Vector Optimization of Thermal Power Plants

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***Abstract*-Optimization is one of the directions of the researching power systems advanced to reducing power generation costs. Mathematical methods and algorithms play an important role in optimizing power systems. This paper presents the basic concepts of vector (multi-objective) optimization and methods by reviewing the articles on this topic.**

I. Introduction

Optimization is the choice of such a regime in which we have the lowest production costs for the same capacity of production.

Electricity is mainly generated in Estonia through the combustion of different types fuel such as: gas, oil shale, biomass. Thus, the study of the equipment characteristics, which are used for the calculation of costs and emissions to environment, their optimization and, consequently, cost reduction plays an important role in the energy sector and in the economic sphere.

The first monograph on this subject was published in 1943 [1]. TTU was also involved in the research of this problem: it developed several systems for thermal power plants – the Estonian power plant and Inkoo power plant in Finland. In 2008 and 2009 two articles were published on the optimization of thermal power plants [2, 3].

At the moment there are two essential tasks: to economize fuel and to reduce emissions of harmful substances into the environment. As far as there are pollution quotas, the optimization is not only the task of preserving the environment. It has econimical meaning as well.

Thus, there is a number of basic problems of vector (multi-objective) optimization of power plants:

- to develop the basic forms for the modeling of static and dynamic characteristics of fuel cost, emissions and flying ash;
- to define a series of concrete characteristics of boilers;
- to check up efficiency of vector optimization for thermal power plants;
- to choose the most effective criteria for optimization of thermal power plants;
- to analyze the efficiency of the criteria Pareto, Hurwitz and others;
- to develop the algorithm of vector optimization for the thermal power plants considering different forms of the information (deterministic, probabilistic, uncertain and fuzzy).

II. Input Fuel Cost Characteristics

The electricity production unit in general can be represented as a block (Figure 1) [3].

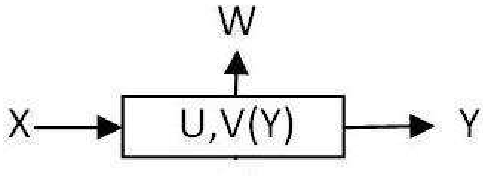

Fig. 1. Model of power generation unit

Following characteristics (functions) are used as the static model of power units:

$$X = X[Y,U,V(Y)] = G_{(U,V(Y))}(Y) , \tag{1}$$

$$W = W[Y,U,V(Y)] = W_{(U,V(Y))}(Y) , \tag{2}$$

$$P^{Aux} = P^{Aux}[Y,U,V(Y)] = P^{Aux}{}_{(U,V(Y))}(Y) , \tag{3}$$

where

X – input vector;

Y – output vector;

W – environmental impact vector;

P^{Aux}– auxiliary power;

V(Y) – state vector functions;

U – vector of state parameters.

The basic input-output characteristics of the power generation unit are:

input cost characteristics

$$X = G(Y) , \tag{4}$$

input incremental cost or marginal cost characteristics

$$b(Y) = \frac{\partial X}{\partial Y} = \frac{\partial G(Y)}{\partial Y} , \tag{5}$$

input fuel cost rate characteristics

$$\delta(Y) = \frac{G(Y)}{Y} , \tag{6}$$

efficiency characteristics

$$\eta(Y) = \frac{Y}{G(Y)} . \tag{7}$$

As seen from 4-7 the following equalities are also true

$$\delta \times \eta = 1 , \tag{8}$$

$$X(Y) = X_0 + \int_{\gamma-}^{\gamma+} \beta(\xi) d(\xi) , \tag{9}$$

$$X(Y) = \delta(Y) \times Y , \tag{10}$$

$$X(Y) = \frac{Y}{\eta(Y)} . \tag{11}$$

It should be noted that the form of input cost characteristics depends on the type of unit.

