Economic Load Dispatch and DC-Optimal Power Flow Problem- PSO versus LR

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***Abstract*— Economic Load Dispatch (EDC) and Direct Current Optimal Power Flow (DCOPF) are the most important techno-economical issues in the power system operation. In this paper, two approaches are incorporated in the EDC and DCOPF problems. One of them is a mathematical optimization technique, Lagrangian Relaxation (LR) and the second is a heuristic one, Particle Swarm Optimization, (PSO). Both techniques have strong and weak points. The LR technique is based on the derivatives and the PSO is a non- derivative technique. These approaches are effective tools which can be implemented for short-term and long-term power system analysis, especially for economic analysis of restructured power systems. The DCOPF methodology has been considered for LMP calculation in LR, which is not available in PSO techniques. In the other hand, PSO technique may be able to provide the optimal solution, where LR usually getting stuck at a local optimum in a large scale power system. The simulation results show that the presented methods are both satisfactory and consistent with expectation.**

***Keywords*—** Particle Swarm Optimization, Lagrangian Relaxation, DC-Optimal Power Flow, Economic Load Dispatch and Power System Economic

List of symbols

i	Index for bus
j	Index for line
ug	Index for generation unit
ud	Index for load demand
NB	Total number of buses
NL	Total number of lines
NU	Total number of units
ND	Total number of loads
$P(i,ug)$	Power produced by unit ug at bus i
$D(i,ud)$	Power demanded by consumer ud at bus i
$C(i,ug)$	Offered price of unit ug at bus i
$PG(i)$	Total generation at bus i
$PD(i)$	Total demand at bus i
$A(i,j)$	Incidence matrix (node and branch)
$X(j,j)$	Diagonal reactance matrix
$\delta(i)$	Voltage angle of bus i
$\lambda(i)$	Dual variable of the balance constraint at bus i
$PL(j)$	Transmission line j capacity

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I. INTRODUCTION

The competitive environment of electricity markets necessitates wide access to transmission and distribution networks that connect dispersed customers and suppliers. Moreover, as power flows influence transmission charges, transmission pricing may not only determine the right of entry but also encourage efficiencies in power markets. For example, transmission constraints could prevent an efficient generating unit from being utilized. A proper transmission pricing scheme that considers transmission constraints or congestion could motivate investors to build new transmission and/or generating capacity for improving the efficiency. In a competitive environment, proper transmission pricing could meet revenue expectations, promote an efficient operation of electricity markets, encourage investment in optimal locations of generation and transmission lines, and adequately reimburse owners of transmission assets. Most important, the pricing scheme should implement fairness and be practical.

However, it is difficult to achieve an efficient transmission pricing scheme that could fit all market structures in different locations. The ongoing research on transmission pricing indicates that there is no generalized agreement on pricing methodology. In practice, each country or each restructuring model has chosen a method that is based on the particular characteristics of its network. Measuring whether or not a certain transmission pricing scheme is technically and economically adequate would require additional standards [1].

In 1962, Carpentier introduced a generalized nonlinear programming (NLP) formulation of the economic dispatch (ED) problem including voltage and other constraints. The problem was later named OPF. The OPF procedure consists of determining the optimal steady-state operation of a power system, which simultaneously minimizes the value of a chosen objective function and satisfies certain physical and operating constraints. Today OPF has been playing a very important role in power system operation and planning: different classes of OPF problems, tailored towards special-purpose applications are defined by selecting different function to be minimized, different sets of controls and different sets of constraints [2].

Since OPF was introduced in 1968 [3], several methods have been employed to solve this problem, e.g., Gradient base [3], linear programming method [4] and quadratic programming [5-7]. However, all of these methods suffer from three main problems. Firstly, they may not be able to provide the optimal solution and usually getting stuck at a local optimum [8]. Secondly, all these methods are based on the assumption of continuity and differentiability of the objective function, which is not true in a practical system [9].

Finally, all these methods cannot be applied with discrete variables which are transformer taps. It seems that heuristic optimization algorithms are appropriate methods to solve this problem, which eliminate the above drawbacks.

When the transmission becomes congested, meaning that no additional power can be transferred from a point of injection to a point of extraction, more expensive generating units may have to be brought on-line on one side of the transmission system. In a competitive market, such an occurrence would cause different locational marginal prices (LMPs) between the two locations. If transmission losses are ignored, a difference in LMPs would appear when lines are congested. Conversely, if flows are within limits, LMPs will be the same at all buses and no congestion charges would apply. The difference in LMPs between the two ends of a congested line is related to the extent of congestion and MW losses on this line. Since LMP acts as a price indicator for both losses and congestion, it should be an elementary part of transmission pricing [10].

