World Academy of Science, Engineering and Technology
International Journal of Energy and Power Engineering
Vol:5, No:2, 2011

Economic Dispatch Fuzzy Linear Regression and Optimization

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***Abstract*—**This study presents a new approach based on Tanaka's fuzzy linear regression (FLP) algorithm to solve well-known power system economic load dispatch problem (ELD). Tanaka's fuzzy linear regression (FLP) formulation will be employed to compute the optimal solution of optimization problem after linearization. The unknowns are expressed as fuzzy numbers with a triangular membership function that has middle and spread value reflected on the unknowns. The proposed fuzzy model is formulated as a linear optimization problem, where the objective is to minimize the sum of the spread of the unknowns, subject to double inequality constraints. Linear programming technique is employed to obtain the middle and the symmetric spread for every unknown (power generation level). Simulation results of the proposed approach will be compared with those reported in literature.

***Kewywords*—**Economic Dispatch, Fuzzy Linear Regression (FLP) and Optimization.

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I. Introduction

SCARCITY of energy resources, increasing power generation cost and ever-growing demand for electric energy necessitates optimal economic dispatch in today's power systems. The main objective of economic dispatch is to reduce the total power generation cost while satisfying various equality and inequality constraints. Traditionally in ED problems, the cost function for generating units has been approximated as a quadratic function.

A wide variety of optimization techniques have been applied in solving economic load dispatch problems (ELD). Some of these techniques are based on classical optimization methods while others are based on artificial intelligence methods or heuristic algorithms. Many references present the application of classical optimization methods, such as linear programming, quadratic programming,, to solve the ELD problem [1, 2]. Classical optimization methods are highly sensitive to staring points and sometimes converge to local optimum solution or diverge altogether. Linear programming methods are fast and reliable but the main disadvantage associated with the piecewise linear cost approximation. Non-linear programming methods have a problem of convergence and algorithmic complexity. Newton based algorithms have a problem in handling a large number of inequality constraints [3].

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Methods based on artificial intelligence techniques, such as artificial neural networks, were also presented in many references [4, 5]. Recently, many heuristic search techniques such as particle swarm optimization [3] and genetic algorithms [6] were applied successfully to the ELD problem. Hybrid methods were also presented in some references such as reference [7]. In this reference, the conventional Lagrangian relaxation approach, first order gradient method and multi-pass dynamic programming are combined together. This paper introduces an optimal minimization technique assisted with Fuzzy Linear Programming Regression FLP [8, 9] in an effort to reduce the computational burden associated with the solution of the nonlinear equations of the economic dispatch problem. The presented method has the advantage of compute the solutions fast enough for online operator to solve non-continues, non-differentiable and multimodal, i.e. multiple local optima, optimization problem. Since the economic dispatch is one such problem, then the proposed method appears to be a good candidate to handle the economic dispatch problem.

II. An Overview of Tanaka's Fuzzy Linear Regression

Fuzzy linear regression was introduced by Tanaka et. al [8] in 1982. The general form of Tanaka's formulation is given by:

$$\underset{\sim}{Y} = f(x) = A_0 + A_1 x_1 + A_2 x_2 + ... + A_n x_n = \boldsymbol{Ax} \qquad (1)$$

where $\underset{\sim}{Y}$ is output (dependant fuzzy variable), $\{x_1, x_2, ...x_n\}$ is a non fuzzy set of crisp independent parameters and $\{A_0, A_1, ..., A_n\}$ is a fuzzy set of symmetric members, unknowns, needs to be estimated. Each fuzzy element in that set may be represented by a symmetrical triangular membership function, shown in figure 1, defined by a middle and a spread values, p_i and c_i respectively. The middle is known as the model value and the spread denotes the fuzziness of that model value. The triangular membership function can be expressed as:

$$\mu_{\underset{\sim}{A_i}}(a_i) = \begin{cases} 1 - \dfrac{|\ p_i - a_i\ |}{c_i} & , \quad p_i - c_i \le a_i \le p_i + c_i \\ 0 & , \quad otherwise \end{cases} \qquad (2)$$

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Therefore, since $A_i = (p_i, c_i)$, then equation (1) may be rewritten as:

$$Y_{\sim} = f(x) = (p_0, c_0) + (p_1, c_1)x_1 + ... + (p_n, c_n)x_n \qquad (3)$$