For example, the boiler characteristic will be the following:

$$B_B(Q_B) = B_{B0} + a_1 Q_B + a_2 Q_B^2 + a_3 Q_B^3, \quad (12)$$

where

B_B – the boiler fuel consumption per unit of time;

Q_B – the heat load of the boiler or power output;

B_{B0} – fuel consumption at idle;

a_1, a_2, a_3 – coefficients of the polynomial.

In practice, we use first - second degree polynomials.

For turbines it will be:

$$Q_T = Q_{TO} + q_{T1} P_T + (q_{T2} - q_{T1})(P_T - P_{T1}), \quad (13)$$

where

Q_T – a turbine steam consumption for a certain period of the time;

P_T – power output;

Q_{T0} – turbine steam consumption at idle;

q_{T1} – marginal cost in the range $P_T^{\min} < P_T < P$;

q_{T2} – marginal cost in the range $P < P_T < P_T^{\max}$;

P_{T1} – power where the valve is opened;

$P_T^{\min}$ $P_T^{\max}$ – maximum and minimum allowable load of turbine.

We can see that, in general, fuel cost characteristics of the power unit depend on active load of the power unit:

$$B_U = B_U(P_U) = B_B(Q_T(P_U)), \quad (14)$$

where

B_B – the boiler fuel consumption per unit of time;

Q_T – a turbine steam consumption for a certain period of the time;

P_u – turbine power output.

Optimization and load distribution is not as straightforward as it seems. Logically, to load a unit with great efficiency more and then load less economical unit.

But in fact, the main role in the load distribution is played by marginal cost characteristics [4].

The cost characteristics of units are determined in special tests at various control points. The data measured during experiments are presented in tabular form.

The number of trial points (5-10) is not enough to create a complete picture. In addition, the table is not suitable for processing and manufacturing computing, as well as for maximum consideration of possible options. That is why, the problem of transformation table data to function appear. In order to conduct it we have to use approximation methods.

Researching power characteristics and their transformation to the linear dependence has already begun in TTU. J. Shuvalova wrote [5] the dissertation and developed a program with help packages MathCAD, MathLAB allowing to approximate the input data characteristics.

III. Output Environmental Impact Characteristics. Vector Optimization

Output environmental impact characteristics are also expressed by polynomials of 2-3 degrees and depend on the load power [3]

$$E_{CO2}(Q_B) = \gamma(k_1 + k_2 Q_B + k_3 Q_B^2), \quad (15)$$

$$E_{NOx}(Q_B) = a_1 + a_2 Q_B + a_3 Q_B^2 + a_4 Q_B^3, \quad (16)$$

where

Q_B – the heat load of the boiler or power output;

γ, k_1, k_2, k_3 ,a_1, a_2, a_3, a_4 – coefficients of the polynomial.

The problem arises to combine the costs of fuel with the reduce emissions. It turns out, that the task of Multiobjective optimization is reducing the function consisting of fuel cost characteristics and emission characteristics.

$$C = \omega_1 F_f + \omega_2 E_{CO2} + \omega_3 E_{NOx}, \quad (17)$$

where

ω_1, ω_2, ω_3 – are weights of cost fuel, SO2 emission and NOx emission accordingly;

F_f – fuel-cost characteristics function;

E_{CO2} – CO_2 environmental impact characteristics;

E_{NOx} – NO_x environmental impact characteristics.

We can add to (17) SO_2 impact characteristics also.

But the main problem is that optimal conditions for one response may be far from optimal or even physically impractical for the others. It means we should minimize all the objective functions, namely the total fuel cost (F_f), the CO_2 emission (E_{CO2}), and NO_x emission (E_{NOx}), simultaneously.