The locational marginal pricing is a dominant approach in energy market operation and planning to identify the nodal price and to manage the transmission congestion LMP has been implemented under consideration at the number of ISO's such as PJM, New York ISO , ISO-New England, California ISO, and Midwest ISO [11-13].

Locational marginal prices may be decomposed into three components: marginal energy price, marginal congestion price, and marginal loss price [10, 14-15]. The LMP can be calculated by the Optimal Power Flow (OPF) and DCOPF-based simulations. The DCOPF has been used by many utilities for price forecasting and system planning [14], [16].

In many paper LMP calculated as a deterministic variable [14]. Considering the uncertainties associated with the input data of load flow, the LMP can be considered as a stochastic variable. Therefore calculation of LMP as a random variable can be very useful in power market forecasting studies [16]. Other method is Point Estimation Method (PEM) [16-17]. This method used two or more point to calculate mean and variance of desired variable and estimate PDF and CDF of this variable.

Point Estimation Method (PEM) has lack of accuracy although has a good speed. It can be seen that the results of point estimation method in [16] have a few differences from deterministic calculation. Several earlier works [18-22] have reported the modeling of LMPs, especially in marginal loss model and related issues. Reference [18] points out the significance of marginal loss price, which may differ up to 20% among different zones in New York Control Area based on actual data. Reference [19] presents a slack-bus-independent approach to calculate LMPs and congestion components.

Reference [20] presents a real-time solution without repeating a traditional power flow analysis to calculate loss sensitivity for any market-based slack bus from traditional Energy Management System (EMS) products based on multiple generator slack buses. Reference [21] demonstrates the usefulness of dc power flow in calculating loss penalty factors, which has a significant impact on generation scheduling. The authors of [21] also point out that it is not advisable to apply predetermined loss penalty factors from a typical scenario to all cases. Reference [22] presents LMP simulation algorithms to address marginal loss pricing based on the dc model. From the viewpoint of generation and transmission planning, it is always crucial to simulate or forecast LMPs, which may be obtained using the traditional production (generation) cost optimization model, given the data on generation, transmission, and load [23], [15]. Typically, dc optimal power flow (DCOPF) is utilized for LMP simulation or forecasting based on production cost model via linear programming (LP) owing to LP's robustness and speed. The popularity of DCOPF lies in its natural fit into the LP model. Moreover, various third-party LP solvers are readily available to plug into DCOPF model to reduce the development effort for the vendors of LMP simulators [14].

This paper is organized as follows: Theoretical consideration of classical economic dispatch is presented in the next section. Direct current optimal power flow and its modeling in LR and PSO are presented in section III. Simulation results are presented in section IV and conclusion of this paper is conducted in last section.

II. CLASSICAL ECONOMIC DISPATCH

The economic dispatch (EDC) problem consists in allocating the total demand among generating units so that the production cost is minimized. Generating units have different production costs depending on the prime energy source used to produce electricity (mainly coal, oil, natural gas, uranium, and water stored in reservoirs). And these costs vary significantly; for example, the marginal costs for nuclear, coal, and gas units may vary considerably, taking on values ranging between \$0.03 and \$0.20 per kWh. In addition to the continuous decisions on how to allocate the demand among generating units (EDC), a decision that involves calculating the MW outputs of all units (a set of continuous variables). Each generating unit is assigned a function, Ci (PGi), characterizing its generating cost in \$/h in terms of the power produced in MW, PGi, during 1 h. This function is obtained by multiplying the heat rate curve, expressing the fuel consumed to produce 1MW during 1 h, by the cost of the fuel consumed during that hour. Note that the heat rate is a measure of the energy efficiency of the generating unit. The cost function is generally approximated by a convex quadratic or piecewise linear function, as illustrated in Fig. 1 [24] or maybe has a non-convex nature as non-convex production function which describes in next section.

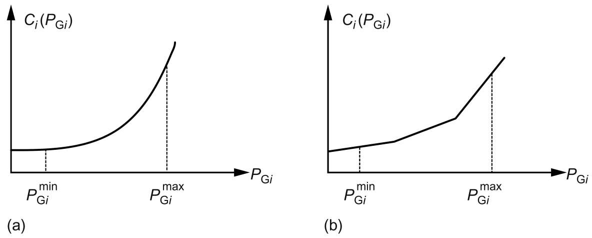

Fig. 1. Examples of cost functions: (a) convex quadratic and (b) piecewise linear [24]

Considering *n* generating units, the total production cost is:

$$C(P_G) = \sum_{i=1}^{n} C_i(P_{Gi}) \qquad (1)$$

where *P*G is the column vector of the unit generation levels *P*G*i*.

