C-GRASP APPLICATION TO THE ECONOMIC DISPATCH PROBLEM

By

INGRIDA RADZIUKYNIENE

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I dedicate this to my wonderful son, Matas

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By

Ingrida Radziukyniene

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Economic dispatch plays an important role in power system operations, which is a complicated nonlinear constrained optimization problem. It has non-smooth and non-convex characteristic when generation unit valve-point effects are taken into account. This work adopts the C-GRASP algorithm to solve differently formulated economic dispatch problems. The comparison of the feasibility and effectiveness of the C-GRASP, SA and GA is given as well.

CHAPTER 1
INTRODUCTION

1.1 Motivation

The economic dispatch (ED) optimization problem is one of the fundamental issues in power systems to obtain optimal benefits with the stability, reliability and security [52]. Essentially, the ED problem is a constrained optimization problem in power systems that have the objective of dividing the total power demand among the on-line participating generators economically while satisfying the various constraints. ED problem have complex and nonlinear nonconvex characteristics with equality and inequality constraints. Therefore, good solutions of the ED problem would result in great economical benefits.

Over the years, many efforts have been made to solve this problem, incorporating different kinds of constraints or multiple objectives, through various mathematical programming and optimization techniques [42]. In the conventional methods such as the lambda-iteration method, the base point and participation factors, and the gradient methods, an essential assumption is that the incremental cost curves of the units are monotonically increasing piece wise linear functions, but the practical systems are nonlinear [52]. Hence, global optimization techniques, such as the genetic algorithms (GAs), simulated annealing (SA), and particle swarm optimization (PSO) have been studied in the past decade and have been successfully used to solve the ED. However, the references with continuous greedy randomized adaptive search procedure (C-GRASP) application to such type of problems hadn't appear yet.

The aim of this work is to apply the C-GRASP to the ED problem and compare its effectiveness and produced solution feasibility with ones of other heuristic methods like the GAs and SA.

1.2 Literature Overview

Since Carpentier introduced a network constrained economic dispatch problem in 1962 [9] and the first paper in the area of dynamic dispatching was published by Bechert and Kwatny in 1972 [6], a lot of researches have employed various mathematical programming optimization methods for solving ED problems [30]. These optimization techniques can be classified into three main categories.

The first category contains deterministic methods that include the linear programming algorithm [26, 57, 69], quadratic programming algorithm [18, 37], non-linear programming algorithm [39], etc. The LP method application to the power-system rescheduling problem with security-constrained economic dispatch/control for multiple-valved-turbine units was given by Stott and Marinho [57]. Rosehart et al. [48] discovered that for the economic dispatch problem, SLP appears to be a better tool than SQP. An approach based on efficient SLP techniques to solve the multi-objective environmental/economic load dispatch problem was presented by Zehar and Sayah [69]. Granelli et al. [18] solved a security constrained economic dispatch problem using modified SQP techniques. A dual feasible starting point is found by relaxing transmission limits and then constraint violations are enforced applying the dual quadratic algorithm. In [59] and [35], a security constrained economic dispatch problem was solved by SLP and the interior point dual-affine scaling algorithm. Momoh et al. [37] proposed an IPM for ED problem formulated as linear and convex QP. However each of traditional methods has some defects: it would generate large errors to use the linear programming algorithm to linearize the ED model; for the quadratic programming and nonlinear programming algorithms, the objective function should be continuous and differentiable [30].

The second category contains the methods based on artificial intelligence. Artificial intelligence technology has been successfully used to solve the ED problem. A chaos optimization algorithm (CAO) has been proposed by Jiang et al. [29] to deal with the economic dispatch problem of a hydro power plant. Zhijiang et al. [71] also applied a

COA and the simulation results verified that the proposed approach is effective and precise. A mutative scale COA was applied by Xu et al. [65] to the economic operation of power plants. However, the results showed that the method is time-consuming. An improved mutative scale COA hes been developed by Han and Lu [19]. According to the authors, their algorithm is highly efficient and can be applied not only to ED but to many power system problems, such as economic operation, OPF, system identification and optimal contro, as welll. In [36], Mahdad et al. proposed an efficient decomposed parallel GA to solve the multi-objective environmental/economic dispatch problem. In the first stage, the original network is decomposed into multi sub-systems and the problem is transformed to optimize the active power demand associated with each partitioned network. In the second stage, an active power dispatch strategy is proposed to enhance the final solution of the optimal power flow of the original network. The proposed approach was tested on the Algerian 59-bus test system. The computational results showed the convergence at the near solution and obtain a competitive solution at a reduced time. GAs with fuzzy logic controllers to adjust its crossover and mutation probabilities was applied by Song et al. [56] to solve a combined environmental economic dispatch problem. SA techniques were used by Roa-Sepulveda and Pavez-Lazo [47], however, long computational time to obtain an optimal solution was reported. Tabu search was applied by Altun and Yalcinoz [2]. Simulation results on power systems consisting of 6 and 20 generating units exhibited good performance. In [38], an application of TS for solving security constrained ED problem was given by Muthuselvan and Somasundaram. Base case and contingency case line flow constraints were considered. Tests on 66-bus and 191-bus Indian utility systems revealed the reliability, efficiency and suitability of the proposed algorithm for practical applications.

The third category consists the hybrid methods, which combine two or more techniques in order to get best features in each algorithm. Typically, signifficant improvement with hybrid methods can be achieved over each of the individual methods.

Hybrid methods gained increasing popularity in the last 10 years. For the ED problem, Wong and Wong [63] combined an incremental GA with SA techniques. Coelho and Mariani [12] proposed a method combining a DE algorithm with self-adaptive mutation factor in the global search stage and chaotic local search techniques in the local search to solve an ED problem associated with the valve-point effect. The same authors report another successful application of chaotic PSO in combination with an implicit filtering local search method to solve economic dispatch problems [13]. The chaotic PSO approach is used to produce good potential solutions, while the implicit filtering is used to fine-tune the final solution of the PSO. The hybrid methodology is validated for a test system consisting of 13 thermal units whose incremental fuel cost function takes into account the valve-point loading effects. In [11], Coelho and Lee improved PSO approaches for solving an ED problem taking into account non-linear generator features such as ramp-rate limits. Prohibited operating zones in the power system operation are developed as well. Their algorithm combines the PSO, Gaussian probability distribution functions and/or chaotic sequences. The PSO and its variants are validated for two test systems consisting of 15 and 20 thermal generation units, respectively. A combination of chaotic and self-organization behavior of ants in the foraging process was presented by Cai et al. [8]. This algorithm was applied to ED problems with thermal generators.

The thesis is organized as follows: In Section 2, we briefly discuss a general ED problem formulation. The methods applied to solve ED are shortly discussed in Section 3. Section 4 describes experimental cases and presents calculation results. We conclude with Section 5.

CHAPTER 2
ECONOMIC DISPATCH (ED) PROBLEM

ED is one of the important optimization problems in power system operations, which is used to determine the optimal combination of power outputs of all generating units to minimize the total fuel cost while satisfying various constraints over the entire dispatch periods [67].

The traditional or static ED problem assumes constant power to be supplied by a given set of units for a given time interval and attempts to minimize the cost of supplying this energy subject to constraints on the static behavior of the generating units like system load demand. Shortly, static ED determines the loads of generators in a system that will meet a power demand during a single scheduling period for the least cost. Therefore, it might fail to capture large variations of the load demand due to the ramp rate limits of the generators. Due to large variation of the customers load demand and the dynamic nature of the power systems, it became necessary to schedule the load beforehand so that the system can anticipate sudden changes in demand in the near future.

Dynamic ED is an extension of static ED to determine the generation schedule of the committed units so that to meet the predicted load demand over the entire dispatch periods at minimum operating cost under ramp rate and other constraints [64]. The ramp rate constraint is a dynamic constraint which used to maintain the life of the generators, i.e. plant operators, to avoid shortening the life of the generator, try to keep thermal stress within the turbines safe limits [20]. Since the violations of the ramp rate constraints are assessed by examining the generators output over a given time interval, this problem cannot be solved for a single value of MW generation [20]. The objective function of dynamic ED is formulated as follows

$$\min C(P) = \sum_{t=1}^{T} \sum_{i=1}^{N} C_i(P_i^t) \tag{2–1}$$

where N is the set of committed units; P_i is the generation of unit i; $C_i(P_i)$ is the cost of producing P_i from unit i; T is the number of intervals in the study period. The fuel cost functions $C_i(\cdot)$ is derived from the fuel consumption function that can be measured and are discussed in Section 2.2.

The dynamic ED is not only the most accurate formulation of the economic dispatch problem but also the most difficult to solve because of its large dimensionality [3]. The DED problem is normally solved by discretization of the entire dispatch period into a number of small time intervals, over which the load demand is assumed to be constant and the system is considered to be in a temporal steady state. Over each time interval a static ED problem is solved under static constraints and the ramp rate constraints are enforced between the consecutive intervals [34]. In the DED problem the optimization is done with respect to the dispatchable powers of the units.

Some researchers have considered the ramp rate constraints by solving SED problem interval by interval and enforcing the ramp rate constraints from one interval to the next. However, this approach can lead to suboptimal solutions [23]; moreover, it does not have the look-ahead capability.

