CONTINUOUS GRASP ALGORITHM APPLIED TO ECONOMIC DISPATCH PROBLEM OF THERMAL UNITS

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Abstract. *The economic dispatch problem (EDP) is one of the fundamental issues in power systems to obtain benefits with the stability, reliability and security. Its objective is to allocate the power demand among committed generators in the most economical manner, while all physical and operational constraints are satisfied. The cost of power generation, particularly in fossil fuel plants, is very high and economic dispatch helps in saving a significant amount of revenue. Recently, as an alternative to the conventional mathematical approaches, modern heuristic optimization techniques such as simulated annealing, evolutionary algorithms, neural networks, ant colony, and tabu search have been given much attention by many researchers due to their ability to find an almost global optimal solution in EDPs. On other hand, continuous GRASP (C-GRASP) is a stochastic local search meta-heuristic for finding cost-efficient solutions to continuous global optimization problems subject to box constraints. Like a greedy randomized adaptive search procedure (GRASP), a C-GRASP is a multi-start procedure where a starting solution for local improvement is constructed in a greedy randomized fashion. The C-GRASP algorithm is validated for a test system consisting of fifteen units, test system that takes into account spinning reserve and prohibited operating zones constrains.*

Keywords*: economic dispatch, thermal units, electrical energy, optimization, C-GRASP.*

1. INTRODUCTION

The economic dispatch optimization problem is one of the fundamental issues in power systems to obtain benefits with the stability, reliability and security. Its objective is to allocate the power demand among committed generators in the most economical manner, while all physical and operational constraints are satisfied. The cost of power generation, particularly in fossil fuel plants, is very high and economic dispatch helps in saving a significant amount of revenue (Chatuverdi *et al*., 2008).

Many optimization methods have been researched. In the conventional methods such as the lambda-iteration method, dynamic programming, interior point method and gradient-based methods, an essential assumption is that the incremental cost curves of the units are monotonically increasing piecewise linear functions, but the practical systems are nonlinear. However, conventional methods like lambda-iteration, quadratically constrained programming, gradient methods, among others, rely heavily on the convexity assumption of generator cost curves and usually approximate these curves using quadratic, piecewise quadratic or higher order polynomial cost functions (Wood and Wollenberg, 1984). When fuel cost function is approximated by nonsmooth or non-convex function, numerical methods are no longer applicable. For example, practical economic dispatch problems with valve-point effects are represented as nonsmooth optimization problems.

Recently, a number of meta-heuristics, for example simulated annealing (Basu, 2005), genetic algorithm (Walters and Sheblé, 1993), evolutionary programming (Sinha *et al*., 2003), differential evolution (Noman and Iba, 2008), cultural differential evolution (Coelho *et al*., 2008), tabu search (Lin *et al*., 2002), improved quantum-inspired evolutionary algorithm (Neto *et al*., 2010), and particle swarm optimization (Panigrahi *et al.*, 2008) have been applied to solve the economic dispatch optimization problem.

In the optimization context based on meta-heuristics, a Continuous-GRASP (C-GRASP) algorithm was initially proposed in Hirsch *et al.* (2006), as a novel global optimization method. C-GRASP extends the Greedy Randomized Adaptive Search Procedure (GRASP) of Feo and Resende (1995) from the discrete to the continuous global optimization field. C-GRASP is a stochastic local search meta-heuristic that doesn't make use of derivative information and is easily implemented, therefore if can be applied to find cost-efficient solutions of a wide range of continuous global optimization problems subject to box constraints. Like GRASP, C-GRASP is a multi-start procedure where a starting solution for local improvement is constructed in a greedy randomized fashion.

In this paper, an economic dispatch problem is employed to demonstrate the performance of the C-GRASP and validate the approach in this field. The benchmark problem used consisted of 15 thermal generators with prohibited operating zones, and it is described in Lee and Breipohl (1993). Simulation results obtained were analyzed and compared with other optimization results reported in literature.

