from 1 to 3. The profitable bidding constant of the supplier 1(K_1) is obtained. Similarly the bidding constant of supplier 1 (K_1) is varied from 1 to 3 and the corresponding maximum profitable value of supplier 2(K_2) is obtained. The variation of profit and the bidding constant for supplier 1 and supplier 2 are plotted in Figure 2 and 3 respectively.

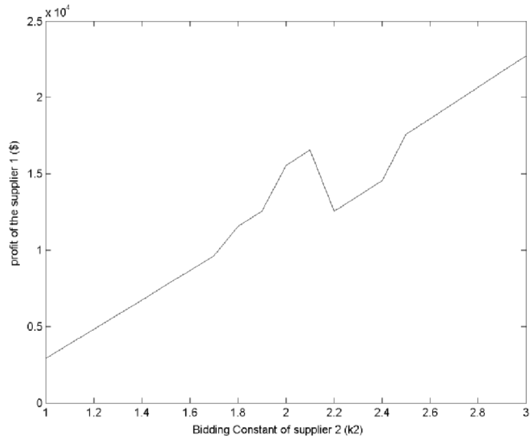

Fig. 2.Profit variation of supplier 1 for the various value of bidding constant K_2

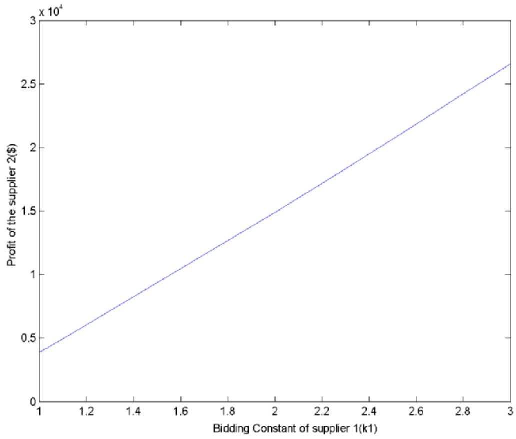

Fig. 3.Profit variation of supplier 2 for the various value of bidding constant K_1

The CPSO parameters used for this simulation are listed below,

Number of agents = 100

Number of iterations = 175

Learning factors (C_1,C_2) = 1.8

The result of a sample run is given in Table 1.

Table.1 Result of the 3 bus systems for the producer surplus maximization

	Fixed bidding constant of the supplier	Profitable Bidding constant		Profit ($/hr)	
		CPSO	CPSO-SQP	CPSO	CPSO-SQP
G1	K2 = 1.8	K1= 2.0	K1= 2.1	10,575	10,590
G2	K1 = 1.8	K2= 1.86	K2=1.86	12,652	12,652

Maximization of Social Welfare Function: -

The difficulty with this problem is both the supplier and load are submitting their bids in the market. CPSO parameters used in the previous test system will not give optimal solution. The high values of learning factors move away the solution vector from the optimal solution. So it is tested the system with various learning factors to find the optimal value of the learning factors.

The CPSO parameters used for this simulation are listed below,

Number of agents = 100
Number of iterations = 75
Learning factors (C_1, C_2) = 1.2

The result of a sample run is given in Table 2.

Table.2 Result of the 3 bus systems for the social welfare maximization

	Bidding constant of the supplier	Profitable Bidding constant		Profit ($)	
		CPSO	CPSO-SQP	CPSO	CPSO-SQP
G1	1.8	K_1=1.85	K_1=1.85	88.175	88.175
G2	1.8	K_2= 2.1	K_2= 2.0	1326.7	1327.9
G3	1.8	K_3=1.25	K_3=1.25	616.07	616.07
G4	1.8	K_4=1.99	K_4=1.99	2463.1	2463.04
G5	1.8	K_5=1.99	K=1.99	891.65	891.65
G6	1.8	K_6=1.95	K_6=1.97	1590.3	1592.6

The maximum value of Social Welfare function is obtained as 58.3798 $/ MWhr. The market price is decreased from 27.031 $/ MWhr to 20.0090 $/ MWhr.