Since dynamic ED was introduced, variuos methods have been used to solve this problem. However, all of those methods may not be able to provide an optimal solution and usually getting stuck at a local optimal.

2.1 ED Constraints

The constrained ED problem is subjected to a variety of constraints depending upon assumptions and practical implications. Usually, formulation of ED problem includes such constraints as load generation balance, minimum and maximum capacity constraints. To maintain system reliability and security, spinning reserve constraints and security constraints can be added to the dynamic ED problem. The inclusion of the prohibited zones, ramp-rate limits and other practical constraints results in nonconvex ED of generating units. All these constraints are discussed bellow.

2.1.1 Load-Generation Balance

The generated power from all the running units must satisfy the load demand and the system losses given by (2–2)

$$\sum_{i=1}^{N} P_i^t = D^t + Loss^t, \quad t = 1, 2, \ldots, T \tag{2–2}$$

where D^t is the demand and $Loss^t$ is the system transmission loss. Their sum represents the effective load to be satisfied at the tth interval. The transmission line losses can be expressed in terms of the unit outputs:

$$\text{Loss}^t = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i^t B_{ij} P_j^t + \sum_{i=1}^{N} B_{i0} P_i^t + B_{00}$$

where B_{ij} is the ijth element of the loss coefficient square matrix, B_{i0} is the ith element of the loss coefficient, and B_{00} is the constant loss coefficient. Sometimes the last two terms are omitted.

In a competitive environment, the load-generation balance constraint is relaxed and each generating company schedules its production to maximize its profits given a forecast of electricity prices for the scheduling period. As a first approximation, each generating unit could be optimized separately in this problem because of the decoupling made possible by the availability of prices at each period. Dynamic constraints (such as ramp rates and minimum up and down time constraints) complicate the problem because a generating company that owns a portfolio of units must then decide whether to buy “flexibility” on the market or meet the dynamic constraints with its own resources [21].

2.1.2 Generation Capacity Constraint

For normal system operations, real power output of each generator is restricted by lower and upper bounds as follows:

$$P_i^t + S_i^t \leq P_i^{\max} \quad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T \tag{2–3}$$

$$P_i^{\min} \leq P_i^t \quad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T \tag{2–4}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum power produced by generator i, S_i^t is the reserve contribution of unit during time interval t.

2.1.3 Generating Unit Ramp Rate Limits

One of unpractical assumption that prevailed for simplifying the problem in many of the earlier research is that the adjustments of the power output are instantaneous [43]. Therefore, the power output of a practical generator cannot be adjusted instantaneously without limits. The operating range of all online units is restricted by their ramp-rate limits during each dispatch period. So, the subsequent dispatch output of a generator should be limited between the constraints of up and down ramp-rates [66] as follows

$$P_i^{t+1} - P_i^t \leq UR_i \cdot \Delta t \tag{2–5}$$

$$P_i^t - P_i^{t+1} \leq DR_i \cdot \Delta t \quad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T-1 \tag{2–6}$$

where UR_i and DR_i are the maximum ramp up/down rates for unit i and Δt is the duration of the time intervals into which the study period is divided. The inclusion of ramp rate limits modifies the generator operation constraints (2–3, 2–4) as follows

$$\max(P_i^{\min}, P_i^{t-1} - DR_i) \leq P_i \leq \min(P_i^{\max}, P_i^{t-1} + UR_i) \tag{2–7}$$

2.1.4 Reserve Contribution

The maximum reserve contribution has to satisfy following constraints:

$$0 \leq S_i^t \leq S_i^{\max} \quad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T \tag{2–8}$$

where $S_i^{\max}$ is the maximum contribution of unit i to the reserve capacity.

Maximum-ramp spinning reserve contribution is defined as in (2–9)

$$0 \leq S_i^t \leq UR_i \cdot \Delta t \quad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T \tag{2–9}$$

where S_i^t is the spinning reserve of unit i.

2.1.5 System Spinning Reserve Requirement

Sufficient spinning reserve is required from all running units to maximize and maintain system reliability [14]. There are many ways to determine the system spinning reserve requirement. It can be calculated as the size of the largest unit in operation or as a percentage of forecast load demand or even as a function of the probability of not having sufficient generation to meet the load [64]. The spinning rezerve can be defined by (2–10)

$$\sum_{i=1}^{N} S_i^t \geq SR^t \quad t = 1, 2, \ldots, T \tag{2–10}$$

where SR_t is the system spinning reserve requirement for time interval t. Also, the system spinning reserve requirement for interval t can sometimes be given by the following equation [20]:

$$SR^t = \alpha_d D^t + \alpha_g \cdot \max(P_i^{\max} \quad \text{scheduled at time } t, \quad i = 1, 2, \ldots N) \tag{2–11}$$

where α_d and α_g are constants which depend on the system required reliability level [55]. Besides the determination of the system spinning reserve requirement, the issue of allocation the spinning reserve among the committed units is very important; however, it has received very little attention in the dynamic ED literature.

2.1.6 Tie-line Limits

The economic dispatch problem can be extended by importing additional constraint like transmission line capacity limit given by (2–12)

$$P_{T_{jk,\min}} \leq P_{T_{jk}} + S_{jk} \leq P_{T_{jk,\max}} \tag{2–12}$$

where $P_{T_{jk,\min}}$ and $P_{T_{jk,\max}}$ specify the tie-line trasnmission capability, i.e. the transfer from area j to area k should not exceed the tie-line transfer capacities for security consideration [28]. Each area has own special load and its spinning reserve [68].

2.1.7 Prohibited Zone

The generating units may have certain ranges where operation is restricted on the grounds of physical limitations of machine components or instability, e.g. due to steam valve or vibration in shaft bearings. So, there is a quest to avoid operation in these zones in order to economize the production [43]. These ranges are prohibited from operation and a generator with prohibited regions (zones) has discontinuous fuel-cost characteristics (Fig. 2.1.7) [53]. The acceptable operating zones of a generating unit can be formulated as follows

$$P_i^{\min} \le P_i^t \le P_{i,1}^l \tag{2–13}$$

$$P_{i,j-1}^u \le P_i^t \le P_{i,j}^l, \quad i \in \theta, \quad j = 2, 3, \dots, n_i, \quad t = 1, 2, \dots, T \tag{2–14}$$

$$P_{i,n_i}^u \le P_i^t \le P_i^{\max} \tag{2–15}$$

where n_i is the number of the prohibited zones in unit i, θ is the set of units that have prohibited zones, $P_{i,j}^l$, $P_{i,j}^u$ are the lower and upper bounds of the jth prohibited zone.

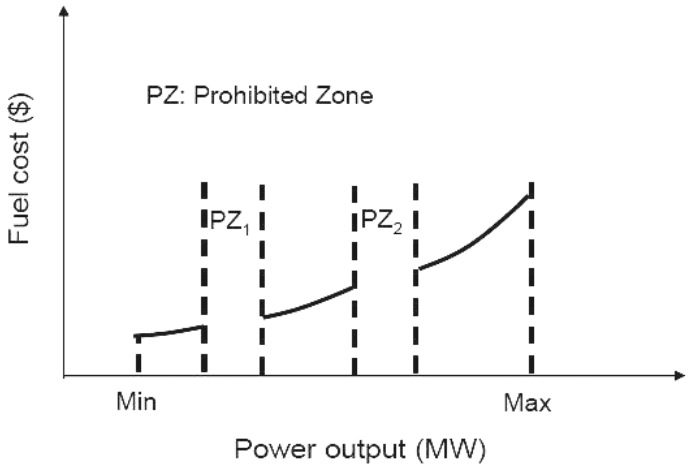

Figure 2-1. Example of cost function with two prohibited operating zones

2.2 Objective Functions

The dynamic ED problem has been solved with many different forms of the cost function, such as the smooth quadratic cost function (2–16) or the nonsmooth cost

function due to the valve-point effects (2–17). Also, a linear cost function [20] and piecewise linear cost function [27, 41] have been employed. For smooth cost function it is usually assumed that its incremental cost function. In some power systems combined cycle units are used to supply the base load. For these units the cost function can be given as linear, piecewise or quadratic with decreasing incremental cost function [41]. For units with prohibited zones, the fuel cost function is discontinuous and nonconvex.

An interesting departure from this standard formulation is the approach proposed by Wang and Shahidehpour [61] who include in the objective function a term representing the reduction in the life of the turbine caused by excessive ramping rates. This flexible technique makes possible a tradeoff between the system operating cost and the life cycle cost of the generating units [21].

2.2.1 Smooth Cost Function

The most simplified cost function of each generator can be represented as a quadratic function as given in (2–16) whose solution can be obtained by the conventional mathematical methods

$$C_i(P_i^t) = a_i + b_i P_i^t + c_i (P_i^t)^2 \tag{2–16}$$

where a_i, b_i,c_i are cost coefficients of generator i.

