www.sjm06.com

Serbian Journal of Management 15 (2) (2020) 371 - 382

Serbian Journal of Management

Review Paper:

A REVIEW ON OPTIMIZATION METHODS APPLIED TO ENERGY MANAGEMENT SYSTEM

Amel Graa[a] and Farid Benhamida[b]*

[a]*MIM laboratory, Department of Commercial Sciences, Faculty of Economics, Commercial and Management, UDL of Sidi Bel Abbes, Algeria.*
[b]*Laboratoire IRECOM, Faculty of Electrical Engineering, UDL of Sidi Bel Abbes, Algeria.*

(Received 12 June 2019; accepted 24 December 2019)

Abstract

Energy is fundamental in supporting people's daily subsists and the continual mission for human life improvement. The computer-aided instruments system used by electric utility grids or microgrids operators to control, monitor, and optimize the power system operation is generally named Energy Management System (EMS). The topic of optimization methods applied to decision making problems in such system is a difficult and complex combination of mathematical formulation, modeling and algorithmic solution. The best result in such process is applied to the problem to be optimized, which must be studied in great depth. Furthermore, difficult mathematical calculations and procedures can be elaborated; also, computer knowledge and software engineering competences must be provided. The subject of this paper is an overview of the existing important optimization methods used in electric power management system such as unit commitment, optimal power flow and economic dispatch.

Keywords: optimization method, quadratic programming, linear programming, energy management system

1. INTRODUCTION

In the past centuries, the electric demand for various energy resources, in both sufficient quantities and satisfactory quality, has been growing worldwide, along with population growth, economic development and living standard enhancement. Thus, designers and decision makers are facing many pressure to deal more effectively to a number of energy-related subjects and conflicts, which can be represented as

* *Corresponding author: farid.benhamida@yahoo.fr*

DOI: 10.5937/sjm15-22519

optimization problem of energy management system, related in many cases to economic and environmental effects.

In EMS, we can deal with several processes such as energy utilization and exploration, conversion and processing, production and load, as well as the associated greenhouse gas emissions. Which are in many case associated with uncertainty giving more complexities to the problem solution.

Since the beginning of the last century, and for many years, a wide range of optimization techniques and methods has been developed and used to solve EMS optimization problems. The base load technique, the incremental scheme and the best point loading are some optimization techniques among others applied to solve this problem. A historical review, which highlights the previous works in this research area, is presented in (El-Hawary, 1979). Currently, a number of methods and procedures are used to resolve EMS optimization problems (Momoh, 2001), which include exact mathematical methods, iterative methods, artificial intelligence methods, and finally hybrid techniques. With the enhancement of the mathematical and calculation techniques, more details of the problem have been addressed.

Many techniques including traditional and modern optimization methods, which have been developed to solve these EMS problems, are classified into three groups: (1) Exact optimization methods (such as NLP, LP, QP, IP, etc.), (2) Intelligence search methods (such as NN, TS, PSO, etc.) and (3) Nonquantity approaches to address uncertainties in objective functions and constraints (such as probabilistic optimization , fuzzy set applications and analytic hierarchical process). In this paper, we focus on the review of the first group.

Hence, in this paper, a review of optimization methods based on advanced mathematical programming to solve problems associated to EMS and descriptions of some EMS optimization functions are discussed in section 2, a classification of optimization methods to solve nonlinear optimization problem is given in section 3, followed by a summary discussion and conclusions in section 4.

2. MATHEMATICAL OPTIMIZATION

Optimization is a process of choosing logically among given alternatives the best solution according to an objective. Most real optimization problems are very difficult or stochastic to be studied or resolved using conventional mathematics. Although, there are very essential problems where a mathematical description is possible, which can be resolved, and is a good estimation of the problem to resolve. Some classic cases are problems of planning (engines, trains, airplane carriers), measurement of (pipes, electric power units, etc.), direction-finding (salespersons, wire, telephone calls), and building (bonds, aircraft, integrated circuits) (Mathworks, 2018; Cheney & Kincaid, 2012).