The membership function of output $Y_{\sim}$ may be given by:

$$\mu_{Y_{\sim}}(y) = \begin{cases} \max(\min([\mu_{A_i}(a_i)]) & , \{a | y = f(x,a)\} \neq \varnothing \\ 0 & , \quad otherwise \end{cases} \qquad (4)$$

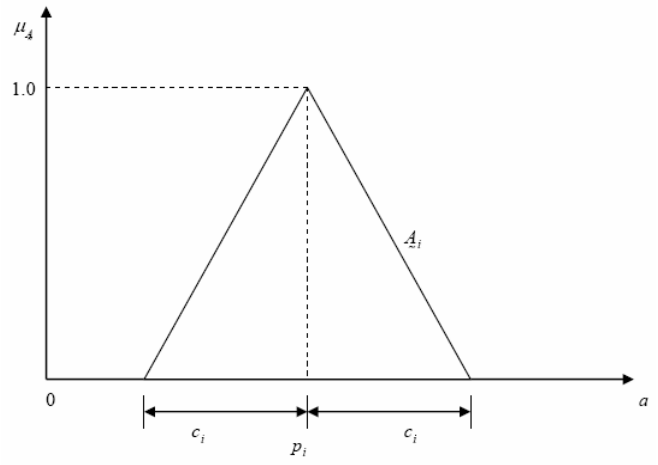


Fig. 1. Membership function of fuzzy coefficient $\boldsymbol{A}$

Now, by substituting equation (3) in (4), the output

From regression point of view, equations (1-5) may be applied to m samples where the output can be either non-fuzzy, (certain or exact), in which no assumption of ambiguity is associated with the output or fuzzy (uncertain), where uncertainty in the out is involved due to human judgment or meters impression [10]. In this study both non fuzzy and fuzzy output will be considered. Membership function is given as:

$$\mu_{Y_{\sim}}(y) = \begin{cases} 1 - \dfrac{\left| y - \sum_{i=1}^{n} p_i x_i \right|}{\sum_{i=1}^{n} c_i \left| x_i \right|} & , x_i \neq 0 \\ 1 & , \ x_i = 0, \ y_i = 0 \\ 0 & , \ x_i = 0, \ y_i \neq 0 \end{cases} \qquad (5)$$

The output membership function is depicted in figure 2.

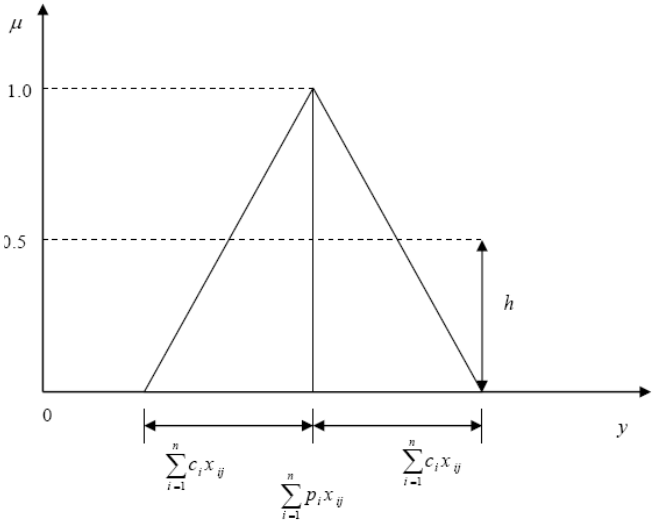


Fig. 2. Membership function of output

A. Non-fuzzy output model [8]:

In this model, Tanaka converted regression model into a linear programming problem [8]. In this case the objective is to solve for the best parameters, i.e. A^*, such that the fuzzy output set is associated with a membership value grater than h as in ;

$$\mu_{Y_j}(y_j) \geq h, \qquad j = 1, ..., m \qquad (6)$$

where $h \in [0,1]$ is the degree of the fuzziness and is normally defined by the user.