2.2.2 Non-smooth Cost Functions with Valve-point Effects

The generating units with multi-valve steam turbines exhibit a greater variation in the fuel cost functions because in order to meet the increased demand a generator with multi-valve steam turbines increase its output and various steam valves are to be opened [67]. This valve-opening process produces ripple like effect in the heat-rate curve of the generator. The inclusion of valve-point loading effects makes the modeling of the incremental fuel cost function of the generators more practical [60]. Therefore, in reality, the objective function of ED problem has non-differentiable property. Consequently, the objective function should be composed of a set of non-smooth cost functions. Considering non-smooth cost functions of generation units with valve-point

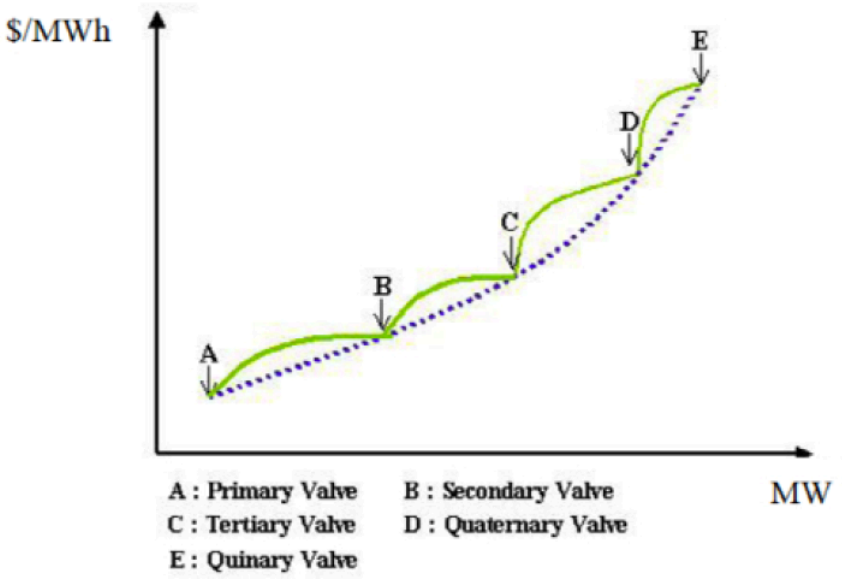

Figure 2-2. Cost function with valve-point effects

effects, the objective function is generally described as the superposition of sinusoidal functions and quadratic functions [52]

$$C_i(P_i^t) = a_i + b_i P_i^t + c_i (P_i^t)^2 + |e_i sin(h_i(P_i^{\min} - P_i^t))| \tag{2–17}$$

where e_i and h_i are the coefficients of generator i reflecting valvepoint effects. As shown in Fig. 2.2.2, this increases the non-linearity of curve as well as number of local optima in the solution space [60] compared with the smooth cost function due to the valvepoint effects. Also the solution procedure can easily trap in the local optima in the vicinity of optimal value.

2.2.3 Non-smooth Cost Functions with Multiple Fuels

Since the dispatching units are practically supplied with multi-fuel sources [49], each unit should be represented with several piecewise quadratic functions reflecting the effects of fuel type changes, and the generator must identify the most economic fuel to burn. The resulting cost function is called a “hybrid cost function.” Each segment of the hybrid cost function implies some information about the fuel being burned or the

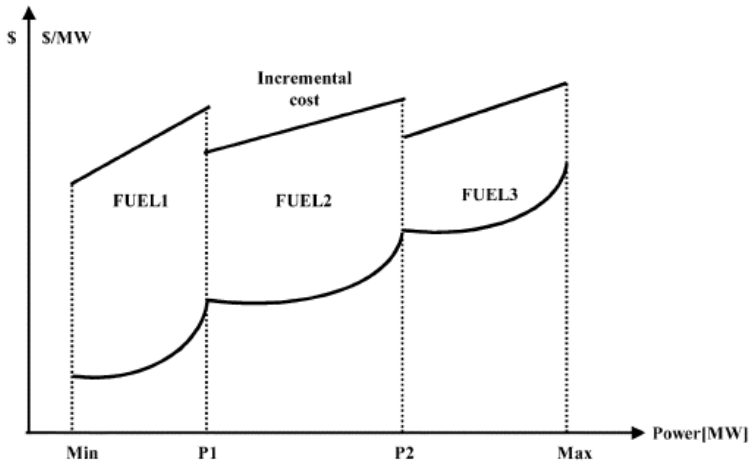

Figure 2-3. Cost function with multiple fuels

units operation. Thus, generally, the fuel cost function is a piecewise quadratic function described as follows

$$c_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i^t + c_{i1}(P_i^t)^2 & \text{if } P_{i,\min}^t \le P_i^t \le P_{i,1}^t \\ a_{i2} + b_{i2}P_i^t + c_{i2}(P_i^t)^2 & \text{if } P_{i,1}^t \le P_i^t \le P_{i,2}^t \\ \vdots & \vdots \\ a_{in} + b_{in}P_i^t + c_{in}(P_i^t)^2 & \text{if } P_{i,n-1}^t \le P_i^t \le P_{i,\max}^t \end{cases} \tag{2–18}$$

where are a_{ip}, b_{ip}, c_{ip} the cost coefficients of generator for the pth power level. The incremental cost functions are illustrated in Fig. (2.2.3)

2.2.4 Non-smooth Cost Functions with Valve-Point Effects and Multiple Fuels

To obtain an accurate and practical economic dispatch solution, the realistic operation of the ED problem should consider both valve-point effects and multiple fuels. The reference [10] proposed an incorporated cost model, which combines the valve-point loadings and the fuel changes into one frame. Therefore, the cost function should combine (2–17) with (2–18), and can be realistically represented as shown in

(2–19)

$$c_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i^t + c_{i1}(P_i^t)^2 + |e_{i,1}sin(h_{i,1}(P_{i,1}^{\min} - P_{i,1}^t))| & \text{if } P_{i,\min}^t \leq P_i^t \leq P_{i,1}^t \\ a_{i2} + b_{i2}P_i^t + c_{i2}(P_i^t)^2 + |e_{i,2}sin(h_{i,2}(P_{i,2}^{\min} - P_{i,2}^t))| & \text{if } P_{i,1}^t \leq P_i^t \leq P_{i,2}^t \\ \vdots & \vdots \\ a_{in} + b_{in}P_i^t + c_{in}(P_i^t)^2 + |e_{i,n}sin(h_{i,n}(P_{i,n}^{\min} - P_{i,n}^t))| & \text{if } P_{i,n-1}^t \leq P_i^t \leq P_{i,\max}^t \end{cases} \tag{2–19}$$

2.2.5 Emission Function

Due to increasing concern over the environmental considerations, society demands adequate and secure electricity, i.e. not only at the cheapest possible price, but also at minimum level of pollution. In this case, two conflicting objectives, i.e., operational costs and pollutant emissions, should be minimized simultaneously [4, 5, 7, 62].

The atmospheric pollutants such as sulphur oxides (SO_x) and nitrogen oxides (NO_x) caused by fossil-fueled generating units can be modeled separately or as the total emission of them which is the sum of a quadratic [4] and an exponential function and can be expressed as

$$\sum_{t=1}^{T}\sum_{i=1}^{N} \alpha_i + \beta_i P_i^t + \gamma_i (P_i^t)^2 + \eta_i \exp(\delta_i P_i^t) \tag{2–20}$$

where α_i, β_i, γ_i, η_i, and δ_i are emission coefficients of ith generating unit.

CHAPTER 3
SOLUTION METHODS

3.1 Continuous Greedy Randomized Adaptive Search Procedure (C-GRASP)

Continuous-GRASP (C-GRASP) extends the greedy randomized adaptive search procedure (GRASP) that was introduced by Feo and Resende [16, 17] from the domain of discrete optimization to that of continuous global optimization in [24, 25]. It is described as a multi-start local search procedure, where each C-GRASP iteration consists of two phases, namely, a construction phase and a local search phase [24]. Construction combines greediness and randomization to produce a diverse set of good-quality starting solutions for local search. The local search phase attempts to improve the solutions found by construction. The best solution over all iterations is kept as the initial solution. The advantages of this method is simplicity to implement and no requirement for derivative information

Pseudo-code for C-GRASP is shown in (3.1). C-GRASP works by discretizing the domain into a uniform grid. Both the construction (see the high level pseudo-code 3.2) and local improvement phases (see the high level pseudo-code 3.3) move along points on the grid. As the algorithm progresses, the grid adaptively becomes more dense. The main difference between GRASP and C-GRASP is that an iteration of C-GRASP does not consist of a single greedy randomized construction followed by local improvement, but rather a series of construction-local improvement cycles with the output of construction serving as the input of the local improvement, as in GRASP, but unlike GRASP, the output of the local improvement serves as the input of the construction procedure [25].