Optimization is a field of mathematics, where the concept is to minimize or maximize a function, (Mathworks, 2018; Ramos de Souza et al., 2017). The domain of optimization programming is compound of numerous sub fields, depending on the properties of the studied function. In the course of the Second World War, many researches are focused on analyzing and formulating several mathematical models for production planning, goods carriage and sharing of rare resources, which lead to the so called of operations research. From then the concept and application of operations research increased rapidly (Ding et al., 2004; Luc, 2015). In mathematical programming the mainly concern is the theory and procedures for optimization. A good review of different subjects in mathematical programming can be found in (Nemhauser et al., 1989), and for some history see (Ambrus-Somogyi, 2012).

Given a mathematical system defined with m equations and n variables. Such system can be: (1) *algebraic* problem (n = m), generally has at minimum a unique solution; (2) *over constrained* (n < m), commonly such problem can't be resolved; (3) *under constrained* problem (n > m), in such problem numerous results could be existent which meet the problem formulation. The latest category is the subject of this review paper.

Thus an optimization problem involves many types of variables and typically is a system with under constrained equation. This function of variables is well-defined as objective function. To match the optimality of several feasible solutions of the under constrained problem, the objective equation has the role to provide a weight for each solution.

When dealing with optimization problem, there are two kinds of variables, the first are the known variables which are generally fixed values and the second are the unknown variables. The optimum numeric values of the latter is the goal to achieve. Within the set of unidentified variables, there are two main subclasses: (1) *Control variables*, which represent parameters directly controlled in the optimization process; (2) *State variables*, which represent parameters not directly controlled in the optimization process. The state variables result from the selection of the control variables and represent the processes image of their values.

2.1. The Mathematical model

In general, optimization problem is defined as follows. Assume n variables; m linear or nonlinear equality constraints and p inequality constraints (Bacher, 2002).

Subject to:

$$\begin{aligned} &\min F(x) \\ &g_i(x) = 0, \text{ for } i = 1,\dots, m, \\ &h_i(x) \le 0, \text{ for } i = 1, \dots, p. \end{aligned} \tag{1}$$

The problematic is to calculate the values of x where the equality equation $g(x)$ and inequality equation $h(x)$ and the objective equation $F(x)$ is at an exact local optimum.

The optimization problem in equation (1) have to be observed with respect to the subsequent points to simplify a solution which return the required optimality conditions (Ambrus-Somogyi, 2012). These points are:

- Differentiate between those active inequality equation, and inactive inequality equation.
- Give those active inequality equation the same consideration as equality function and define the optimality conditions for the augmented equality function problem similarly as for "standard" equality constrained optimization problem.
- Assume that the Lagrangian multipliers (μ_i) of the active $g(x)$ constraints are positive.
- Assume that inactive $h(x)$ inequality constraints are less than zero (else $h(x)$ are inactive).

The Lagrangian equation where all equality and all active inequality constraints are taken in consideration is given by:

$$\text{minimum}(L) = F(\text{x}) + \sum\nolimits_{k=1}^{m} \lambda_k g_k(\text{x}) + $$
$$+ \sum\nolimits_{k=1}^{m} \lambda_k g_k(\text{x}) + \sum\nolimits_{l=1}^{p'} \mu_l h_l(\text{x}) = \qquad (2)$$
$$= F(\text{x}) + \lambda^{tr} g(\text{x}) + \mu^{tr} h(\text{x})$$

where λ_i and μ_i are the Lagrange-multipliers elements of vectors λ and μ, respectively. We suppose the number p' of $h(x)$ constraints are active $h(x)$ constraints and the last $h(x)$ constraints are inactive. The notation *tr* in equation (2) define the transpose of a matrix or vector (*tr* is an operator which flips a matrix or a vector over its diagonal). The problem given by equation (2) have the following optimality conditions:

$$\frac{\partial}{\partial x}(F(\text{x}) + \lambda^{tr} g(\text{x}) + \mu^{tr} h(\text{x})) = 0 \qquad (3)$$

$$h(x) = 0, \mu \geq 0 \qquad (4)$$

$$g(x) = 0 \qquad (5)$$

If $h_j(x) = 0$, so $h(x)$ is active constraint, and if $h_j(x) < 0$, so $h(x)$ is inactive constraint, which are the set of needed optimality conditions for the optimization problem formulated by equation (1).