The remainder of this paper is organized as follows: section 2 describes the formulation of the economic dispatch problem, while section 3 explains the fundamentals of C-GRASP. Subsequently, section 4 provides the simulation results for the 15-unit test system. Lastly, conclusion is given in the section 5.

2. FUNDAMENTALS OF ECONOMIC DISPATCH OPTIMIZATION PROBLEM

The primary concern of an economic dispatch problem is to minimize the total fuel cost at thermal power plants subjected to the operating constraints of a power system. Therefore, it can be formulated mathematically with an objective function and two constraints. The equality and inequality constraints are represented by Eqs. (1) and (2) given by:

$$\sum_{i=1}^{n} P_i - P_L - P_D = 0 \tag{1}$$

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{2}$$

In the power balance criterion, an equality constraint must be satisfied, as shown in Eq. (1). The generated power should be the same as the total load demand plus total line losses. The generating power of each generator should lie between maximum and minimum limits represented by Eq. (2), where P_i is the power of generator i (in MW); n is the number of generators in the system; P_D is the system's total demand (in MW); P_L represents the total line losses (in MW) and $P_i^{\min}$ and $P_i^{\max}$ are, respectively, the output of the minimum and maximum operation of the generating unit i (in MW). The objective of minimization of the total fuel cost function is formulated as follows:

$$\min\ f = \sum_{i=1}^{n} F_i(P_i) \tag{3}$$

where F_i is the total fuel cost for the generator unit i (in \$/h), which is defined by equation:

$$F_i(P_i) = c_i P_i^2 + b_i P_i + a_i \tag{4}$$

where a_i , b_i and c_i are cost coefficients of generator i. In the case study presented here, we disregarded the transmission losses, P_L (mentioned in Eq. (1)), i.e., in this work $P_L = 0$. In this study, the spinning reserve and prohibited operating zone-constraints are considered (Lee and Breipohl, 1993; Papageorgiou and Fraga, 2007). The constraints can be represented by equations given by:

(i) spinning reserve constraints (Papageorgiou and Fraga, 2007):

$$\sum_{i=1}^{n} S_i \ge S_R \tag{5}$$

$$S_i = \min\left\{\left(P_i^{\max} - P_i\right), S_i^{\max}\right\}, \qquad \forall i \notin \omega \tag{6}$$

$$S_i = 0, \qquad \forall i \in \omega \tag{7}$$

where S_i is the spinning reserve contribution of unit i, S_R the system spinning reserve requirement, $S_i^{\max}$ the maximum spinning reserve contribution of unit i, and ω is the set of on-line units with prohibited operating zones.

(ii) prohibited operating zones constraints:

$$P_i \in \begin{cases} P_i^{\min} \le P_i \le P_{i,1}^{l} \\ P_{i,k-1}^{u} \le P_i \le P_{i,k}^{l}, \qquad k = 1,\dots, zo_i \\ P_{i,z_i}^{u} \le P_i \le P_i^{\max} \end{cases} \tag{8}$$

where $P^l_{i,k}$ and $P^u_{i,k}$ are the lower and upper bounds of the *k*-th prohibited zone of unit *i*; *k* is the index of prohibited zones (zo_i).

3. C-GRASP

Optimization problems arise in many situations when dealing with science and engineering. In many cases, convexity of the search space cannot be verified, thus it is assumed that there are multiple local optimum. Global minimization, or optimization, which can be discrete or continuous, consists of seeking a solution that presents the lowest value for the objective function analyzed, within all possible search space solutions. Such a solution is called global minimum, whereas local minimum is defined similarly, but considering a bounded search space region, called neighborhood.