Since C-GRASP is essentially an unconstrained optimization algorithm, the constraints handling strategy needs to be incorporated into it in order to deal with the constrained ED problem. Approaches to manage these constraints are discussed in section 3.4.

pseudo-code 3.1 C-GRASP $(n, l, u, f(\cdot)$,MaxIters, MaxNumIterNoImprov, NumTimesToRun, MaxDirToTry,$\alpha)$

```
1: f* ← ∞
2: for j ← 1, ... , NumTimesToRun do
3:    x ← UnifRand(l, u); h ← 1; NumIterNoImprov ← 0;
4:    for Iter ← 1, ... , MaxIters do
5:       x ← ConstructGreedyRandomized(x, f(·), n, h, l, u, α);
6:       x ← LocalSearch(x, f(·), n, h, l, u, MaxDirToTry);
7:       if f(x) < f* then
8:          x* ← x; f* ← f(x); NumIterNoImprov ← 0;
9:       else
10:         NumIterNoImprov← NumIterNoImprov+1
11:      end if
12:      if NumIterNoImprov≥ MaxNumIterNoImprov then
13:         h ← h/2; NumIterNoImprov ← 0; {/}*make grid more dense*/
14:      end if
15:   end for
16: end for
17: return x*
```

pseudo-code 3.2 `ConstructGreedyRandomizedSolution` (Problem Instance)

```
1: Solution ← ∅;
2: while Solution construction not done do
3:    MakeRCL(RCL);
4:    S ← SelectRandomElement(RCL);
5:    Solution← Solution ∪ S;
6:    AdaptGreedyFunction(S);
7: end while
8: return (Solution);
```

pseudo-code 3.3 `LocalSearch`(Solution,Neighborhood)

```
1: Solution* ← Solution
2: while Solution* not locally optimal do
3:    Solution*← SelectRandomElement(Neighborhood(Solution*));
4:    if Solution better than Solution* then
5:       Solution*← Solution;
6:    end if
7: end while
8: return (Solution*)
```

3.2 Genetic Algorithms (GA)

This section engages into the concept of genetic algorithms that reflects the nature of chromosomes in genetic engineering. GAs are a class of stochastic search algorithms that start with the generation of an initial population or set of random solutions for the problem at hand. Each individual solution in the population called a chromosome or string represents a feasible solution. The objective function is then evaluated for these individuals. If the best string (or strings) satisfies the termination criteria, the process terminates, assuming that this best string is the solution of the problem. If the termination criteria are not met, the creation of new generation starts, pairs, or individuals are selected randomly and subjected to crossover and mutation operations. The resulting individuals are selected according to their fitness for the production of the new offspring. Genetic algorithms combine the elements of directed and stochastic search while exploiting and exploring the search space [31]. More details about GA can be found in [22, 46, 58].

pseudocode 3.4 Genetic algorithm

```
1: initialize population()
2: while not converge do
3:    assign population fitness()
4:    for 1, ... , npopsiz do
5:       select parents(p1,p2)
6:       reproduction(p1,p2,child)
7:    end for
8:    select next generation()
9: end while
```

The advantages of GA over other traditional optimization techniques can be summarized as follows:

- GA searches from a population of points, not a single point. The population can move over hills and across valleys. GA can therefore discover a globally optimal point, because the computation for each individual in the population is independent of others. GA has inherent parallel computation ability.

- GA uses payoff (fitness or objective functions) information directly for the search direction, not derivatives or other auxiliary knowledge. GA therefore can deal with non-smooth, non-continuous and non-differentiable functions that are the real-life optimization problems. This property also relieves GA of the approximate assumptions for a lot of practical optimization problems, which are quite often required in traditional optimization methods.

- GA uses probabilistic transition rules to select generations, not deterministic rules. They can search a complicated and uncertain area to find the global optimum. GA is more flexible and robust than the conventional methods [33].

The first attempt of the application of genetic algorithms in power systems is in the load flow problem [70]. It has been found that the simple genetic algorithm quickly finds the normal load flow solution for small-size networks by specifying an additional term in the objective function. A number of approaches to improving convergence and global performance of GAs have been investigated [70].

3.3 Simulated Annealing (SA)

The SA is a generic probabilistic meta-heuristic for the global optimization problem that was proposed by Kirkpatric et al. [32]. In the SA method, each point s of the search space is analogous to a state of some physical system, and the function `E(s)` to be minimized is analogous to the internal energy of the system in that state. The goal is to bring the system, from an arbitrary initial state, to a state with the minimum possible energy. In each step of the SA algorithm the current solution is replaced by a random "nearby" solution, chosen with a probability that depends on the difference between the corresponding function values and on a global parameter T (called the temperature), that is gradually decreased during the process. The dependency is such that the current solution changes almost randomly when T is large, but increasingly "downhill" as T goes to zero. The allowance for "uphill" moves saves the method from becoming stuck at local minima which are the bane of greedier methods. For certain problems, SA may be more effective than exhaustive enumeration. It has been shown that this technique converges asymptotically to the global optimal solution with probability one [1].

SA is an effective global optimization algorithm because of the following advantages [50]:

- suitability to problem in wide area,
- no restriction on the form of cost function,
- high probability to find global optimization,
- easy implementation by programming.

The pseudocode implementing SA is given bellow. It starts from state $s0$ and continue for $kmax$ of steps or until a state with energy $emax$ or less is found. The call `neighbour(s)` should generate a randomly chosen neighbour of a given state s; the call `random()` should return a random value in the range [0,1]. The annealing schedule is defined by the `temp(r)`, which should yield the temperature to use, given the fraction r of the time budget that has been expended so far.

pseudocode 3.5 Simmulated Annealing

```
 1: s ← s0; e ← E(s)
 2: s_best ← s; e_best ← e;
 3: k ← 0;
 4: while k < k_max and e > e_max do
 5:    s_new ← neighbour(s)
 6:    e_new ← E(s_new)
 7:    if e_new ≤ e_best then
 8:       s_best ← s_new; e_best ← e_new
 9:    end if
10:    if P(e, e_new, temp(k/max)) > random() then
11:       s ← s_new; e ← e_new
12:       k ← k + 1
13:    end if
14: end while
15: return s_best
```

Actually, the “pure” SA algorithm does not keep track of the best solution found so far: it does not use the variables s_{best} and e_{best}, it lacks the first `if` inside the loop, and, at the end, it returns the current state s instead of s_{best}. While saving the best state is a

standard optimization, that can be used in any metaheuristic, it breaks the analogy with physical annealing since a physical system can “store” a single state only.

In strict mathematical terms, saving the best state is not necessarily an improvement, since one may have to specify a smaller k_{max} in order to compensate for the higher cost per iteration. However, the step $s_{best} \leftarrow s_{new}$ happens only on a small fraction of the moves. Therefore, the optimization is usually worthwhile, even when state-copying is an expensive operation.

SA has the ability to avoid getting local solutions; then it can generate global or near global optimal solutions for optimization problems without any restriction on the shape of the objective functions [44]. SA is not memory intensive [45]. However, the setting of control parameters of the SA algorithm is a difficult task and the computation time is high [3]. The computational burden can be reduced by means of parallel processing [44].

3.4 Constraints Handling

Constraints lie at the hear to fall constrained engineering optimization applications. Practical constraints, which are often nonlinear and non-trivial,confine the feasible solutions to a small subset of the entire search space. There are several approaches which can be applied to handle constraints in heuristic approaches. These methods can be grouped into four categories: methods that preserve the feasibility of solutions, penalty-based methods, methods that clearly distinguish between feasible and unfeasible solutions, and hybrid methods [15, 62].

3.4.1 Penalty-Based Approach

The penalty function method is frequently applied to manage constraints in evolutionary algorithms. Such a technique converts the primal constrained problem into an unconstrained problem by penalizing constraint violations. The penalty function method is simple in concept and implementation. However, its primal limitation is the degree to which each constraint is penalized. These penalty terms have certain weaknesses that become fatal when penalty parameters are large. Such a penalty

function tends to be ill conditioned near the boundary of the feasible domain where the optimum point is usually located [10]. The penalized fuel cost function in ED problem was employed in [51].

In [40] the ED problem was transformed into an unconstrained one by constructing an augmented objective function incorporating penalty factors for any value violating the constraints:

$$H(X) = J(X) + k_1 \sum_{j=1}^{N_{eq}} (h_j(X))^2 + k_2 \sum_{j=1}^{N_{ueq}} \max[0, -g_j(X)]^2 \tag{3–1}$$

where $J(X)$ is the objective function value of the ED problem. N_{eq} and N_{ueq} are the number of equality and inequality constraints, respectivel; $h_j(X)$ and $g_j(X)$ are the equality and inequality constraints, respectively; k_1 and k_2 are the penalty factors. Since the constraints should be met, the value of thek_1 and k_2 parameters were chosen to have high value of 10,000. This approach was epmpoyed when applying SA method. The heuristic startegy that is discussed in nex section was used to get a feasible solution while applying C-GRASP method.

3.4.2 Heuristic Strategy

When the C-GRASP is applied to solve ED problem, a key problem is how to handle constraints with efficiency. In this section we mainly focus on handling the real power limits and generators ramp-up constraints. Other than penalty based way to satisfy the real power balance equality constraints (2–2), is to specify the output of $(N-1)$ generating units and to find the Nth from the equality constraint like in [4, 67]. In reference [67], authors employed a dependent generation power p_l^t of randomly selected unit l.

The heuristic strategy applied in `LocalSearch()` procedure in C-GRASP algorithm can be formulated in a following way:

Step 1. Set the dispatch period index $t = 1$ and iteration $i = 1$.

Step 2. Calculate the violation of power blance constraint P_{err}^t at dispatch time t is calculated from 3–2 as follows

$$P_{err}^t = D^t + Loss^t - \sum_{i=1}^{N} P_i^t \tag{3–2}$$

If $P_{err}^t = 0$, then go to Step 5, otherwise to Step 3.

