An Auction Based Dispatch Algorithm for Deregulated Power Systems using Differential Evolution Technique

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Abstract - In this paper, a new approach to auction based dispatch algorithm in a deregulated power system using differential evolution technique is presented. In a deregulated power system, the production cost is replaced by seller’s bidden cost function including not only the production cost, but also the market strategy, which may become concave, whereas the conventional economic dispatch (ED) algorithm relies on the convexity of the cost function. Evolutionary algorithms are heuristic methods that have yielded promising results for solving non-linear, nondifferentiable, and multimodal optimization problems in power system area. The differential evolution algorithm is an evolutionary algorithm that uses a rather greedy and less stochastic approach to problem solving than the classical evolutionary programming algorithms, such as genetic algorithm, evolutionary programming and evolution strategies. In this paper, an auction-based dispatch problem in a deregulated power system is formulated as the least bidden cost optimization problem, in which the seller’s total bidden cost is minimized while the balance of supply and demand constraint and the capacity limit constraints are satisfied. The proposed algorithm is validated for three test systems consisting of 3 and 8 seller’s system. The results obtained by the proposed method indicate that it outperforms the other algorithm reported in literature (GA) for obtaining the fair market competition in a deregulated power market.

Index Terms- Differential Evolution Technique, Auction-based Dispatch Algorithm, Deregulated Power System, Economic Dispatch, Seller’s Bidden Cost

I. INTRODUCTION

A need for optimality exists in the highly nonlinear and computationally difficult power system analysis environment. In the classical economic dispatch algorithm, the quadratic production cost function and incremental cost function are used to make the algorithm simple, accurate and efficient. However, the conventional ED algorithm relies heavily on the production cost function property: “the higher the output, the higher the incremental cost” [1]-[7]. In a deregulated power system, the production cost function is replaced by seller’s bidden cost function including not only the production cost, but also the market strategy. The property of the bidden cost function may become, “higher the output, lower the incremental cost” [8], [9] which makes the conventional ED algorithm inapplicable.

To solve this kind of problem, some optimization techniques such as genetic algorithm (GA), simulated annealing (SA), evolutionary programming (EP), particle swarm optimization (PSO) and differential evolution (DE) can be applied effectively. It is quite apparent from the literature survey that, not much of the works have been reported in the area of auction based dispatch problems in deregulated power markets. Hwang et al, [10] have proposed an auction-based dispatch algorithm for deregulated power system using genetic algorithm. In their work, an heuristic search algorithm has been proposed by them, which combines the powerful search mechanism of GA with mathematical foundation of global optimization. Unlike some existing GA algorithms [11], [12], their proposed algorithm searches for the global optimal solution in a space constructed by the vectors containing the discrete status of the seller’s contracted amount instead of seller’s contracted amount. So, the size of the search space is much simpler and the efficiency has been improved greatly. The results produced are acceptable, yet the computational time is relatively more in view of the real time operation particularly, when applied to large scale system. Further, the authors have applied their algorithm only to small systems like 3 seller’s and 8 seller’s systems. In another work, the same authors [13] have proposed an efficient market allocation method where, the deregulated power market allocation has been formulated as a multiobjective optimization. With the advent of stochastic search algorithms, the simulated annealing was also devoted to solving the highly nonlinear ED problems without restriction to the shape of fuel cost functions. Nevertheless, the SA based algorithm is difficult to tune the related control parameters of the annealing schedule and may be to slow when applied to practical sized power systems. An evolutionary programming (EP) algorithm has been proposed by many researchers to solve large-scale real valued combinational optimization. But, the weakness of the optimization is adjustment of scaling factor and offspring generation. A novel stochastic optimization method called differential evolution (DE) [14-16] is considered as a realistic and powerful solution scheme to obtain global or quasi-global optimums in deregulated power system within an acceptable computational time.

Differential evolution is a stochastic search algorithm that is originally motivated by mechanism of natural selection. The DE algorithm is an evolutionary algorithm that uses rather greedy and less stochastic approach to problem solving than
the classical evolutionary algorithms, such as genetic algorithm, evolutionary programming and evolution strategy. The DE algorithm was successfully applied in the optimization of some well known non-linear, non-differentiable and non-convex function. The fitness of an offspring is one to one competed with that of corresponding parent in DE. This one to one competition will have a faster convergence speed than other evolutionary algorithms. The potentialities DE are its simple structure, easy use, local searching property and speediness. Nevertheless, this faster convergence yields in a higher probability of searching towards a local optimum or getting premature convergence [17]-[18]. This drawback can be alleviated by employing a larger population. However, by doing so more time is required to estimate the fitness function. Recently, DE and its hybridization techniques with other optimization tools have been successfully applied to the power system optimization problems like economic dispatch [19-22] and optimal power flow with FACTs devices [23].

This paper suggests a methodology using differential evolution algorithm to obtain the optimal generation dispatch solutions for an auction based dispatch problem in deregulated power system. The proposed methodology has been applied to 3 and 8 seller’s test systems to show its effectiveness and applicability. The results obtained from the proposed methodology are compared with those obtained from GA method [10].