In this context, C-GRASP was proposed by Hirsch *et al.* (2006) considering a domain *S* in a *n*-dimensional search space, where an arbitrary solution is made of *n* variables $x_1,..., x_n$, with $l \leq x \leq u$, *l* and *u* being respectively the lower and upper bound vectors, and $l, x, u \in \Re^n$. The minimization problem is to find the global minimum x^* to the objective function $f(x)$, $f : \Re^n \rightarrow \Re$.

```
procedure C-GRASP(n, l, u, f(.), MaxIters, MaxNumIterNoImprov, NumTimesToRun, MaxDirToTry, α)
    f* ← ∞;
    for j = 1,..., NumTimesToRun do
        x ← UnifRand(l, u); h ← 1; NumIterNoImprov ← 0;
        for Iter = 1,..., MaxIters do
            x ← ConstructGreedyRandomized(x, f(.), n, h, l, u, α);
            x ← LocalImprovement(x, f(.), n, h, l, u, MaxDirToTry);
            if f(x) < f* then
                x* ← x; f* ← f(x); NumIterNoImprov ← 0;
            else
                NumIterNoImprov ← NumIterNoImprov + 1;
            end if
            if NumIterNoImprov ≥ MaxNumIterNoImprov then
                h ← h/2; NumIterNoImprov ← 0;      /* make the grid more dense */
            end if
        end for
    end for
    return(x*);
end C-GRASP;
```

Figure 1. Pseudo-code for C-GRASP.

As earlier mentioned, C-GRASP is a multi-start stochastic search meta-heuristic, and uses a greedy randomized procedure to generate input solutions for a local improvement method. At Fig. 1, it can be seen that one iteration of the algorithm consists of a series of construction and local improvement cycles, and at each of these cycles the discrete grid of the search space is made denser. At the C-GRASP pseudo-code, *MaxIters*, *MaxNumIterNoImprov*, *NumTimesToRun*, *MaxDirToTry* e α are input parameters and represent, respectively: the maximum number of construction and local improvement cycles per main iteration; maximum number of calls to the local improvement procedure when the solution is not improving; maximum number of multi-start iterations (main iterations); maximum number of directions to be analyzed in the construction phase; and requirement parameter to form the restricted candidate list in the construction phase. f^* represents $f(x^*)$, where x^* is the best solution found so far, *h* is the discretization value for the search space, *UnifRand*(*l*, *u*) is a procedure that defines a random spot in the problem domain, and *ConstructGreedyRandomized*(*x*, *f*(.), *n*, *h*, *l*, *u*, α) and *LocalImprovement*(*x*, *f*(.), *n*, *h*, *l*, *u*, *MaxDirToTry*) are the calls to the construction and local improvement phases, which have their respective pseudo-codes illustrated in Figs. 2 and 3.

The goal of the construction phase is to produce a good-quality solution from which to start a local search. In Fig. 2, *S* represents the set of unfixed coordinates of *x*, which initially contains all coordinates and at the end of the construction phase contains none. *LineSearch*(*x*, *h*, *i*, *n*, *f*(.), *l*, *u*) executes a linear discrete search at the *i*-th coordinate of *x*, seeking the value z_i that minimizes the objective function, with respect to the discretization parameter *h*. g_i is the value for the objective function for the solution with z_i. *min* and *max* keep the maximum and minimum values of g_i among all unfixed coordinates of *x*. Between the lines 12 and 17, a restricted candidate list *RCL* is formed, which contains the unfixed coordinates that satisfy the condition on line 14, where $\alpha \in [0,1]$. *RandomlySelectElement*(*RCL*) is a method that randomly selects an element of *RCL*, which will be the coordinate to be fixed, on line 19. Such a procedure ensures the randomness in the construction phase. As soon as all the coordinates are fixed, the solution *x* is then returned from this phase.

```
procedure ConstructGreedyRandomized(x, f(.), n, h, l, u, α)
    S ← {1, 2,..., n};
    while S ≠ 0 do
        min ← +∞; max ← –∞;
        for i = 1,..., n do
            if i ∈ S then
                z_i ← LineSearch(x, h, i, n, f(.), l, u);
                g_i ← f(z_i);
                if min > g_i then min ← g_i;
                if max < g_i then max ← g_i;
            end if
        end for
        RCL ← 0;
        for i = 1,..., n do
            if i ∈ S and g_i ≤ (1 – α).min + α.max then
                RCL ← RCL ∪ {i};
            end if
        end for
        j ← RandomlySelectElement(RCL);
        x_j ← z_j; S ← S \ { j};
    end while
    return(x);
end ConstructGreedyRandomized;
```