Test System2: A modified IEEE 30 bus system with 6 suppliers and 21 loads are considered. The network diagram is shown in Figure 4.

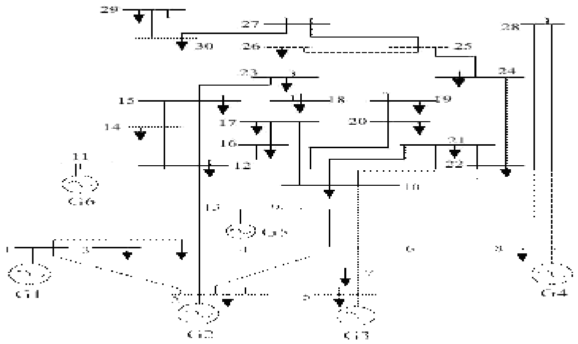

fig4. Network diagram of IEEE 30 bus systems

The generalized quadratic function and the corresponding values with their unit capacity limits are given in Table 3.

Table.3 Cost coefficients and limits of the modified IEEE 30-bus systems

Generators	**Cost coefficients**			**$P_{i,max}$**	**$P_{i,min}$**
	a_i	**b_i**	**c_i**		
G1	0.010	20	200	150	5
G2	0.012	15	150	150	5
G3	0.040	18	250	150	5
G4	0.006	10	100	200	5
G5	0.040	18	200	150	5
G6	0.010	15	150	150	5

For demand side bidding, the generalized bidding equation given in [11] is used and it is given below,

$$B_i = d_{1i}P_i - 0.5d_{2i}P_i^2$$

The total system load is 600MW.

Producer surplus maximization: -

The CPSO parameters used for this simulation are listed below,

Number of agents = 100
Number of iterations = 75
Learning factors (C_1 & C_2) = 1.7

The result of a sample run is given in Table 4.

Table.4 Results of the IEEE 30 bus systems for the producer surplus maximization

	Quantity (MW)		**Profit($/hr)**	
	CPSO	**CPSO-SQP**	**CPSO**	**CPSO-SQP**
G1	400.4325	400.4495	0	0
G2	343.9042	344.8045	1262.982	1263.6740
L1	616.2451	616.6551	21411.931	21412.731
L2	128.1213	128.5989	2569.9707	2570.8206

Maximization of Social Welfare Function: -

The procedure to obtain the maximum social welfare function is similar to 3-bus test system. For this test system, the results of three cases are discussed and it is given in Table 5. The CPSO parameters are adjusted with respect to the constraint to get the optimal solution. The results obtained from integrated CPSO-SQP method is superior to the results obtained from CPSO method. The convergence comparison of results with out considering losses and with loss allocation is given in Fig 5.

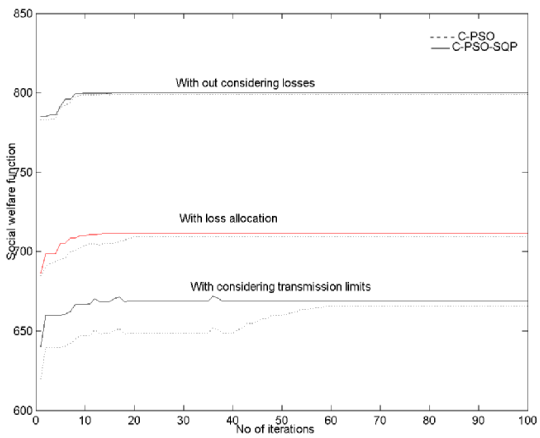

Fig.5. Convergence characteristics with losses and with loss allocation

The results of all the three cases with the quantity and the profit of all the entities are tabulated in Table 5.