II FORMULATION OF AUCTION BASED DISPATCH PROBLEM FOR Deregulated POWER SYSTEMS

The sellers bidden cost function is assumed to be a quadric function, which is in the form of:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2$$

The incremental cost is defined of the bidden cost function.

$$IC_i(P_i) = b_i + 2c_i P_i$$

The auction-based dispatch problem is formulated as the least bidden cost optimization problem, in which the seller’s total bidden cost is minimized while the balance of the supply an demand constraint and the capacity limit constraints are satisfied.

$$Min: \sum_{i=1}^{Ng} F_i(P_i)$$

$$S.t: \sum_{i=1}^{Ng} P_i = P_d$$

$$P_{i_{min}} \leq P_i \leq P_{i_{max}}, i \in [1, Ng]$$

This is the formulation for classical economic dispatch problem, but the difference is that the objective function used here is the seller’s bidden cost. The necessary condition for optimal solution is

When $\sum_{i=1}^{Ng} P_{i_{min}} > P_d$ or $\sum_{i=1}^{Ng} P_{i_{max}} = P_d$, there is no feasible solution; when $\sum_{i=1}^{Ng} P_{i_{min}} = P_d$, each seller’s contracted amount is at its capacity lower limit; when $\sum_{i=1}^{Ng} P_{i_{max}} = P_d$, each seller’s contracted amount is at its capacity upper limit.

In the non-trivial case, when $\sum_{i=1}^{Ng} P_{i_{min}} < P_d$ and

$$\sum_{i=1}^{Ng} P_{i_{max}} > P_d$$

The following equations can be obtained from Kuhn-Tucker theorem.

$$\frac{\partial F_i}{\partial P_i} = \lambda - \mu_{i_{min}} + \mu_{i_{max}} = 0, i = 1, ..., Ng$$

$$\sum_{i=1}^{Ng} P_i = P_d$$

$$\mu_{i_{min}} * (P_{i_{min}} - P_i) = 0, i = 1, ..., Ng$$

$$\mu_{i_{max}} * (P_i - P_{i_{max}}) = 0, i = 1, ..., Ng$$

$$\mu_{i_{min}} \geq 0, i = 1, ..., Ng$$

$$\mu_{i_{max}} \geq 0, i = 1, ..., Ng$$

For the seller’s contracted amounts that do not hit the capacity limits, $P_{i_{min}} < P_i < P_{i_{max}}, i \in [1, Ng]$

$$\frac{\partial F_i}{\partial P_i} = \lambda$$

For the seller’s contracted amounts that hit the capacity upper limits, $P_i = P_{i_{max}}, i \in [1, Ng]$

$$\frac{\partial F_i}{\partial P_i} = \lambda - \mu_{i_{max}} \leq \lambda$$

For the seller’s contracted amounts that hit the capacity lower limits, $P_i = P_{i_{min}}, i \in [1, Ng]$

$$\frac{\partial F_i}{\partial P_i} = \lambda + \mu_{i_{min}} \geq \lambda$$

A Necessary Condition for Optimal Solution

Suppose $P^* = (P_{1}^*, ..., P_{Ng}^*)$ is an optimal solution of problem define

$$\lambda = IC_i(P_i^*)$$

for $P_{i_{min}} < P_i^* < P_{i_{max}}, i \in [1, Ng]$ then,
IC_i(P^*) \geq \lambda \text{ for } P^*_i = P_{i_{min}} \\
IC_i(P^*) \leq \lambda \text{ for } P^*_i = P_{i_{max}}

The following notations are used are used consistently in this paper:

\( N_g \) : the number of sellers;

\( a_i, b_i, c_i \) : The parameters in the i-th sellers bid cost function;

\( P_i \) : The contracted amount of i-th sellers;

\( P_{i_{max}}, P_{i_{min}} \) : The capacity upper and lower limit of i-th sellers bid amount;

\( P_d \) : The total market demand;

\( \lambda, \mu_{i_{max}}, \mu_{i_{min}} \) : Lagrange multipliers.

\( F_i(P) \) : i-th sellers bid cost function;

\( IC_i(P) \) : i-th sellers bid incremental cost;

III. DIFFERENTIAL EVOLUTION

In this section, the differential evolution (DE) algorithm has been reviewed that is used for searching the optimum solution of auction based dispatch problem. DE is a population based stochastic search technique that works in the general framework of EAs. It starts to explore the search space by randomly choosing the initial candidate solutions within the boundary. Then the algorithm tries to locate the global optimum solution for the problem by iterated refining of the generation process. This optimization process is repeated for several generations to reach an optimal solution. Each individual \( X_i \) is a vector that contains as many parameters as the problem decision variables D. The population size \( N_p \) is an algorithm control parameter selected by the user, which remains constant throughout the optimization process.

\[
P^{(G)} = [X_1^{(G)}, ..., X_{N_p}^{(G)}]
\]

\[
X_j^{(c)} = [X_{i,j}^{(G)}, ..., X_{D,i,j}^{(G)}], j = 1, ..., N_p
\]

The optimization process in differential evolution is carried out with three basic operations: mutation, crossover and selection. This algorithm starts by creating an initial population of \( N_p \) vectors. Random values are assigned to each decision parameter in every vector according to:

\[
X_{i,j}^{(0)} = X_{i_{min}} + \eta_i (X_{i_{max}} - X_{i_{min}})
\]

Where, \( i = 1, ..., D \) and \( j = 1, ..., N_p \). \( X_{i_{min}} \) and \( X_{i_{max}} \) are the lower and upper bounds of the \( i \)th decision parameter; and \( \eta_i \) is a uniformly distributed random number within \([0, 1]\). generated for each value of \( i \). \( X_{i,j}^{(0)} \) is the \( i \)th parameter of the \( j \)th individual of the initial population.