Figure 2. Pseudo-code for the C-GRASP construction phase.

```
procedure LocalImprovement(x, f(.), n, h, l, u, MaxDirToTry)
    Improved ← true; D ← 0;
    x* ← x; f* ← f(x);
    NumDirToTry ← min(3^n – 1, MaxDirToTry);
    while Improved do
        Improved ← false;
        while |D| ≤ NumDirToTry and not Improved do
            r ← ⌈UnifRand(1, 3^n – 1)⌉ ∉ D;
            D ← D ∪ {r};
            d ← Ternary'(r); x ← x* + h.d;
            if l ≤ x ≤ u then
                if f(x) < f* then
                    x* ← x; f* ← f(x);
                    D ← 0;
                    Improved ← true;
                end if
            end if
        end while
    end while
    return(x*);
end LocalImprovement;
```

Figure 3. Pseudo-code for the C-GRASP local improvement phase.

In the local improvement phase pseudo-code, the variables *Improved*, *D*, *r* and *d* represent, respectively: a flag to the occurrence of improvement on the evaluated direction; the set of directions already evaluated; a new random direction;

and the directional vector that corresponds to the new direction. There are $3^n - 1$ possible directions, and $min(3^n - 1, MaxDirToTry)$ defines the exact number of directions to be evaluated, that is the least value between the total possible directions and the parameter *MaxDirToTry*. $\lceil UnifRand(1, 3^n - 1) \rceil \notin D$ defines a random whole number r between 1 and $3^n - 1$, with uniform distribution and non-belonging to D. Ternary'(r) converts r from decimal base to ternary base, then exchanges each '2' digit for a '–1' digit, forming a n-dimensional vector of '1's, '0's and '–1's, which corresponds to the directional vector d.

The local improvement phase approximates the role of the objective function gradient. From a given initial solution, this phase generates a series of directions, and determines in which of the directions, if any, the objective function value improves. This procedure runs until a solution is found which is better evaluated then the other corresponding solutions on all analyzed directions.

For more details on C-GRASP the reader is referred to Hirsch *et al.* (2006).

4. SIMULATION RESULTS

The case study of 15 thermal units must satisfy a load demand of P_D = 2650 MW and a system spinning reserve requirement of 200 MW. The system data are presented in Tab. 1 (Lee and Breipohl, 1993; Papageorgiou and Fraga, 2007). The prohibited zones are given in Tab. 2. Among the thermal units, four of them (units 2, 5, 6 and 12) have prohibited operating zones. The remaining units have simple operational zone.

The optimization method was implemented in Matlab (MathWorks). All the programs were run on a 3.2 GHz Pentium IV processor with 2 GB of random access memory. In the case study, 50 independent runs were made for the optimization method involving 50 different initial trial solutions.

Table 1. Data for the benchmark of 15 thermal units.

Thermal unit	a_i($/h)	b_i($/MWh)	c_i($/MWh^2)	P_i^{min}(MW)	P_i^{max}(MW)	spinning reserve S_i^{max}(MW)
1	671.03	10.07	0.000299	150	455	50
2	574.54	10.22	0.000183	150	455	0
3	374.59	8.8	0.001126	20	130	30
4	374.59	8.8	0.001126	20	130	30
5	461.37	10.4	0.000205	150	470	0
6	630.14	10.1	0.000301	135	460	0
7	548.2	9.87	0.000364	135	465	50
8	227.09	11.5	0.000338	60	300	50
9	173.72	11.21	0.000807	25	162	30
10	175.95	10.72	0.001203	20	160	30
11	186.86	11.21	0.003586	20	80	20
12	230.27	9.9	0.005513	20	80	0
13	225.28	13.12	0.000371	25	85	20
14	309.03	12.12	0.001929	15	55	40
15	323.79	12.41	0.004447	15	55	40

Table 2. Prohibited zones for the benchmark of 15 thermal units.