Some institutions have begun to explore this issue. The research has been described as well in the article [6] by Tankut Yalcinoz and Onur Koeksoy. The review includes the first use of multi-objective programming with power systems has been applied by Cheong and Dillon [7]. A summary of environmental dispatch algorithms dating back to 1970 and has been provided (see [8]) by Kermanshahi et al. [9] proposed the goal technique to evaluate the environmental marginal cost. Nanda et al. [10] tried to find the best compromise solutions between the conflicting targets of minimum cost and minimum emission by means of suitable multi-objective procedures. Granelli et al. [11] suggested an emission constrained dynamic dispatch algorithm. It minimizes fuel cost during a pre-selected time horizon and thoroughly takes into account the environmental constraints. King et al. [12] reported an improved Hopfield NN for the economic-environmental dispatch problem and illustrated 3-unit and 12-unit systems. A price penalty factor for solving the environmentally constrained economic dispatch (ECED) problem which combines the emission costs with the normal fuel costs was offered by Kulkarni et al. [13]. Wong [14] invented a cooling mutation technique in evolutionary algorithm to solve the ECED problem for a 9-unit system.

Few articles concentrate on algorithm development.

The article by T. Yalcinoz and O. KoEksoy [6] consider the NIMBUS algorithm. It is based on standard multi-objective programming and software. In this paper a new approach to the environmental economic dispatch using a standard nonlinear multi-objective programming technique has been presented. A highly flexible optimization technique based on the ideas of the interactive multiple criteria decision making has been suggested.

This method has been tested on a 3-unit system and a 10-unit system. The computational results of the proposed method are compared with the genetic algorithm with arithmetic crossover, where the cost and emissions were combined using the weight factors and a neural network approach which is based on an improved Hopfield neural networks. The overall performances of the method are better than those of GAAC and NNA. The results show that the method May be applied to the environmentally economic dispatch problem.

Some articles present Non-dominated Sorting Genetic Algorithm (NSGA-II) [15].

NSGA-II is one of the most widely used algorithms for multi-objective optimization and have the main properties: it's highly efficient in finding a diverse set of Pareto-optimal solutions.

Differential evolution (DE) is one of the very fast and robust and accurate evolutionary algorithms for global optimization and solution of economic emission load dispatch (EELD) problems.

Aniruddha Bhattacharya and P.K. Chattopadhyay article [16] presents combination of DE and biogeography-based optimization (BBO) algorithm to solve complex EELD problems of thermal generators of power systems. Emission substances like NO_X, SO_X, CO_X, Power demand equality constraint and operating limit constraint are considered here. To show the advantages of the BBO algorithm, it has been applied for solving multi-objective EELD problems in a 3-generator system with NO_X and SO_X emission, in a 6-generators system `considering NO_X emission.

The Huazhong University of Science and Technology article [17] presents hybrid multi-objective cultural algorithm (HMOCA). Calculations of Pareto optimal front were completed and results were obtained with the NSGA-II algorithm results.

Research paper "Energy, economy and environment as objectives in multi-criterion optimization of thermal systems design"[18] consider the Pareto front on the difference between single- and multi-objective approaches and defining the environmental objective in the energetic, economic and environmental multi-objective approach.

Some investigations consider the particular cases of power system.

For example V. Kouprianova and V. Tanetsakunvatanab consider two approaches for the excess air optimization for the 150 MW boiler firing Thailignite for the improvement of environmental performance [19]. Another article by Hongwei Li et al. [20] focused on four types of optimal plant configurations in case study of Beijing. Finally optimum was selected with followed thermal-economic optimization of a distributed multi-generation energy system.

IV. CONCLUSIONS

TTU has begun vector optimization research only recently. At the moment there is a bibliographical search on the topic as well as the process of getting aquatinted with the research papers from other universities.

This paper is an overview and introduction of the concept of vector optimization.

Not so many articles were found when I attempted to find any. Basically they are devoted to modeling and programming algorithms. Several papers research only optimization emission.

The task of multi-optimization is complicated because of the lack of direct measurements and basic developments. It's likely due to the fact that this area is still new and hasn't shaped public opinion about the importance of these studies yet.