2.2. Linear Programming method (LP)

Linear programming (LP) method is used to linearize the nonlinear EMS optimization model, with the aim of linearizing the form of objective function and constraints of EMS optimization. The most effective method known for solving LP problems is the simplex method. Among the many advantages of LP method, the LP method is reliable, particularly with respect to convergence properties and detect rapidly infeasibility. LP method deals with a wide range of EMS operating limits, including contingency equation constraints. The drawbacks of LP method are inability to find an exact solution and inaccurate estimation of system power losses compared to the original nonlinear EMS formulation. On the other hand, plenty of practical applications show solutions using LP method usually satisfy the engineering accuracy standards. Therefore LP method is commonly used to resolve EMS operation problems such as reactive power optimization, optimal power flow, security - constrained economic dispatch, steady - state security regions, etc.

Mathematically, linear programming problem is defined as the problem of maximizing or minimizing of a linear function subject to linear equalities and inequalities constraints (Cheney & Kincaid, 2012; Bacher, 2002; Ding et al., 2004).

Standard LP problem is stated as:

$$\text{minimum } (F) = c^{tr} x \qquad (6)$$

Subject to:

$$A_1 x = b_1 \qquad (7)$$
$$A_2 x \leq b_2$$

$$x \geq 0 \qquad (8)$$

In some cases, a part of variables may be constrained to be nonnegative and others are not constrained. Some of the main constraints may be equalities ($A_1 x = b_1$) and others inequalities ($A_2 x \leq b_2$).

2.3. Quadratic Programming method

Quadratic programming (QP) is a special method of nonlinear programming. The objective function of QP is quadratic, and the constraints are in linear function. QP has higher accuracy than Linear Programming -

based methods. Particularly, often most used objective function in EMS optimization is the unit production cost function, which is usually assumed as a quadratic equation. Therefore, there is no approximation for such objective function for an EMS optimization resolved by QP. Mathematically, QP is an area of mathematics that treats the determination of the optimum of a quadratic function constrained by linear equalities and inequalities equations (Cheney & Kincaid, 2012; Michael, 2017).

The standard objective equation of a QP problem is set as follows:

$$\text{minimum } (F) = (1/2)\, x^{tr} Qx + c^{tr} x \tag{9}$$

Subject to linear equality and inequality equations:

$$\begin{aligned} A_1 x - b_1 &= 0 \\ A_2 x - b_2 &\leq 0 \end{aligned} \tag{10}$$

where x is the variables vector, c represent the cost constants vector, n is the dimension of vector x and vector c; dimension of matrix Q is $(n\times n)$; dimension of matrix A_1 is $(m\times n)$ matrix; dimension of matrix A_2 is $(p\times n)$ matrix; b_1 is the right sides vector identifying the equality equation, with a dimension m and b_2 is the right sides vector identifying the inequality equation, with a dimension p.

Matrices Q, A_1, A_2 and vectors b_1, b_2 are numerically known. Furthermore, the matrix Q have to be symmetric and positive definite. ($y^{tr}\times Q\times y > 0$ for y different to zero). In such conditions, the QP problem is convex. Depending on the optimization problem, matrices Q, A_1 and A_2 can be sparse or compact matrices.

2.4. Difinition of Certain EMS functions

The Economic load Dispatch (ELD): It is the main and simple function where the objective is to minimize the total production cost of active power generation of an entire power system, by supposing that each generator has a well-known cost curve which is related to its own real power generation. Each power unit has maximum and minimum real power generating limits. It is supposed to that the whole generated real powers have to be equal to an assumed total system load (forecasted value) plus total power losses.