Step 3. Randomly generate l the index of generating unit and calculate the real power of selected dependent generating unit p_l^t from (3–3).

$$P_l^t = D^t - \sum_{\substack{i=1 \\ i \neq l}}^{N} P_i^t \quad t = 1, 2, \ldots, T \tag{3–3}$$

However, considering transmission losses (2.1.1), these equality constraints become nonlinear and the output of dependent generating unit for every dispatch period t can be found from by solving a following equation

$$B_{ll}(P_l^t)^2 + (2\sum_{\substack{i=1 \\ i \neq l}}^{N} B_{li} P_i^t + B_{l0} - 1) P_l^t + (D^t + \sum_{\substack{i=1 \\ i \neq l}}^{N} \sum_{\substack{j=1 \\ j \neq l}}^{N} P_i^t B_{ij} P_j^t + B_{00} + \sum_{\substack{i=1 \\ i \neq l}}^{N} B_{l0} P_i^t - \sum_{\substack{i=1 \\ i \neq l}}^{N} P_i^t) = 0 \tag{3–4}$$

If it doesn't violate the generator operating limits and ramp-up constraints (if they are present), go to Step 5. Otherwise, the value has to be modified according to 3–5

$$P_l^t = \begin{cases} P_l^{\max} & \text{if } P_l^t > P_l^{\max} \\ P_l^{\min} & \text{if } P_l^t < P_l^{\min} \end{cases} \tag{3–5}$$

If ED incorporates ramp-up limits and dispatch period $t > 1$, then dependent unit output has to be calculated as 3–6

$$P_l^t = \begin{cases} \max(P_l^{\min}, P_l^{t-1} - DR_l) & \text{if } P_l^t > \max(P_l^{\min}, P_l^{t-1} - DR_l) \\ \min(P_l^{\max}, P_i^{t-1} + UR_l) & \text{if } P_l^t < \min(P_l^{\max}, P_i^{t-1} + UR_l) \end{cases} \tag{3–6}$$

After adjustment, go to Step 4.

Step 4. Increase the iteration number by 1, i.e. $l = l + 1$. If $l < l_{max}$, go to Step 2, otherwise go to Step 5.

Step 5. Increase the period number by 1, i.e. $t = t + 1$. If $t \leq T$, go to Step 2, otherwise stop.

The applied strategy for constraints handling will produce solutions satisfying real power limits constraint and generating unit ramp rate limits constraint, howerver not always the the real power balance constraint will be satisfied in dynamic ED due to ramp-up limits. The situation can be that in one dispatch period demand will meet generation, however in the next period the demand can be not because due to generating unit power increase or reduction limitation. In order not to consider such infeasible solution a large penalty is added to objective function value.

CHAPTER 4
EXPERIMENTS AND RESULTS

4.1 Experiments

In order to verify the feasibility and effectiveness of adopted C-GRASP capabilities for solving ED problems, different ED problem formulations, i.e. static and dynamic ED and different systems were used. The C-GRASP algotihm with heuristic strategy to deal with constraints was implemented in Matlab 7.5. For GA and SA algorithms, the standard Matlab functions form Genetic Algorithm and Direct Search Toolbox were employed. In standard GA function `ga()`, it is possible to include both linear and nonlinear equality and inequality constraints. However, SA function `simulannealbnd()` incorporates only lower and upper bound constraints, other constraints as a penalty function is added to objective function. Next, we will provide descriptions of systems used for our experiments.

4.1.1 System 1

The system consists of five generating units, whose the maximum total output is 925 MW. On this system dynamic ED problem was solved with the dispatch horizon one day with 12 intervals of one hour each. The demand of the system and generating unit data are given in Tables (4-1) and (4-2), respectively.

Table 4-1. Generating units characteristics of five-unit system

	a_i, \$ /h	b_i, \$ /MWh	c_i, \$ /(MW)^{2}h	$P_i^{\min}$, MW	$P_i^{\max}$, MW
Unit 1	25.000	2.000	0.008	10.000	75.000
Unit 2	60.000	1.800	0.003	20.000	125.000
Unit 3	100.000	2.100	0.0012	30.000	175.000
Unit 4	120.000	2.000	0.001	40.000	250.000
Unit 5	40.000	1.800	0.0015	50.000	300.000

4.1.2 System 2

The system contains six thermal generating units. The total maximum output of generating units is 1470 MW. This system was used to solve static ED problem where load demand on the system is 1263 MW. Parameters of all the thermal units are

Table 4-2. Load demand

Time, h	Load, MW	Time, h	Load, MW
1	410	7	626
2	435	8	654
3	475	9	690
4	530	10	704
5	558	11	720
6	608	12	740

reported in [30] and are given in Tables 4-3 and 4-4. In normal operation of the system, the loss coefficients B are as follows:

$$B_{ij} = \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0001 & -0.001 & -0.0006 \\ -0.0001 & 0.0001 & 0 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.001 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.015 \end{bmatrix} \times 10^{-2}$$

$$B_{0i} = [-0.3908 - 0.12970.70470.05910.2161 - 0.6635] \times 10^{-3}$$

$$B_{00} = 0.056$$

Table 4-3. Generating units characteristics of six-unit system

Unit	$P_i^{\min}$, MW	$P_i^{\max}$, MW	a_i, \$ /h	b_i, \$ /MWh	c_i, \$ /(MW)^{2}h	P_{0i}, MW
1	100	500	0.007	7	240	440
2	50	200	0.0095	10	200	170
3	80	300	0.009	8.5	220	200
4	50	150	0.009	11	200	150
5	50	200	0.008	10.5	220	190
6	50	120	0.0075	12	190	110

Table 4-4. Rump-up limits and prohibited zones of six-unit system

Unit	UR_i,MW	DR_i,MW	Prohibited zone
1	80	120	[210 240] [350 380]
2	50	90	[90 110] [140 160]
3	65	100	[150 170] [210 240]
4	50	90	[80 90] [110 120]
5	50	90	[90 110] [140 150]
6	50	90	[75 85] [100 105]

4.1.3 System 3

This system consists of 13 generating units with valve-point loading as given in Table (4-5). The parameters of this system showed is taken from [54]. The expected demand is 1800 MW and 2520 MW.

Table 4-5. Generating units characteristics of 13-unit system

Unit	P_i^{min}, MW	P_i^{max}, MW	a_i	b_i	c_i	e_i	f_i
1	0	680	0.00028	8.1	550	300	0.035
2	0	360	0.00056	8.1	309	200	0.042
3	0	360	0.00056	8.1	307	200	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.6	126	100	0.084
11	40	120	0.00284	8.6	126	100	0.084
12	55	120	0.00284	8.6	126	100	0.084
13	55	120	0.00284	8.6	126	100	0.084

4.1.4 System 4

This system is composed of 40 generating units with valve-point loading effects supplying a total demand of 10500 MW. Therefore, this system has nonconvex solution spaces and there are many local minima due to valve-point effects and the global minimum is very difficult to determine. The parameters of this system showed in the Table (4-6) are available in [54] as well.

Table 4-6. Generating units characteristics of 40-unit system

Unit	P_i^{min}, MW	P_i^{max}, MW	a_i	b_i	c_i	e_i	f_i
1	36	114	0.0069	6.73	94.705	100	0.084
2	36	114	0.0069	6.73	94.705	100	0.084
3	60	120	0.02028	7.07	309.54	100	0.084
4	80	190	0.00942	8.18	369.03	150	0.063
5	47	97	0.0114	5.35	148.89	120	0.077
6	68	140	0.01142	8.05	222.33	100	0.084
7	110	300	0.00357	8.03	287.71	200	0.042
8	135	300	0.00492	6.99	391.98	200	0.042
9	135	300	0.00573	6.6	455.76	200	0.042
10	130	300	0.00605	12.9	722.82	200	0.042
11	94	375	0.00515	12.9	635.2	200	0.042
12	94	375	0.00569	12.8	654.69	200	0.042
13	125	500	0.00421	12.5	913.4	300	0.035
14	125	500	0.00752	8.84	1760.4	300	0.035
15	125	500	0.00708	9.15	1728.3	300	0.035
16	125	500	0.00708	9.15	1728.3	300	0.035
17	220	500	0.00313	7.97	647.85	300	0.035
18	220	500	0.00313	7.95	649.69	300	0.035
19	242	550	0.00313	7.97	647.83	300	0.035
20	242	550	0.00313	7.97	647.81	300	0.035
21	254	550	0.00298	6.63	785.96	300	0.035
22	254	550	0.00298	6.63	785.96	300	0.035
23	254	550	0.00284	6.66	794.53	300	0.035
24	254	550	0.00284	6.66	794.53	300	0.035
25	254	550	0.00277	7.1	801.32	300	0.035
26	254	550	0.00277	7.1	801.32	300	0.035
27	10	150	0.52124	3.33	1055.1	120	0.077
28	10	150	0.52124	3.33	1055.1	120	0.077
29	10	150	0.52124	3.33	1055.1	120	0.077
30	47	97	0.0114	5.35	148.89	120	0.077
31	60	190	0.0016	6.43	222.92	150	0.063
32	60	190	0.0016	6.43	222.92	150	0.063
33	60	190	0.0016	6.43	222.92	150	0.063
34	90	200	0.0001	8.95	107.87	200	0.042
35	90	200	0.0001	8.62	116.58	200	0.042
36	90	200	0.0001	8.62	116.58	200	0.042
37	25	110	0.0161	5.88	307.45	80	0.098
38	25	110	0.0161	5.88	307.45	80	0.098
39	25	110	0.0161	5.88	307.45	80	0.098
40	242	550	0.00313	7.97	647.83	300	0.035

4.1.5 System 5

This system has 10 generating units with valve-point loading effects. Therefore, this system has nonconvex solution spaces and there are many local minima due to valve-point effects. The parameters of this system are given in the Table 4-10 and are available in [4] as well. The forecasted demand with the dispatch horizon one day with 24 intervals of one hour each is shown in Table 4-8.