Table.5 Results of the IEEE 30 bus systems for the social welfare maximization (CPSO – SQP)

List of Generators and Loads	**With out considering loses**		**With loss allocation**		**Loss allocation with transmission limits**	
	SWF = 800.065$/Mwhr		**SWF** = 711.289 $/MWh		**SWF** = 668.7058$/Mwh	
	Quantity (MW)	Profit ($/h)	Quantity (MW)	Profit ($/h)	Quantity (MW)	Profit ($/h)
P1	108.45	580.50	91.270	602.82	76.322	506.34
P2	68.067	741.17	117.09	1243.5	132.33	1321.3
P3	88.740	214.96	130.38	0	127.01	0
P4	129.06	2061.5	80.310	1402.7	94.038	1601.7
P5	119.02	0	63.575	339.76	80.926	298.33
P6	41.173	481.65	116.47	1292.9	71.308	836.77
L1	7.514	-123.17	36.437	834.66	19.738	9.3282
L2	11.953	-118.92	16.705	-67.988	36.478	847.40
L3	27.841	342.49	44.770	1509.4	36.205	827.97
L4	24.077	172.03	33.968	667.01	13.083	-117.28
L5	21.553	78.598	41.330	1210.8	27.873	326.31
L6	9.551	-128.20	32.112	551.02	29.249	397.01
L7	41.819	1289.5	37.075	880.38	25.253	205.17
L8	27.325	316.93	28.061	328.10	33.510	646.65
L9	29.261	416.36	40.124	1112.7	24.967	193.03
L10	36.700	886.74	44.862	1517.7	13.394	-114.09
L11	17.007	-46.513	29.192	386.17	11.366	-129.97
L12	29.644	437.15	21.352	52.497	18.095	-33.247
L13	22.980	129.33	20.072	13.448	39.64	1084.3
L14	31.763	559.04	27.306	291.19	38.031	961.02
L15	34.649	743.23	4.398	-96.227	38.706	1012.1
L16	35.645	811.60	41.719	1243.1	39.899	1105.5
L17	31.397	537.16	26.267	242.83	20.273	24.745
L18	25.908	250.33	2.554	-62.875	38.724	1013.8
L19	39.296	1083.1	10.291	131.12	21.860	75.085
L20	32.640	612.83	11.753	-131.00	12.999	-118.00
L21	15.931	-67.861	24.499	166.96	7.5059	-127.91

The value of social welfare function is 800.0654 $/MWh, if the losses are not considered. When the losses are considered and it is allocated equally among all the entities (Pro – rata method) then the value of welfare function is decreased to 711.2896 $/MWh. This value is further reduced to 668.7058 $/MWh when we include the transmission line limits in to the problem.

C. Computation Analysis of proposed Algorithm

The efficiency of the proposed algorithm is checked with various test cases. Using canonical PSO (CPSO) and CPSO integrated with SQP does the simulation of test cases. The analysis is carried out with respect to computational time and the capability of the algorithm to tackle the variations in parameters. By comparing the various test case results, it is found that CPSO take lesser iterations to give the optimal solution compare to General PSO (GPSO). The results are improved after incorporating SQP as a local optimizer. Initially the SQP subroutine is used at the end of the CPSO, i.e., the final results obtained by using CPSO are taken as initial values for the SQP. The results are improved further by integrating SQP with PSO in such a way that, it will search for the better solution whenever the value of G_{best} is replaced. This will explore the solution space effectively to obtain the global optimal solution. CPSO integrated with SQP gives very good results with little more computational time than other methods. It will effectively take up the variations in the input parameters than other methods.

6. Conclusion

The proposed CPSO-SQP method is simple, reliable and gives accurate results with in the reasonable computation time. The CPSO with constriction factor explores the solution space to obtain near global solution. The application of scaling factor for inertia constant ensures the convergence of the solution. SQP is used to fine tune the solution obtained from CPSO. The proposed algorithm is tested with two test systems and the results are tabulated. Three various conditions are considered to find the maximum value of social welfare function. In the first case the losses are not considered, in the second case the losses are considered and allocated equally to all the entities. In the third case the line limits are considered. The variation of social welfare function for all the cases is analyzed by using the proposed algorithm.

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