Optimal load Flow (OPF): is a model which represents the question of determining the best operating outputs for electric power plants permitting to meet the total system demands given throughout a transmission network, usually with the objective of minimizing operating cost. At the same time the OPF model take in consideration all equations of power flow and operational constraints on the network elements (i.e. limits on voltage magnitude on generator bus and limits on transmission branch current).

Electrical power flows equation are nonlinear, nonconvex functions of the system's physical characteristics, so the problem of OPF can be a difficult problem. On the other hand, in real operations, a case with the total distribution network must be resolved in real time (every 5 minutes for many Independent System Operators) to guarantee that demand is met precisely.

The deregulated electricity market calls also to robust optimal power flow (OPF) tools that can provide deterministic convergence with accurate computation of nodal prices which support of both smooth and nonsmooth costing of a variety of resources and services, such as real energy, reactive energy, voltages support. (Wang, 2007)

Unit Commitment: Since power units cannot rapidly turn on and generate power, unit commitment (UC) have be planned beforehand so that enough production is always available to satisfy system demand with an tolerable reserve margin (in case of go out of generators or transmission lines or power demand increases). UC handles the production unit schedule for minimizing operating cost and satisfying typical constraints such as load demand and system reserve requirements over a set of time periods (Zhu, 2015). The standard UC problem objective is to define the start - up and shutdown time calendars of production thermal units to satisfy predicted demand for a determined time (24 h to 1 week). This problem is a combinatorial optimization problems category. Many methods that have been used to solve such problem until now can be classified into approximately three categories: mathematical programming, heuristic search, and hybrid methods. Some mathematical Optimization programming techniques used such problem are the priority list, dynamic programming, augmented Lagrangian relaxation, and the branch – and – bound algorithm. Heuristic search such Genetic algorithms (GA), simulated annealing (SA), and particle swarm optimization (PSO) have also been used for UC problem since the beginning of the last decade time (Wu & Shahidehpour, 2016).

3. CLASSIFYING OF OPTIMIZATION METHODS TO SOLVE NL-OPTIMIZATION PROBLEM

In this section, the general optimization problem is solved by a combined method. The constraint equations and the objective function are smooth and differentiable. Vector of unknown x are and continuous variables. The aim is to find the objective solution for this problem. The nonlinear optimization problem procedures are presented in two categories:

3.1. Category A: Iterative solution of approached LP or QP

The algorithms of this category are the procedures by which the optimization starts from a resolved and fixed nonlinear system of equations or Newton-Raphson (NR) process (Bacher, 2002). The sensitivity relationships and the Jacobian matrix based on LP or QP usually are used in the optimization procedure, which are iterative as a whole. The NR process is solved after each approached LP or QP iteration.

3.1.1. Consecutive QP solution of approached optimization problem

An approached formulation around an assumed point x^0 give to the subsequent QP system: A quadratic approached objective function:

$$\text{minimum } (F) = (1/2)\Delta x^{tr} Q \Delta x + c^{tr} \Delta x \quad (11)$$

Subject to the following linear equality and inequality function (constraints):

$$A_1 \Delta x - b_1 = 0 \quad (12)$$
$$A_2 \Delta x - b_2 \leq 0$$

x is the vector of variables, where n is the dimension of vector x .

$c = \partial F/\partial x|_{x^\circ}$, where c is the cost coefficients vector of the of the linear objective function, where n is the dimension of vector c.

$Q = \partial^2 F/\partial x^2|_{x^\circ}$ is a square matrix of dimension ($n \times n$); $A_1 = \partial g/\partial x|_{x^\circ}$, is a matrix of dimension ($m \times n$); $A_2 = \partial h/\partial x|_{x^\circ}$, is a matrix of dimension ($p \times n$); b1= - $g(x^0)$ is the right sides vector identifying the equality equation, with a dimension m; b_2= - $h(x^0)$ is the right sides vector identifying the inequality equation, with a dimension p.