Table 4-7. Generating units characteristics of 10-unit system

Unit	P_i^{min}, MW	P_i^{max}, MW	a_i	b_i	c_i	e_i	f_i	UR_i	UR_i
1	150	470	786.7988	38.5397	0.1524	450	0.041	80	80
2	135	470	451.3251	46.1591	0.1058	600	0.036	80	80
3	73	340	1049.9977	40.3965	0.028	320	0.028	80	80
4	60	300	1243.5311	38.3055	0.0354	260	0.052	50	50
5	73	243	1658.5696	36.3278	0.0211	280	0.063	50	50
6	57	160	1356.6592	38.2704	0.0179	310	0.048	50	50
7	20	130	1450.7045	36.5104	0.0121	300	0.086	30	30
8	47	120	1450.7045	36.5104	0.0121	340	0.082	30	30
9	20	80	1455.6056	39.5804	0.109	270	0.098	30	30
10	10	55	1469.4026	40.5407	0.1295	380	0.094	30	30

Table 4-8. Load demand for 24 hours

Time, h	Load, MW	Time, h	Load, MW	Time, h	Load, MW
1	1036	9	1924	17	1480
2	1110	10	2022	18	1628
3	1258	11	2106	19	1776
4	1406	12	2150	20	1972
5	1480	13	2072	21	1924
6	1628	14	1924	22	1628
7	1702	15	1776	23	1332
8	1776	16	1554	24	1184

4.2 Results

One of the features that the heuristic algorithms possess is randomness. Therefore, their performances cannot be judged by the result of a single run and many trials with different initializations should be made to reach a valid conclusion about the performance of the algorithms. An algorithm is robust, if it can guarantee an acceptable

performance level under different conditions. In this paper, 50 different runs of C-GRASP have been carried out.

4.2.1 Case 1

In this case, the dynamic ED problem on system 1 is solved. It can be seen from Table (4-9) that the C-GRASP provided the best solution compared to SA and GA.

Table 4-9. Generation costs for case 1

Method	Min	Avg	Max	St.Dev.
C-GRASP	**19645.87118**	**19725.6329**	**19837.55210**	26.8471
GA	19817.50206	19819.44773	19817.50206	**0.93349**
SA	19675.35508	19777.37761	19855.63880	36.1006

The smallest total production cost is obtained by SA and it is $19645.87. Morever, we can notice that on the average C-GRASP algorithm perfoms better than SA and GA. The lowest maximum value is provided by C-GRASP as well, while the highest maximum value was produced by SA. shows that SA solutions are very sensitive to starting points and are more volatile. The best found solution satisfying demand and power limits is given in Table 4-10.

Table 4-10. Best solution for case 1

Hour	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
1	10.00006975	20.00005644	80.00001477	105.6819645	194.3178945
2	10.00003632	52.60222864	30.00004416	151.8901212	190.5075697
3	26.00796462	87.4541663	80.84053733	45.99580774	234.701524
4	26.75734182	95.20329384	170.8232815	68.03647655	169.1796063
5	49.04650601	56.01226378	91.33351254	110.4114641	251.1962536
6	19.63298415	103.7721597	51.19984471	196.8271002	236.5679112
7	36.5415225	92.86540909	61.43881398	157.4967338	277.6575207
8	13.70517701	92.67194012	138.6821921	178.1269249	230.8137659
9	41.8141424	102.4755387	123.5565313	244.850131	177.3036566
10	21.88623928	102.6285523	129.2017437	249.9999302	200.2835345
11	28.88128653	58.20434065	161.8266865	222.1801306	248.9075557
12	25.81847079	113.8283152	174.999958	147.8022832	277.5509728

4.2.2 Case 2

Here, the static ED problem includes the nonlinear generation-demand equality constraints due to included transmission losses. The ramp up limits and prohibited

zones of generators are incorporated as well. The efficient of C-GRASP is tested on six-unit systems that is discribed in Section 4.1.2. The same problem has been solved in [30] and their best solution and applied methods are presented in Table 4-11. The losses and total generation cost are given in Table 4-12. The best solutions among all solutions have been illustrated in the bold prints. From these data we can see that their provided objective function values are smaller that one obtained by C-GRASP, but it should be noted that solutions gained by CPSO 1 and CPSO 2 violate the ramp-up limits of generator 3. When the solution of PSO has been pluged, it has been found the violation of generation-demand balance equality by 0.4661 MW, because according to given solution, the generation is equal to 1275.9571 MW and loss is 12.4910 MW.

The minimum generation cost found by C-GRASP is $15456.54469, while the average cost is $15507.10954 with standard deviation of value $28.10037477. According to these facts, it can be stated that C-GRASP approch with applied heuristic strategy can produced feasible and good solutions. The results produced by SA and GA were not feasible or reasonably close to results presneted here, so they are not presneted here.

Table 4-11. Best solutions for case 2

	P_1	P_2	P_3	P_4	P_5	P_6
PSO	447.4970	173.3221	263.4745	139.0594	165.4761	87.1280
CPSO 1	434.4236	173.4385	274.2247	128.0183	179.7042	85.9082
CPSO 2	434.4295	173.3231	274.4735	128.0598	179.4759	85.9281
C-GRASP	447.8181	200	253.5570	149.9999	150.3202	73.5022

Table 4-12. Best results, when demand is1263 MW

	Total output	Loss	Total generation cost
PSO	1276.0	12.9584	15451
CPSO 1	1276.0	12.9583	15447
CPSO 2	1276.0	12.9582	15446
C-GRASP	1275.1974	12.1974	15456.54

4.2.3 Case 3

In this case, the static ED problem with nonsmooth cost function due to the valve-point effects is considered to check the ability of C-GRASP to solve such type problems and its competitiveness with both GA and SA approches. The experiment is performed on two different systems, namely, system 3 and system 4. The final fuel costs obtained using applied approches are summarized in Table 4-13. It shows the minimum, average and maximum cost and standard deviation achieved by applied methods for 75 runs. From the computational results, the minimum cost achieved by C-GRASP was the best, followed by SA and GA. The minimum cost, maximum cost and the mean cost values obtained by C-GRASP are 18394.07 $/h, 18699.339 $/h, and 18550.105 $/h, respectively, which are lower than those obtained by SA and GA. The worst results are obtained by GA. It can be noticed that results produced by GA vary the least, this can be confirmed by the low standard deviation that is $12.562. In literature [54], the lowest reported generation cost for 1800 MW is $17994.07, however the solution is not presented.

Table 4-13. Generation costs for 13-unit system with demand 1800 MW

Method	Min	Avg	Max	St.Dev.
C-GRASP	**18394.070**	**18550.105**	**18699.339**	65.729
GA	19384.229	19417.964	19438.914	**12.562**
SA	18950.174	19393.114	19782.516	181.920

The results on 40-units are presented in table 4-14. C-GRASP, SA and GA algorithms were run for 75 times and the minimum, maximum and average value of objective function are reported.

Table 4-14. Generation costs for 40-unit system with demand 10500 MW

Method	Min	Avg	Max	St.Dev.
C-GRASP	**128883.1965**	**130268.9796**	**132839.2181**	972.757
GA	163401.9977	163534.9817	163623.3423	**64.0606**
SA	138975.7844	150757.5002	162578.6271	6118.65

4.2.4 Case 4

The last problem solved by C-GRASP is dynamic ED problem including ramp-up limits, that makes this problem more difficult than in a case 1. For simplicity, the transmission losses are neglected. The minimum cost obtained by the C-GRASP coupled with heuristic strategy is found to be $1,735,176.10, the best solution that satisfies demand-balance constraints as well as generators operation constraints including ones of ramp-up is given in Table 4-15. GA ans SA applied in this work couldn't produce the feasible solution.