If the system total demand is *PD* and all generating units contribute to supply this demand, total production or generation must equal the total demand.

$$\sum_{i=1}^{n} P_{Gi} = PD \qquad (2)$$

The EDC problem consists of minimizing the total cost (1) with respect to the unit generation outputs, *P*G*i*, subject to the power balance (2), and to the generating unit operational limits,

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \qquad (3)$$

where superscripts "*min*" and "*max*" indicate minimum and maximum, respectively [24].

III. DIRECT CURRENT OPTIMAL POWER FLOW

The lossless DCOPF can be modeled as the minimization of the total production cost subject to energy balance and transmission constraints. The voltage magnitudes are assumed to be unity and reactive power is ignored. Also, it is assumed that there is no demand elasticity. This model may be written as NLP:

$$Min \sum_{i=1}^{NB} \sum_{ug=1}^{NU} [f\,(P(i,ug))] \qquad (4)$$

Where $f\,(P(i,ug)) = aP^2(i,ug) + bP(i,ug) + c$

Subject to:

$$PG(i) = \sum_{ug=1}^{NU} P(i,ug) \qquad (5)$$

$$PD(i) = \sum_{ud=1}^{ND} D(i,ud) \qquad (6)$$

$$PG(i) - PD(i) = \sum_{j=1}^{NL} A(i,j) * PL(j) \perp \lambda(i) \qquad (7)$$

$$\sum_{i=1}^{NB} A^T(i,j) * \delta(i) = \sum_{j=1}^{NL} X(j,j) * PL(j) \qquad (8)$$

$$PL^{\min}(j) \le PL(j) \le PL^{\max}(j) \qquad (9)$$

$$P^{\min}(i,ug) \le P(i,ug) \le P^{\max}(i,ug) \qquad (10)$$

A. *Lagrangian Relaxation DCOPF* [1]

Aggregated generation and demand at each bus are represented in (5) and (6), respectively. Generation and demand balance addressed in (7) by implementing the incidence matrix, this equation corresponds with injection power through power transmission lines connected to bus *i*. Locational marginal price is the dual variable of the balance constraint at bus *i* and indicated as λ(i). Power transmitted through transmission lines is indicated as (8) using correspondence diagonal reactance matrix, X.

Constraints (9) and (10) enforce the transmission capacity limits of each line and each generation unit, respectively. The first step is extracting corresponding incidence matrix of the network. Fig. 2 shows a simple network which consists of three buses and three lines. Each network can be represented as a graph and such a directional graph. Each bus indicated as a node and each transmission line addressed as a directed branch. In the corresponding incidence matrix, nodes and branches indicated as rows and columns, respectively. In the incidence matrix, "1" indicates if branch leaves node, "-1" if branch arrives at node and "0" if no connection.

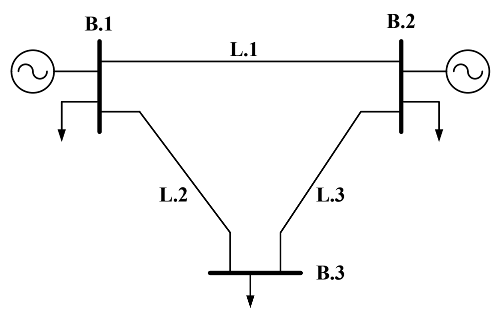

Fig. 2 Simple power system

It should be noted that the mathematical formulation in this paper extends the general formulation of single generator and single load for each bus. Aggregated production and load demand are modeled in this paper. Despite of recent papers which claim that actual implementation can be more complicated considering multiple generators and loads [14], the incidence matrix based formulation ignores both multiple generation units and multiple transmission lines between buses.

It also should be noticed that implementing the incidence matrix methodology eliminates the network interdependencies because of admittance matrix structure in conventional power flow. This approach would be useful in contingency analysis of power network. In contingency analysis it is very important to utilize a fix algorithm and eliminating the topological changes. For multiple generation units which installed in each bus, contingency analysis would be easily carried out, but for transmission line contingencies because of changing the admittance elements but in the incidence matrix formulation this objection has been removed.