The iteration loop is represented by the following algorithm:

Step 1. Choose a initial values for x^0; initiate k=0

Step 2. Determine the QP solution of approached optimization problem around x^k

Step 3. Calculate Δx^k

Step 4. Update of all variables $x^{k+1} = x^k + \Delta x^k$, update $k = k + 1$

Step 5. Return to step 2

3.1.2. Consecutive QP solution of approached optimization problem based on NR

There is many difficult when dealing with the iterative process of consecutive QP solution discussed in the earlier paragraph, especially when selecting the value of a starting solution x^0. This initial point affect significantly the convergence. The first aim of the procedure is determine a starting solution satisfying principally the equation of equality constraints $g(x^0) = 0$, without necessarily satisfying the inequality constraints. The dimensions of the problem have been already stated, where m equality equation (g) and n unknown variables (x). Assuming also ($n > m$), number of variables is superior to number of equality constraints. Therefore, a degree of lack of restrictions exists for the solution of the equality function (g). Now, we have to divide the vector x into two sub vectors allowing the solution of a part of equations which have identical number of variables and number of equations. That is, the equality functions (g) can be expressed like this: $x^{tr} = [x_1^{tr}, x_2^{tr}]$ and $g(x_1, x_2^0) = 0$, where m is the dimension of (x_1) and (n-m) is the dimension of (x_2).

Therefore, the earlier mathematical procedure discussed of the iterative QP implementation can be prolonged to the following iterative execution, (1) a NR resolution and (2) a QP solution procedure. (3) Update the iterative value of Δx, (4) began a new NR procedure with the new updated values of x_2^0, (5) Starting again a new QP solution, etc. The previous iterative procedure is called a consecutive execution of a QP, although the iterative procedure of QP starts continuously around a solved set of non-linear equations as represented by the following algorithm.

Step 1. Choose a starting values x^0; initiate $k = 0$

Step 2. Splitting x so that, $x^{tr}=[x_1^{tr}, x_2^{tr}]$

Step 3. Solve $g(x_1, x_2^k) = 0$. For the vector x_1 (x_2^k = constants)

Step 4. Determine the QP solution of approached optimization problem around x^k

Step 5. Calculate Δx^k

Step 6. Update of all variables $x^{k+1}=x^k+\Delta x^k$, update $k = k+1$

Step 7. Return to step 3

3.1.3. Consecutive compacted QP procedure of approached optimization problem with NR support

The word compact QP is given to quadratic programming where the number of variable and equality constraint are reduced. From equation (12), the variables Δx_1 is removed, which lead to the compact formulation. The equality functions in Eq. (10) are divided as follows:

$$A_{11}\Delta x_1 + A_{12}\Delta x_2 = b_1 \tag{13}$$

The value of Δx_1 can be calculated from equation (13):

$$\Delta x_1 = (A_{11})^{inv} (- A_{12}\Delta x_2 + b_1) \tag{14}$$

The solution of equation (14) exists if A_{11} is square non-singular matrix where the dimension is (m x m). So the solution Δx_1 can be replaced in the original quadratic programming model of equation (11) and equation (12), which give the subsequent compact quadratic programming:

$$\text{minimum } (F) = (1/2)\Delta x_2^{tr} P \Delta x_2 + c_2^{'tr}\Delta x_2 \tag{15}$$

Having the subsequent inequality equation (linearized) as constraint to satisfy:

$$A'_{22}\,\Delta x_2 - b'_2 \le 0 \tag{16}$$

where

$$\left.\begin{aligned} c_2^{'tr} &= c_2^{tr} - c_1^{tr} A_{11}^{-1} A_{12} \\ A_{22}^{'} &= A_{22} - A_{21} A_{11}^{-1} A_{12} \\ b_2^{'} &= b_2 - A_{21} A_{11}^{-1} b_1 \end{aligned}\right\} \tag{17}$$

$$P = \left[-A_{12}^{T} (A_{11}^{-1})^{tr} \;,\; I \right] \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix} \begin{bmatrix} -A_{11}^{-1} A_{12} \\ I \end{bmatrix} \tag{18}$$