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REFERENCES

[1] M. Steinberg, T.H. Smith, "Economy Loading of Power Plants and Electric Systems," *New York, Joh n& Sons*, 1943.

[2] M.Valdma, H.Tammoja, M. Keel, "Soojuselektrijaamade talitluse optimeerimine," *TTÜ Kirjastus*, 2008.

[3] M. Valdma, H. Tammoja, M. Keel, "Optimization of Thermal Power Plants Operation," Tallin Tehnikaulikool, 2009.

[4] V.Gronstein et al., "Methods of optimization of energy system," *Energoizdat*, 1981.

[5] J. Shuvalova, "Optimal approximation of input-output characteristics of power units and plants," *TUT Press*, 2004.

[6] T. Yalcinoz, O.KoËksoy, "A multiobjective optimization method to environmental economic dispatch Electrical Power and Energy Systems*," Electrical Power and Energy Systems*, 29 (2007) 42–50

[7] H. Cheong, T. Dillon, "Application of multiobjective optimization methods to the problem of generation expansion planning" In: proceedings Sixth Power System Computation Conference (PSCC-6), Damstadt, West Germany, 1978, p. 3–11.

[8] J. Talaq, F. El Hawary, ME El Hawary, "A summary of environmental economic dispatch algorithms," *IEEE Trans Power Systems*,№9/1508, 1994, p.16.

[9] B. Kermanshahi, Y Wu, K. Yasuda, R. Yokoyama, "Environmental marginal cost evaluation by non-inferiority surface". *IEEE Trans Power Systems*, 1990;5(4):1151–9.

[10] J. Nanda, DP. Kothari, KS. Lingamuth, "Economic-emission load dispatch through goal programming techniques," *IEEE Trans Energy Conv.*, 1988;3(1):26–32.

[11] GP. Granelli, M. Montagna, GL. Pasini, "Emission constrained dynamic dispatch," *Electro Power System* Res 1992;24:55–64.

[12] TD. King, ME. El-Hawary, F. El-Hawary, "Optimal environmental dispatching of electric power systems via an improved hopfield neural network model," *IEEE Trans Power Systems*, 1995;10(3):1559–65.

[13] PS. Kulkarni, AG. Kothari, DP. Kothari, "Combined economic and emission dispatch using improved back propagation neural network," *International Journal Electric Mach Power System*, 2000;28:31–44.

[14] KP. Wong, J. Yuryevich, "Evolutionary-programming based algorithm for environmentally constrained economic dispatch," *IEEE Trans Power System*, 1998;13(2):301–6.

[15] K. Deb, A. Pratap, "A fast and elitist multi-objective genetic algorithm: NSGA-II," *IEEE Trans Evol Comput* 2002;6(2):182–97.

[16] A. Bhattacharya, P.K. Chattopadhyay, "Hybrid differential evolution with biogeography-based optimization algorithm for solution of economic emission load dispatch problems," *Expert Systems with Applications*, 38 (2011) 14001–14010

[17] Lu Youlin, Zhou Jianzhong, Qin Hui, Wang Ying, Zhang Yongchuan, "A hybrid multi-objective cultural algorithm for short-term environmental/economic hydrothermal scheduling," *Energy Conversion and Management*, 52 (2011) 2121–2134

[18] A. Lazzaretto, A. Toffolo, "Energy, economy and environment as objectives in multi-criterion optimization of thermal systems design," *Energy*, № 29 pp.1139–1157, 2004.

[19] V. Kouprianova, V. Tanetsakunvatanab, "Optimization of excess air for the improvement of environmental performance of a 150 MW boiler fired with Thai lignite," *Applied Energy*,№ 74, pp.445–453, 2003.

[20] Hongwei Li, Razi Nalim, P.-A. Haldi, "Thermal-economic optimization of a distributed multi-generation energy system—A case study of Beijing, "*Applied Thermal Engineering*," Volume 26, Issue 7, pp. 709-719, 2006.