Table 4-15. Best solution for case 4

Hour	P_1	P_2	P_3	P_4	P_5
1	197.5775	181.2115	163.4175	62.3581	127.0141
2	199.3353	142.0086	243.3161	112.3580	115.8294
3	279.3352	222.0086	163.3161	162.3580	80.9696
4	357.6864	196.9907	83.3162	212.3580	130.9696
5	341.5554	276.9907	104.5803	226.3765	180.9696
6	364.4919	356.9907	92.7176	205.6510	202.5198
7	291.8407	436.9906	162.9068	249.2158	210.4313
8	275.9255	452.7053	238.0856	230.3986	196.6733
9	355.9255	382.1891	318.0856	233.8956	197.8604
10	373.6142	395.9434	310.8613	235.4000	242.9999
11	453.6141	447.3342	339.9999	285.3999	197.8604
12	469.9999	469.9999	327.0836	235.4000	229.2473
13	405.7058	425.0176	281.3943	279.5788	226.4663
14	325.7058	367.8957	339.9999	229.5788	240.9742
15	308.0081	320.2882	284.4522	279.5788	190.9742
16	228.0081	369.5967	235.5079	230.6255	174.2616
17	252.7930	361.9796	165.9723	237.6272	169.1177
18	214.1486	441.9796	160.0032	187.6272	211.3444
19	253.8865	470.0000	240.0032	137.6272	242.9999
20	333.8865	448.3762	320.0032	149.1631	211.3444
21	334.2637	375.3046	329.5451	195.2469	242.9999
22	254.2637	295.3046	249.5451	245.2469	195.4727
23	174.2637	215.3046	218.8263	256.1493	161.5679
24	150.0001	171.8146	144.0519	259.4389	132.1630

Best solutions for case 4 continued

Hour	P_6	P_7	P_8	P_9	P_{10}
1	84.1156	77.5922	83.0176	20.0001	39.6960
2	87.3169	63.8052	90.0000	46.0304	10.0001
3	60.2349	93.8052	119.9999	46.7507	29.2219
4	107.8558	111.1225	108.2973	59.4590	37.9445
5	128.7563	81.1226	78.2974	38.9946	22.3567
6	140.9288	76.3086	98.3418	56.9712	33.0785
7	137.0179	46.3086	68.3418	71.6510	27.2956
8	89.7335	76.3086	84.7578	80.0000	51.4117
9	139.7335	106.3086	93.1458	62.0940	34.7621
10	159.9999	128.7672	84.5977	73.0386	16.7777
11	112.7650	98.7671	114.5977	43.0386	12.6230
12	112.5501	128.7671	84.5977	73.0386	19.3156
13	88.9431	129.9999	114.5977	77.8105	42.4861
14	65.2257	127.7126	95.1739	76.7334	54.9999
15	70.0661	97.7126	119.9999	62.4338	42.4861
16	108.1979	67.7126	90.2077	32.4338	17.4482
17	62.7680	70.2996	97.6767	32.8367	28.9293
18	112.7679	99.9863	119.9999	48.3857	31.7572
19	122.1729	97.8341	112.1255	55.9241	43.4265
20	159.9999	126.0825	105.6771	78.8549	38.6122
21	153.7373	100.4907	119.9999	48.8549	23.5569
22	127.9852	70.4907	96.0201	70.0305	23.6405
23	122.7771	40.4908	66.0202	56.0837	20.5164
24	72.7771	70.4908	73.5756	60.6486	49.0393

CHAPTER 5
CONCLUSION

- Economic disatch problem can be formulated in very different ways: as a simple linear programing problem to nonlinear nonconvex problem.
- In this work, four different cases were analysed and three heuristic methods: C-GRASP, GA and SA were applied to solve ED problem.
- Since C-GRASP is able to cope with optimization problem having box constraints, the heuristic strategy to deal with equality and inequality constraints for ED problem was incorporated.
- The experimental results revealed, that C-GRASP adopted to ED problem is able to provide good results and can outperfom SA and GA.

REFERENCES

[1] Aarts, E., J. Korst. 1989. *Simulated Annealing and Boltzmann Machines*. John Wiley & Sons Ltd.

[2] Altun, H., T. Yalcinoz. 2008. Implementing soft computing techniques to solve economic dispatch problem in power systems. *Expert Systems with Applications* **35** 1668–1678.

[3] Attaviriyanupap, P., H. Kita, E. Tanaka, J. Hasegawa. 2002. A Hybrid EP and SQP for Dynamic Economic Dispatch With Nonsmooth Fuel Cost Function. *IEEE TRANSACTIONS ON POWER SYSTEMS* **17** 411–416.

[4] Basu, M. 2008. Dynamic economic emission dispatch using nondominated sorting genetic algorithm-II. *Electrical Power and Energy Systems* **30** 140–149.

[5] Basu, M. 2010. Economic environmental dispatch of hydrothermal power system. *Electrical Power and Energy Systems* **32** 711–720.

[6] Bechert, T.E., H.G. Kwatny. 1972. On the optimal dynamic dispatch of real power. *IEEE Transactions on Power Apparatus and Systems* **PAS-91** 889–898.

[7] Brini, S., H.H. Abdallah, A. Ouali. 2009. Economic Dispatch for Power System included Wind and Solar Thermal energy. *Leonardo Journal of Sciences* **14** 204–220.

[8] Cai, J., X. Maa, L. Li, Y. Yang, H. Peng, X. Wang. 2007. Chaotic Ant Swarm Optimization to Economic Dispatch. *Chaos, Solitons and Fractals* **34** 1366–1375.

[9] Carpentier, J. 1962. Contribution ltude du dispatching conomique. *Bulletin de la Socit Franaise des Electriciens* **3**.

[10] Chiang, Ch.-L. 2005. Improved Genetic Algorithm for Power Economic Dispatch of Units With Valve-Point Effects and Multiple Fuels. *IEEE TRANSACTIONS ON POWER SYSTEMS* **20** 1690–1699.

[11] Coelho, L.S., C.-S. Lee. 2008. Solving economic load dispatch problems in power systems using chaotic and Gaussian particle swarm optimization approaches. *Electrical Power and Energy Systems* **30** 297–307.

[12] Coelho, L.S., V.C. Mariani. 2008. *Advances in Differential Evolution*, chap. Self-adaptive Differential Evolution Using Chaotic Local Search for Solving Power Economic Dispatch with Nonsmooth Fuel Cost Function. Springer-Verlag Berlin Heidelberg, 275–286.

[13] Coelho, L.S., V.C. Mariani. 2009. A novel chaotic particle swarm optimization approach using Henon map and implicit filtering local search for economic load dispatch. *Chaos, Solitons and Fractals* **39** 510–518.

[14] Dillon, T.S., K.W. Edwin, H.D. Kochs R.J. Taud. 1978. Integer programming approach to the problem of optimal unit commitment with probabilistic reserve determination. *IEEE Transactions on Power Apparatus Systems* **6** 2154–66.

[15] dos Santos Coelho, L., V.C. Mariani. 2006. Combining of Chaotic Differential Evolution and Quadratic Programming for Economic Dispatch Optimization With Valve-Point Effect. *IEEE TRANSACTIONS ON POWER SYSTEMS* **21** 989–996.

[16] Feo, T.A., M.G.C. Resende. 1989. A probabilistic heuristic for a computationally difficult set covering problem. *Operations Research Letters* **8** 67–71.

[17] Feo, T.A., M.G.C. Resende. 1995. Greedy randomized adaptive search procedures. *Journal of Global Optimization* **6** 109–133.

[18] Granelli, G.P., M. Montagna. 2000. Security constrained economic dispatch using dual quadratic programming. *Electric Power Systems Research* **56** 71–80.

[19] Han, F., Q.-S. Lu. 2008. An improved chaos optimization algorithm and its application in the economic load dispatch problem. *International Journal of Computer Mathematics* **85**(6) 969–982.

[20] Han, X.S., H.B. Gooi. 2007. Effective economic dispatch model and algorithm. *Electrical Power and Energy Systems* **29** 113–120.

[21] Han, X.S., and D.S. Kirschen H.B. Gooi. 2001. Dynamic Economic Dispatch: Feasible and Optimal Solutions. *IEEE TRANSACTIONS ON POWER SYSTEMS* **16** 22–28.

[22] Haupt, R.L. 2004. *Practical genetic algorithms*. Wiley-IEEE.

[23] Hindi, K.S., M.R. Ab Ghani. 1989. Multi-period economic dispatch for large scale power systems. *Proc. IEE Pt. C* **136** 130136.

[24] Hirsch, M.J., C.N. Meneses, P.M. Pardalos, M.G.C. Resende. 2007. Global Optimization by Continuous GRASP. *Optimization Letters* **1** 201–212.

[25] Hirsch, M.J., P.M. Pardalos, M.G.C. Resende. 2010. Speeding up continuous GRASP. *European Journal of Operational Research* **205**(3) 507–521.

[26] Jabr, R., A.H. Coonick, B.J. Cory. 2000. A homogeneous linear programming algorithm for the security constrained economic dispatch problem. *IEEE Transactions on Power Systems* **15** 930–937.

[27] Jabr, R.A., A.H. Coonick, B.J. Cory. 2000. A study of the homogeneous algorithm for dynamic economic dispatch with network constraints and transmission losses. *IEEE TRANSACTIONS ON POWER SYSTEMS* **15** 605–611.

[28] Jeyakumar, D.N., T. Jayabarathi, T. Raghunathan. 2006. Particle swarm optimization for various types of economic dispatch problems. *Electrical Power and Energy Systems* **28** 36–42.

[29] Jiang, C.W., X.Z. Quan, Y.C. Zhang. 1999. A chaotic optimization method for economical operation of hydro power plants. *Journal of Huangzhong University of Science and Technology* **27** 39–40.

[30] Jiejin, C., M. Xiaoqian, L. Lixiang, P. Haipeng. 2007. Chaotic particle swarm optimization for economic dispatch considering the generator constraints. *Energy Conversion and Management* **48** 645–653.