I is unity matrix;

The QP formulated by Equation (15) and (16) is a compact quadratic programming where the number of variables Δx_2 is equal to (n-m) with no need to deal with equality constraints equations because they have been excluded. The main variable remaining for the compact QP model is now Δx_2. As soon as the vector Δx_2 values are calculated, the optimal solution of vector Δx_1 values are calculated by equation (14). This is the principle of the iterative procedure represented by the following steps:

Step 1. Choose a starting values x^0; initiate $k = 0$;

Step 2. Splitting x so that, $x^{tr} = [x_1^{tr}, x_2^{tr}]$;

Step 3. Solve $g(x_1, x2k) = 0$. For the vector x_1 (x_2^k =constants);

Step 4. Compute the compact QP form by eliminating the variables Δx_1;

Step 5. Compact QP solution of approximated optimization problem around x^k;

Step 6. Calculate Δx^k;

Step 7. Update of all variables $x^{k+1}=x^k+ \Delta x^k$, update $k = k+1$;

Step 8. Return to step 3.

3.2. Category B: Integrated iterative solution of (Kuhn-Tucker) KT-optimality conditions

The algorithms of this category are the methods dealing with strict formulation of optimality conditions by which the equality equations are involved. There is no previous information (solution) concerning any part of equality equation as mentioned in category (A). The procedure as a whole is iterative and every solution during the iterative process come close to the optimality conditions.

In this category, integrated method are used to solve optimization problem in comparison to category (A), where Newton Raphson solution of a part of equations are detached from the optimization formulation (Bacher, 2002; Ding et al., 2004). A unique method is presented in this paper. Which is commonly named nonlinear Interior Point

(IP) method (Cheney & Kincaid, 2012; Michael, 2017). This method is derived from a solution of the nonlinear optimality conditions of (KT) by means of a combination of Newton Raphson and barrier function parameter diminution (ζ) through the iteration processes. Many other procedures can be used which can be found in previous research in this category (B) optimization. In all category (B) procedures, the iterative solution of optimality conditions (transformed nonlinear KT) must to be completed.

3.2.1. Interior Point procedure for Kuhn-Tucker optimality conditions

The augmented optimization problem is stated as follows:

$$L = F(x) + \lambda^{tr}\, g(x) + \mu^{tr}\, h(x) \tag{19}$$

Reminder that variables x only are handled in the category (B) method. This is to some extent unlike the category (A) method in which a difference concerning the state variables and control variables is beneficial. The optimality conditions resulting from first order derivative of the Lagrange function in equation (18) represent the necessary optimality conditions:

$$\begin{aligned}&(1)\frac{\partial F(x)}{\partial x}+\left(\frac{\partial g(x)}{\partial x}\right)^{tr}\lambda+\left(\frac{\partial h(x)}{\partial x}\right)^{tr}\mu=0,\ (2)\, g(x)=0\\&(3)\mathrm{diag}\{\mu_{\mathrm{i}}\}.h(x)=0\ \ ,\ (4)\ h(x)\le 0,\ (5)\mu\ge 0\end{aligned} \tag{20}$$

The notation diag in equation (20) is the diagonal matrix. The constraint set (3) and (5) mean that an inequality equation is active if $\mu > 0$, so $h(x) = 0$. An inequality equation is inactive, $h_i(x) < 0$, if $\mu = 0$.

3.2.2. Interior Point (IP) method

Interior point (IP) technique is initially used to solve linear programming problem. It is better than the conventional simplex algorithm in linear programming with respect to speed. IP approaches were first used to resolve Optimal Power Flow (OPF) problems in the 1990s, and lately, the IP technique has been prolonged and enhanced to resolve OPF with QP and NLP formulas.