The incidence graph is illustrated as Fig. 3, and Table I represents the corresponding incidence matrix.

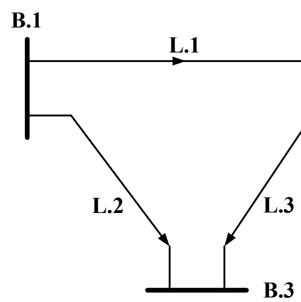

Fig. 3 Directional graph of simple power system

Table I Incidence matrix of simple power network

A(i,j)		Lines 1	2	3
Buses	1	1	1	0
	2	-1	0	1
	3	0	-1	-1

The diagonal reactance matrix is easily extracted from grid. For example X(1,1) indicates the first line, L.1 in the grid. Similarly, X(2,2) and X(3,3) imply L.2 and L.3, respectively.

One of the advantages of this network representation by using incidence matrix is appeared in contingency analysis which outages of both generation units and transmission lines would be modeled easily. For example, when a transmission line outage is occurred, by assigning "0" in line capacity, the entire impacts of corresponding transmission line is eliminated easily.

B. Particle Swarm Optimization DCOPF

In this section particle swarm optimization DCOPF is presented in which the hourly EDC is also included.

Particle Swarm Optimization (PSO) is an algorithm developed by [25] that simulates the social behaviors of bird flocking or fish schooling and the methods by which they find roosting places, food sources, and suitable habitat.

In the basic PSO technique, suppose that the search space is d-dimensional, such that:

- Each member is called a *particle*, and each particle (*i*-th particle) is represented by d-dimensional vector and described as $X_i = [x_{i1}, x_{i2}, \dots, x_{id}]$
- The set of n particles in the swarm are called *population* and described as $pop = [X_1, X_2, \dots, X_n]$
- The best previous position for each particle (the positions giving the best fitness value) is called *particle best* and described as $PB_i = [pb_{i1}, pb_{i2}, \dots, pb_{id}]$
- The best position among all of the particle best position achieved so far is called *global best* and described as $GB = [gb_1, gb_2, \dots, gb_d]$
- The rate of position change for each particle is called *the particle velocity* and it is described as $V_i = [v_{i1}, v_{i2}, \dots, v_{id}]$
- At iteration *k* the velocity for d-dimension of *i* particle is updated by:

$$v_{id}^{k+1} = wv_{id}^k + c_1 r_1 \left(pb_{id}^k - x_{id}^k \right) + c_2 r_2 \left(gb_d^k - x_{id}^k \right)$$

where $i = 1, 2, \dots, n$, and n is the size of population, w is the inertia weight, c_1 and c_2 are the acceleration constants, and r_1 and r_2 are two random values in range [0,1]. The optimal selection of previous parameters is found in [26-27]

- The *i*-particle position is updated by:

$$v_{id}^{k+1} = wv_{id}^k + c_1 r_1 (pb_{id}^k - x_{id}^k) + c_2 r_2 (gb_d^k - x_{id}^k) \qquad (11)$$

The PSO technique can be expressed as follow:

Step 1. *(Initialization):* Set the iteration to number k=0. Generate randomly n particles, $\{X^0_i$, i = 1, 2, …., n$\}$, where $X_i^0 = \left[X_{i1}^0, X_{i2}^0, \dots, X_{id}^0 \right]$, and their initial velocities $V_i^0 = \left[V_{i1}^0, V_{i2}^0, \dots, V_{id}^0 \right]$. Evaluate the objective function for each particle $f(X^0_i)$. If the constraints are satisfied, then set the *particle best* $PB^0_i = X^0_i$, and set the *particle best* which gives the best objective function among all of the particle bests to *global best*, GB^0. Otherwise, repeat the initialization.

Step 2. *Update iteration counter k=k+*1

Step 3. *Update velocity* using Eq. (11)

Step 4. *Update particle best:*

$$\textit{if} \;\; f_i\left(X_i^k\right) < f_i\left(PB_i^{k-1}\right) \; \textit{then} \;\; PB_i^k = X_i^k$$

$$\textit{else} \;\; PB_i^k = PB_i^{k-1}$$

Step 5. *Update global best* :

$$f\left(GB^k\right) = \min\left\{ f_i\left(PB_i^k\right) \right\}$$

$$\textit{if} \;\; f\left(GB^k\right) < f\left(GB^{k-1}\right) \; \textit{then} \;\; GB^k = GB^k$$

$$\textit{else} \;\; GB^k = GB^{k-1}$$

Step 6. *Stopping criterion:* If the number of iterations exceeds the maximum number iteration, then stop, otherwise go to step 2 [28].