[31] Kamal, M.F.M., T.K.A. Rahman, I. Musirin. 2004. Application of Improved Genetic Algorithms for Loss Minimisation in Power System. *Proceedings National Power and Energy Conference*. 258–262.

[32] Kirkpatrick, S., C.D. Gelatt, M.P. Vecchi. 1983. Optimization by Simulated Annealing. *Science. New Series* **220** 671–680.

[33] Leung, H.C., T.S. Chung. 2000. Optimal Power Flow with a Versatile FACTS Controller by Genetic Algorithm Approach. *International Conference on Advances in Power System Control, Operation and Management*, vol. 1. 178–183.

[34] Li, F., R. Morgan, D. Williams. 1997. Hybrid genetic approaches to ramping rate constrained dynamic economic dispatch . *Electric Power System Research* **43** 97–103.

[35] Lu, N., M.R. Unum. 1993. Network constrained security control using an interior point algorithm. *IEEE Transactions on Power Systems* **8**(3) 1068–1076.

[36] Mahdad, B., K. Srairi, T. Bouktir. 2009. Optimal Power Flow with Environmental Constraints of the Algerian Network using Decomposed Parallel GA. *IEEE Bucharest Power Tech Conference*. Bucharest, Romania.

[37] Momoh, J.A., S.X. Guo, E.C. Ogbuobiri, R. Adapa. 1994. The quadratic interior point method solving power system optimization problems. *IEEE Transactions on Power Systems* **9**(3) 1327–1336.

[38] Muthuselvan, N.B., P. Somasundaram. 2009. Application of Tabu Search Algorithm to Security Constrained Economic Dispatch. *Journal of Theoretical and Applied Information Technology* **5** 602–608.

[39] Nanda, J., L. Hari, M.L. Kothari. 1994. Economic emission load dispatch with line flow constraints using a classical technique. *IEE Proceedings-Generation, Transmission and Distribution* **141** 1–10.

[40] Niknam, T. 2010. A new fuzzy adaptive hybrid particle swarm optimization algorithm for non-linear, non-smooth and non-convex economic dispatch problem. *Applied Energy* **87** 327–339.

[41] Ongsakul, W., J. Tippayachai. 2002. Parallel micro genetic algorithm based on merit order loading solutions for constrained dynamic economic dispatch. *Electric Power System Research* **61** 77–88.

[42] Panigrahi, B.K., V.R. Pandi, S. Das. 2008. Adaptive particle swarm optimization approach for static and dynamic economic load dispatch. *Energy Conversion and Management* **49** 1407–1415.

[43] Panigrahi, B.K., S.R. Yadav, S. Agrawal, M.K. Tiwari. 2007. A clonal algorithm to solve economic load dispatch. *Electric Power System Research* **77** 1381–1389.

[44] Panigrahi, C.K., P.K. Chattopadhyay, R.N. Chakrabarti, M. Basu. 2006. Simulated annealing technique for dynamic economic dispatch. *Electric Power Components and Systems* **34** 577–586.

[45] Rajan, C.C.A., M.R. Mohan. 2007. An evolutionary programming based simulated annealing method for solving the unit commitment problem. *Electric Power and Energy Systems* **29** 540–550.

[46] Reeves, C.R., J.E. Rowe. 2003. *Genetic algorithms: principles and perspectives: a guide to GA theory*. 2nd ed. Springer.

[47] Roa-Sepulveda, C.A., B.J. Pavez-Lazo. 2001. A Solution to the Optimal Power Flow Using Simulated Annealing. *IEEE Porto Power Tech Conference*. Porto, Portugal.

[48] Rosehart, W., C. Canizares, A. Vannelli. 1997. Sequential Methods in Solving Economic Power Flow Problems. *IEEE Canadian Conference on Electrical and Computer Engineering*, vol. 1. 281–284.

[49] Saber, A.Y., S. Chakraborty, S.M. Abdur Razzak, T. Senjyu. 2009. Optimization of economic load dispatch of higher order general cost polynomials and its sensitivity using modified particle swarm optimization. *Electric Power Systems Research* **79** 98–106.

[50] Sadati, N., T. Amraee, A.M. Ranjbar. 2009. A global Particle Swarm-Based-Simulated Annealing Optimization technique for under-voltage load shedding problem. *Applied Soft Computing* **9** 652–657.

[51] Selvakumar, A.I., K. Thanushkodi. 2007. A New Particle Swarm Optimization Solution to Nonconvex Economic Dispatch Problems. *IEEE TRANSACTIONS ON POWER SYSTEMS* **22** 42–50.

[52] Selvakumar, A.I., K. Thanushkodi. 2008. Anti-predatory particle swarm optimization: Solution to nonconvex economic dispatch problems. *Electric Power System Research* **78** 2–10.

[53] Selvakumar, A.I., K. Thanushkodi. 2009. Optimization using civilized swarm: Solution to economic dispatch with multiple minima. *Electric Power System Research* **79** 8–16.

[54] Sinha, N, R. Chakrabarti, P.K. Chattopadhyay. 2003. Evolutionary programming techniques for economic load dispatch. *IEEE Trans Evol Comput* **7** 83–94.

[55] Somuah, C.B., N. Khunaizi. 1990. Application of linear programming redispatch technique to dynamic generation allocation. *IEEE TRANSACTIONS ON POWER SYSTEMS* **5** 20–26.

[56] Song, Y.H., G.S. Wang, P.Y. Wang, A.T. Johns. 1997. Environmental/econoimic dispatch using fuzzy logic controlled genetic algiorithms. *IEE Proceedings-Generation, Transmission and Distribution* **144**(4) 377–382.

[57] Stott, B., J.L. Marinho. 1979. Linear Programming for Power System Network Security Applications. *IEEE Transactions on Power Apparatus and Systems* **PAS-98** 837–848.

[58] Tang, K.S., S. Kwong. 1999. *Genetic algorithms: concepts and designs*. 2nd ed. Springer.

[59] Vargas, L.S., V.H. Quintana, A. Vannelli. 1993. A tutorial description of an interior point method and its applications to security-constrained economic dispatch. *IEEE Transactions on Power Systems* **8**(3) 1315–1323.

[60] Victoire, T.A.A., A.E. Jeyakumar. 2005. Hybrid PSOSQP for economic dispatch with valve-point effect. *Electric Power System Research* **71** 51–59.

[61] Wang, C., S.M. Shahidehpour. 1994. Ramp-rate limits in unit commitment and economic dispatch incorporating rotor fatigue effect. *IEEE TRANSACTIONS ON POWER SYSTEMS* **9**(3) 1539 –1545.

[62] Wang, L., C. Singh. 2009. Reserve-constrained multiarea environmental/economic dispatch based on particle swarm optimization with local search. *Engineering Applications of Artificial Intelligence* **22** 298–307.

[63] Wong, K.P., Y.W. Wong. 1994. Genetic and genetic/simulated-annealing approaches to economic dispatch. *IEE Proceedings-Generation, Transmission and Distribution*, vol. 141. 507–513.

[64] Xia, X., A.M. Elaiw. 2010. Optimal dynamic economic dispatch of generation: A review. *Electric Power System Research* **80** 975–986.

[65] Xu, H.P., Y. Zhu, T. Zhang. 2000. Application of mutative scale chaos optimization algorithm in power plant units economic dispatch. *Journal of Harbin Institute of Technology* **32** 55–58.

[66] Yare, Y., G.K. Venayagamoorthy, A.Y. Saber. 2009. Heuristic Algorithms for Solving Convex and Nonconvex Economic Dispatch. *The 15th International Conference on Intelligent System Applications to Power Systems* .

[67] Yuan, X., L. Wang, Y. Zhang, Y. Yuan. 2009. A hybrid differential evolution method for dynamic economic dispatch with valve-point effects. *Expert Systems with Applications* **36** 4042–4048.

[68] Zarei, M., A. Roozegar, R. Kazemzadeh, J.M. Kauffmann. 2007. Two Area Power Systems Economic Dispatch Problem Solving Considering Transmission Capacity Constraints. *World Academy of Science, Engineering and Technology* **33** 147–152.

[69] Zehar, K., S. Sayah. 2008. Optimal Power flow with environmental constraint using a fast successive linear programming algorithm: Application to the algerian power system. *Energy Conversion and Management* **49** 3361–3365.

[70] Zhao, B., C.X. Guo, Y.J. Cao. 2005. An Improved Particle Swarm Optimization Algorithm for Optimal Reactive Power Dispatch. *IEEE Power Engineering Society General Meeting*, vol. 1. 272–279.

[71] Zhijiang, Y., H. Zhijian, J. Chuanwen. 2002. Economic Dispatch and Optimal Power Flow Based on Chaotic Optimization. *Proceedings of International Conference on Power System Technology, 2002. PowerCon* **4** 2313–2317.

BIOGRAPHICAL SKETCH

Ingrida Radziukyniene got Bachelor of Science and Master of Science in computer science at Vytautas Magnus University, Lithuania in 2003 and 2005, respectively. In addition, she got a certificate of bussiness management from Department of Business at Vytautas Magnus University. In 2010, she earned the Master of Science in industrial engineering from University of Florida. More information about her research interest can be found in her webpage http://plaza.ufl.edu/ingridar/.