The concept of the Newton Raphson applied to equality constraints equation is spread out to comprise in the formulation the inequality constraints equation. To comprehend the main ideas behind IP procedure for a nonlinear optimization problem (Ramos de Souza et al., 2017; Quintana, 2000; Luc, 2015). The original optimization problem is expressed as (Michael, 2017):

With the constraints $g(x) = 0$; $h(x) + z = 0$ and $z > 0$

The next two conditions must be satisfied:

$$\text{minimum } F(x)-\zeta\sum_{i=1}^{p}\ln(z_i)\quad(\zeta>0) \tag{21}$$

1. ζ in equation (21) converge to zero during the iterative process.

2. the variables z in equation (21) must kept positive during iterations process, which gives the name Interior point to this algorithm. In other hand, the word barrier came from the barrier equation ($\zeta \sum_i \ln(z_i)$ for i=1 to p) associated with the objective function in equation (21), which can’t travers the limit zero (ζ > 0).

The KT optimality conditions can be now derived from the so-called IP-oriented

Lagrangian as follow:

$$L_{IP} = F(x) - \zeta \sum_{i=1}^{p} \ln(z_i) + \lambda^{tr} g(x) + \mu^{tr}(h(x)+z) \quad (22)$$

$$\frac{\partial F(x)}{\partial x} + \lambda \times \left(\frac{\partial g(x)}{\partial x}\right)^{tr} + \mu \times \left(\frac{\partial h(x)}{\partial x}\right)^{tr} = 0$$

$$g(x) = 0,\ \mu - \zeta \times \mathrm{diag}\left(\frac{1}{\mathrm{z_i}}\right) \times e = 0 \quad (23)$$

$$h(x) + z = 0,\ \mu \geq 0;\ z > 0$$

Where e is an all-ones vector. For any value of $\zeta > 0$, the problem reach an optimum where the necessary conditions of equation (23) must be valid. The dimension of vectors e, μ and z is equal to p. The main idea behind the IP-KT solution procedure for necessary conditions of equation (23) is summarized in the following points:

a. Find a solution of equality equation by Newton Raphson method.

b. Select an initial positive value for the variables z and μ. Note that initial value is quite delicate for procedure convergence.

c. After calculating the optimal Δ values of x_{opt}, λ_{opt} , z_{opt}, and μ_{opt}, by the previous procedure, update all variables, by using step- length control so that the variables z and μ stay positive through the iterative process.

d. At the optimum ζ must close to zero. If not the optimization problem solved differ from the original one.

4. CONCLUSION

Optimization is a part of mathematics, which is the concept of optimizing (finding a minimal or a maxima) an equation, by satisfying certain equality and/or inequality constraints. The optimization approaches are weighted by their performance related to robustness, versatility and speed.

From the view of optimization, the various techniques including traditional and modern optimization methods, which have been developed to solve these EMS operation problems, are classified into three groups: (1) Conventional optimization methods (such as NLP, LP, QP, IP, etc.), (2) Intelligence search methods (such as NN, TS, PSO, etc.) and (3) Nonquantity approaches to address uncertainties in objectives and constraints (such as Probabilistic optimization, Fuzzy set applications and Analytic hierarchical process). The first optimization group is the subject of this paper.

Methods of category (A) and (B) have relative qualities and performance for a specific application. However, in any single problem, a particular method could demonstrate reduced performance. Category (A) and (B) procedures together have identical dimension of the linear inequality equation set. Therefore, there is no existence of difference between both categories related to this point. Methods of Category (B) are known for their robustness, they have a tough benefit compared to category (A) methods by resolving all functions of optimization problems with no specific differences in the course of the solution procedure. Which result, generally because the category (B) procedures resolve directly the optimality conditions of the original optimization problem. In the other hand, category (A) procedures resolve simply the optimality conditions equations of the approached optimization problem. Main drawbacks of category (B) procedures is that the number of variables to be deal with is relatively huge, compared to the category (A) procedures. We have to underline that among all optimization method class, no existence of a single one which satisfy all performance suitably and has to be categorized as the better non-linear optimization problem solution procedure. To conclude, the choice can be established based on the best combination of computer code effectiveness, procedure robustness, and computer code credibility (Bacher, 2002).