Thermal unit	Zone 1 (MW)	Zone 2 (MW)	Zone 3 (MW)
2	[185–225]	[305–335]	[420–450]
5	[180–200]	[260–335]	[390–420]
6	[230–255]	[365–395]	[430–455]
12	[30–55]	[65–75]	–

Table 3. C-GRASP input parameters values used.

Parameter	*MaxIters*	*MaxNumIterNoImprov*	*NumTimesToRun*	*MaxDirToTry*	α
Value	200	20	20	30	0.4

The values for C-GRASP input parameters used in this work are given by Tab. 3. A key factor in the application of optimization methods is how the algorithm handles the constraints relating to the problem. In this work, a penalty-based method inspired in Noman and Iba (2008) was used. In this context, to avoid the violation of equality constraint given by Eq. (1) of the power balance criterion, a repair process is applied to each solution in order to guarantee that a generated solution by C-GRASP will be feasible.

Table 4. Convergence results (50 runs) of a case study of 15 thermal units

Optimization Method	Minimum Cost ($/h)	Maximum Cost ($/h)	Mean Cost ($/h)	Standard Deviation ($/h)
QEA (Neto *et al*., 2010)	32548.48	32806.89	32679.54	$6.4 \cdot 10^{-3}$
C-GRASP	32544.97	32699.56	32575.35	$5.4 \cdot 10^{-3}$

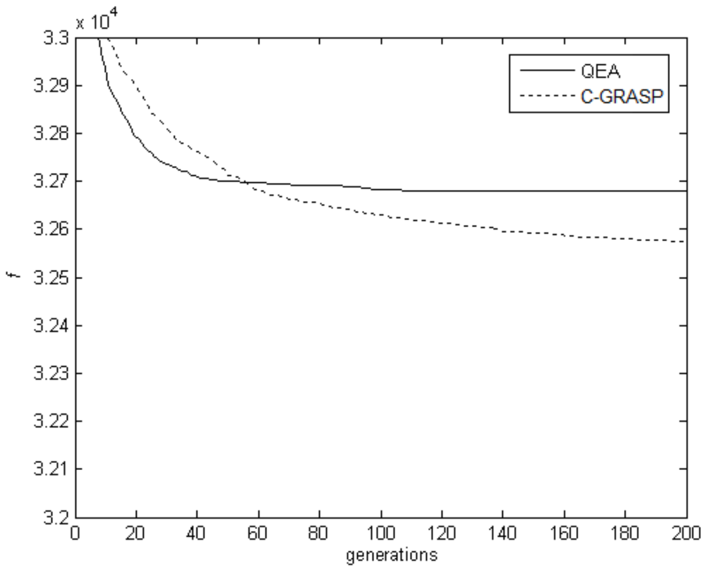

Figure 4. Convergence of mean of *f** value for C-GRASP and QEA approaches in 50 runs.

Table 5. Best result (50 runs) obtained for the case study proposed in Lee and Breipohl (1993) using C-GRASP.

Power	Generation (MW)	Power	Generation (MW)	Power	Generation (MW)	Power	Generation (MW)
P_1	450.0	P_5	335.0	P_9	25.0	P_{13}	25.0
P_2	450.0	P_6	455.0	P_{10}	20.0	P_{14}	15.0
P_3	130.0	P_7	465.0	P_{11}	20.0	P_{15}	15.0
P_4	130.0	P_8	60.0	P_{12}	55.0	$\sum_{i=1}^{15} P_i$	2650

Numerical results obtained for this case study are given in Tab. 4 and Fig. 4, which showed that the C-GRASP has both a better economic cost and lower mean cost than the classical quantum-inspired evolutionary algorithm (QEA) presented in Neto *et al*. (2010). The best result obtained for solution vector P_i, i = 1,...,15 by C-GRASP approach with minimum cost of 32544.97 $/h is given in Tab. 5. Table 6 compares the results obtained in this paper with those of other studies reported in the literature. Note that in the studied case, the best result reported here using C-GRASP is comparatively lower than results presented in Lee and Breipohl (1993). However, the C-GRASP presented the same best result of mixed integer quadratic programming proposed in Papageorgiou and Fraga (2007).