In order to implement the PSO to the DCOPF problem, the variable matrix is included production level of generation units and bus angles, except slack bus in which the bus angle is set to zero. In the other words, $X_i = [x_{i1}, x_{i2}, \dots, x_{id}]$ is constructed by the PG_i and δ_i where δ_{Slack}=0.

The main objective function includes total operation cost, transmission flow violation penalty and load imbalance penalty and represent as follows:

$$Z = f(P(i,ug)) + \left(\sum_{i=1}^{NB} PG(i) - \sum_{i=1}^{NB} PD(i)\right)^2 * Penalty + \sum_{j=1}^{NL}\left(\left|X(j,j)*PL(j)\right| - PL^{\max}(j)\right)*Penalty \quad (12)$$

In the next section we present a simple case study in order to illustrate the feasibility and compatibility of the both LR and PSO DCOPF problem.

IV. SIMULATION STUDIES

In order to validate the LR and PSO DCOPF calculation, a simple three-bus test case, is considered here. The benchmark parameters are listed in Tables II and III.

Demanded load at buses 1, 2 and 3, are 400MW, 300MW and 150MW, respectively.

The system is slightly modified from the presented in fig. 3 and will be used for the rest of this paper. The third generation unit is located at bus 3 for better illustration. It also should be noticed that the aforementioned incidence matrix is similar with the Table I.

Table II. Line impedance and flow limits

Line Number	1	2	3
Connection	1-2	1-3	2-3
R(pu)	0.00	0.00	0.00
X(pu)	0.10	0.20	0.20
Limit(MW)	1000	1000	1000

Table III. Generation unit's data

Unit	Pmax	Pmin	a	b	c
1.1	1000	0	0.012	20	400
2.1	1000	0	0.010	10	200
3.1	1000	0	0.015	12	150

As it mentioned above, in LR method LMP at each bus would be available by calculating the locational dual variables of (7) at each bus.

In PSO algorithm, the matrix $X_i = [PG_1, PG_2, PG_3, \delta_2, \delta_3]$ and reference bus angle is set to zero. The violation penalty factor is 1E+10 and the PSO parameters are as follows:

Table IV. PSO's Parameters

PSO Parameters	Value	PSO Parameters	Value
No. Variables	3.00	Iteration	1000
Variable ^{min}	0.00	Inertia Weight	1.000
Variable ^{max}	1000	Damping Ratio	0.950
Velocity ^{max}	50.0	C1	2.000
No. Population	1000	C2	2.000

The optimal power flow and economic load dispatch results are presented in table V. Simulation results show that the final results of both LR and PSO are identical. In order to illustrate the PSO could reach the best cost and parameter initialization set in an optimal fashion. Figure 4 shows the PSO trend.

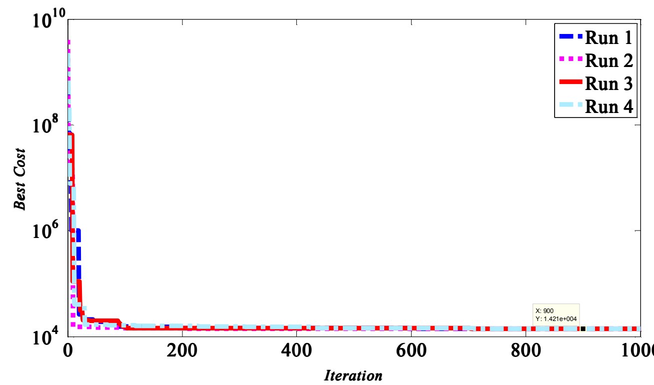

Fig. 4. Optimal results of PSO in DCOPF (All cases reach the identical results)

Table V. Generation unit's data

Unit	PG(MW)	LMP($/MWh)	Line	PL(MW)
1.1	27.780	20.667	1-2	-242.22
2.1	533.33	20.667	1-3	-130.00
3.1	288.89	20.667	2-3	-8.8900

V. CONCLUSION

The PSO and LR DCOPF which contain EDC are presented in this paper, are simple approaches to calculating the short-term operation. In LR which is based on the mathematical methodology, the LMP would be available but the convergence of this approach is not guaranty for large scale power system. In the other words, the PSO would overcome this challenge however it couldn't render the LMP. Simulation results also show that the presented method is both satisfactory and consistent with expectation.

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