References

Ambrus-Somogyi, K. (2012). Mathematical programming in the engineering education. IEEE 10th Jubilee International Symposium on Intelligent Systems and Informatics, Subotica, Serbia, 445 – 450.

Bacher, R. (2002). Optimization of Lineralized Electric Power Systems, html, http://www.eus.ee.ethz.ch/people/bacher.

Cheney, W., & Kincaid D. (2012). Numerical Mathematics and computing, 7th Revised ed. New York, US: Wadsworth Publishing Co Inc.

Ding, X., Wang, X., & Song, Y.H. (2004). Interior point cutting plane method for optimal power flow. IMA Journal of Management Mathematics, 15(4), 355-368.

Luc, D.T. (2015). Multiobjective Linear Programming: An Introduction. Springer.

Mathworks. (2018). The Help document of Optimization Toolbox, included in MATLAB R2018b, help, html, http://www.mathwork.com.

Michael, J.B. (2017). Quadratic Programming with Computer Programs. 1st Edition, Chapman and Hall/CRC.

Nemhauser, G.L., Rinnooy Kan, A.H.G.,

ПРЕГЛЕД МЕТОДА ОПТИМИЗАЦИЈЕ ПРИМЕЊЕНИХ НА СИСТЕМ УПРАВЉАЊА ЕНЕРГИЈОМ

Amel Graaa, Farid Benhamidab

Извод

Енергија је основа у подршци свакодневном животу људи, као и континуираној мисији за побољшање људских живота. Систем рачунарско потпомогнутих инструмената који користе оператори електричних комуналних мрежа или микро мрежа за управљање, надгледање и оптимизацију рада електроенергетског система обично се назива Систем за управљање енергијом (ЕМС). Методе оптимизације примењене на проблеме доношења одлука у таквом систему су тешка и сложена комбинација математичке формулације, моделирања и алгоритамског решења. Најбољи резултат у таквом процесу примењује се на проблем који треба оптимизовати, а који се мора проучити са великом пажњом. Даље, могу се разрадити комплексни математички прорачуни и поступци; такође, мора се поседовати знање о информационим технологијама и софтверско инжењерство. Предмет овог рада је преглед постојећих важних метода оптимизације који се користе у систему управљања електричном енергијом, као што су ангажовање јединице, оптималан проток снаге и економска испорука.

Кључне речи: метода оптимизације, квадратно програмирање, линеарно програмирање, систем управљања енергијом

& Todd, M.J. (1989). Optimization. Handbooks in operations research and management science, 1st Edition, North-Holland: Elsevier Science.

Quintana, V.H., Torres, G.L., & Palomo J.M. (2000). Interior-Point Methods and Their Applications to Power Systems: A Classification of Publications and Software Codes. IEEE Trans. on Power Systems, 15 (1), 170-176.

Ramos de Souza, R., Balbo, A.R., Nepomuceno, L., Baptista, E.C., Soler, E.M. & Pinheiro, R.B.N. (2017). A primal-dual interior/exterior point method, with combined directions and quadratic test in reactive optimal power flow problems. IEEE Latin America Transactions, 15 (8), 1413-1421.

Wang, H., Murillo-Sanchez, C.E., Zimmerman, R.D., & Thomas, R.J. (2007). On Computational Issues of Market-Based Optimal Power Flow. IEEE Transactions on Power Systems, 22 (3), 1185-1193.

Wu, L., & Shahidehpour, M. Security (2016). Constrained Unit Commitment with Uncertainties. Power Grid Operation in a Market Environment: Economic Efficiency and Risk Mitigation, 115-168.

El-Hawary, M.E., Christensen, G.S. (1979). Optimal Economic Operation of Electric Power Systems. New York, US: Academic Press.

Momoh, J.A. (2001). Electric Power System Applications of Optimization. New York, US: Marcel Dekker.

Zhu, J. (2015), Optimization of power system operation, Second Edition. New Jersey, US: John Wiley & Sons.