Table 6. Comparison of best results for the economic dispatch optimization problem with 15 thermal units as presented by Lee and Breipohl (1993).

Optimization Technique	Objective function value
Decision space decomposition method (Lee and Breipohl, 1993)	32549.80
QEA (Neto *et al*., 2010)	32548.4839
Mixed integer quadratic programming (Papageorgiou and Fraga, 2007)	32544.97
C-GRASP (this paper)	32544.9700

Orero and Irving (1996) presented a slightly modified version of the problem with 15 thermal units. The modified version of this problem is essentially the same as that presented in Lee and Breipohl (1993) except for changes to three parameters. Specifically, the changes are two of the cost coefficients, b_8 = 11.21 instead of 11.50 and b_{11} = 10.21 instead of 11.21, and one of the bounds on the power generated, the lower bound on the 5th generator being 105 MW instead of 150 MW (Papageorgiou and Fraga, 2007).

Table 7 presents best result of C-GRASP (in 50 runs) and results in the literature for the 15 thermal units problem as presented in Orero and Irving (1996). Results using C-GRASP found a solution better than the deterministic crowding genetic algorithm (Orero and Irving, 1996) and the particle swarm optimization (Jeyakumar *et al.*, 2006). The best solution obtained using C-GRASP in 50 runs is presented in Tab. 8.

Table 7. Comparison of best results for the economic dispatch problem with 15 thermal units as presented by Orero and Irving (1996).

Optimization Technique	Objective function value
Deterministic crowding genetic algorithm (Orero and Irving, 1996)	32514
QEA (Neto *et al*. 2010)	32507.4852
Particle swarm optimization (Jeyakumar *et al.*, 2006)	32506.3
Mixed integer quadratic programming (Papageorgiou and Fraga, 2007)	32506.14
C-GRASP (this paper)	32506.1394

Table 8. Best result (50 runs) obtained for the case study as presented by Orero and Irving (1996) using C-GRASP.

Power	Generation (MW)	Power	Generation (MW)	Power	Generation (MW)	Power	Generation (MW)
P_1	455.0	P_5	260.0	P_9	25.0	P_{13}	25.0
P_2	455.0	P_6	460.0	P_{10}	20.0	P_{14}	15.0
P_3	130.0	P_7	465.0	P_{11}	60.0	P_{15}	15.0
P_4	130.0	P_8	60.0	P_{12}	75.0	$\sum_{i=1}^{15} P_i$	2650

5. CONCLUSION

Recently, Hirsch *et al.* (2006) proposed C-GRASP, for minimization problems, which is a multi-start randomized search algorithm, where a greedy randomized procedure generates input solutions for a local improvement method. Each iteration of this algorithm consists of a series of construction and local improvement cycles, and the discrete grid of the search space is made more dense as C-GRASP evolves.

In this paper, the performance of C-GRASP was tested by solving a benchmark economic dispatch problem of 15 generating units, which takes into account spinning reserve and prohibited operating zones constrains. It was found that the C-GRASP approach handles well problems of this kind. Furthermore, C-GRASP outperformed other methods reported in literature in terms of best solution for the economic dispatch problem analyzed.

In general terms, simulation results reveal that the C-GRASP algorithm works satisfactorily. In the future studies, other issues can also be addressed in economic dispatch problems, including transmission losses, valve-point loading effect, and multiple fuels.

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