Therefore, with equation (6) as a condition, the main objective is to find the fuzzy coefficients that minimize the spread of all fuzzy output for all data set. Note that the fuzziness in the output is due to fuzziness assumed in the system structure A^*. Thus, given non-fuzzy data (y_i, x_i), the fuzzy parameters $\boldsymbol{A}^* = (\boldsymbol{p}, \boldsymbol{c})$ may be solve for by the linear programming formulation as:

$$F_{non-fuzzy} = \min(\sum_{j=1}^{m} \sum_{i=1}^{n} c_i x_{ij}) \qquad (7)$$

Subject to:

$$y_j \geq \sum_{i=1}^{n} p_i x_{ij} - (1-h) \sum_{i=1}^{n} c_i x_{ij} \qquad (8)$$

$$y_j \leq \sum_{i=1}^{n} p_i x_{ij} + (1-h) \sum_{i=1}^{n} c_i x_{ij} \qquad (9)$$

Note that from in (8) and (9), $\sum_{i=1}^{n} p_i x_{ij}$, defines the middle value and $\sum_{i=1}^{n} c_i x_{ij}$ defines the sympatric spread to the left, constraint (8), and to the right, constraint (9), as illustrated in figure 2. As can be seen from the figure 2, as the degree of fuzziness, h, increases the spread, c_i, increases and

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therefore the uncertainty associated with the p_i would increase [11]. The prove and detailed derivation may be found in [8, 9].

III. Proposed Problem Formulation

The traditional formulated of the economic load dispatch problem is a minimization of summation of the fuel costs of the individual dispatchable generators subject to the real power balanced with the total load demand as well as the limits on generators outputs. In mathematical form the problem can be stated as:

$$F = \sum_{i=1}^{N} F_i(P_{gi}) \quad (10)$$

The incremental fuel cost function of the generation units with value-point loading are represented as follows [10]:

$$F_i(P_{gi}) = a_i P_{gi}^2 + b_i P_{gi} + c_i + \left| e_i \times \sin(f_i \times (P_{gi\ \min} - P_{gi})) \right| \quad (11)$$

Subject to

$$\sum_{i=1}^{N} P_{gi} = P_D + P_L \quad (12)$$

$$P_{gi_{(\min)}} < P_{gi} < P_{gi_{(\max)}}, i \in N_s \quad (13)$$

where:

F	System overall cost function
N	Number of generators in the system
d_i, b_i, c_i	Constants of fuel function of generator # i
e_i, f_i	Constants of the value point effect of gen. # i
P_{gi}	Active power generation of generator number i
P_D	Total power system demand
P_L	Total system transmission losses
$P_{gi_{(\min)}}$	Minimum limit on active power gen. of gen. i
$P_{gi_{(\max)}}$	Maximum limit on active power gen. of gen. i
N_s	Set of generators in the system

The sinusoidal term added to the fuel cost function which models the value-point effect introduces ripples to heat-rate curve and therefore introducing more local minima to the search space.

It is important to mention that the system losses will be ignored for all test systems considered in this study for simplification purposes.

IV. Implementation of Case Study

This test case consists of three generating units with quadratic cost function combined. The units data (upper and lower bounds) along with the cost coefficients for the fuel cost (a, b, c, e, and f) for the three generators with value point loading are given in [12, 13].

The FLP has been executed for 100 with different starting points to study its performance and effectiveness. The solution of FLP method and the execution time for a 100 runs were compared with the outcome of other evolutionary methods, for example simple Genetic Algorithm (GA) and Evolutionary Programming (EP), applied to the same test system in [13]. This experimentation compares the performance of FLP with the other methods in terms of dispatching cost. Table 1 shows the optimal solutions determined by FLP for the three units.

TABLE I
GENERATOR LOADING AND FUEL COST DETERMINED BY FLP WITH TOTAL LOAD DEMAND OF 850 MW

Generator	Generator Production (MW)
Pg_1	**302.2001**
Pg_2	**151.8541**
Pg_3	**398.7544**
Σ Pg_i = 850 MW	**Total cost: $8385.38**

V. Conclusion

This paper introduces a new solution approach based on fuzzy linear regression optimization to solve the problem of power system economic dispatch with. The problem is formulated as a constrained optimization problem. The proposed method has been tested on a three generator systems. FLP, however, unlike GA and EP, is very sensitive to the initial guess and therefore, it appears to rely heavily on how close the given initial point to the global solution. This in tern makes the FLP method quit susceptible to getting trapped in local minima.

Based on the analysis and the outcome of this study the, it is worth mentioning that FLP can be applied to a wide range of optimization problem in the area of power system.

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