The mutation operator creates mutant vectors \( \left( X_j^{(c)} \right) \) by perturbing a randomly selected vector \( (X_a) \) with the difference of two other randomly selected vectors \( (X_b, X_c) \):

\[
X_j^{(G)} = X_a^{(G)} + M \left( X_b^{(G)} - X_c^{(G)} \right) \quad j = 1, ..., N_p
\]

Where \( X_a, X_b, X_c \) are randomly chosen vectors \( \in [1, N_p] \) and \( a \neq b \neq c \neq j \). \( X_a, X_b, \) and \( X_c \) are selected anew for each parent vector. The scaling constant \( M \) is an algorithm control parameter used to control the perturbation size in the mutation operator and improve algorithm convergence.

The crossover operation generates trial vector \( (X_j^{(t)}) \) by mixing the parameter of the mutant vector with the target vector \( (X_j) \), according to a selected probability distribution as given below:

\[
X_{i,j}^{(t)} = \begin{cases} 
X_{i,j}^{(G)}, & \text{if } \hat{\eta}_i \leq C_{ori} = q \\
X_{i,j}^{(G)}, & \text{otherwise}
\end{cases}
\]

Where \( i = 1, ..., D \) and \( j = 1, ..., N_p \), \( q \) is randomly chosen index \( \in [1, N_p] \) that guarantees that the trial vector gets at least one parameter from the mutant vector; \( \hat{\eta}_i \) is a uniformly distributed random number within \([0,1]\) generated anew for each value of \( i \). Crossover constant \( C_{ori} \) is an algorithm parameter that control the diversity of the population and aids the algorithm to escape from local optima. \( X_{i,j}^{(G)} \), \( X_{i,j}^{(c)} \) and \( X_{i,j}^{(t)} \) are the \( i \)th parameter of the \( j \)th target vector, mutant vector, and trial vector at generation \( G \), respectively.

Finally, the selection operator determines the population by choosing between the trial vectors and their predecessors (target vectors) those individuals that presents fitness or are more optimal according to:

\[
X_{j}^{(G+1)} = \begin{cases} 
X_{j}^{(t)}, & \text{if } f(X_{j}^{(t)}) \leq f(X_{j}^{(G)}) \\
X_{j}^{(G)}, & \text{otherwise}
\end{cases}
\]

This optimization process is repeated for several generations, allowing individuals to improve their fitness as they explore the solution space in the search for optimal values.

IV. DE APPLICATION FOR AUCTION BASED DISPATCH PROBLEM

Differential evolution can be applied to solve the deregulated power market problem. The proposed algorithm can be described in the following steps:

1) Initialization and structure of individuals
In the initialization process, a set of individuals is created at random. In this paper, the structure of an individual for auction problem is composed as a set of elements (i.e., generator outputs). Therefore, individual’s j’s position at iteration 0 can be represented as the vector of

\[ P_j^0 = [P_{j1}^0, P_{j2}^0, ..., P_{jN_g}^0] \]

where \( N_g \) is the number of generator. The summation of all element of individual \( j (i.e. \sum_{i=1}^{N_g} P_{i,j}^0 = P_j^0) \) should be equal to the total system demand \( P_d \) and the created element \( i \) of individual \( j \) at random that should be located within boundary. Although we can create element \( i \) of individual \( j \) at random satisfying the equality and inequality constraints by mapping \([0,1]\) into \([P_{i,\text{min}}, P_{i,\text{max}}]\). To do this, the following procedure is suggested for any individual in a group

Step 1) Set \( i = 1 \).

Step 2) Select an element (i.e., generator) of an individual at random.

Step 3) Create the value of element (i.e., generation output) at random satisfying its inequality constraint.

Step 4) if \( i = N_g-1 \) then go to step 5; otherwise \( i = i + 1 \) and go to step 2.

Step 5) The value of last element of an individual is determined by subtracting \( \sum_{i=1}^{N_g} P_{i,j}^0 \) from the total system demand \( P_d \). If the value is in the range of its operating region then go to step 6; otherwise go to step 1.

Step 6) Stop initialization process.

2) Evaluate the fitness value

The fitness value of each individual is calculated by using equation (3)

3) Mutation

The mutation operator creates mutant vectors \( \{P_j^\prime\} \) by perturbing a randomly selected vector \( P_j^\prime \) with the difference of two other randomly selected vectors \( P_a \) and \( P_c \).

\[ P_j^{\prime(G)} = P_a^{(G)} + F(P_b^{(G)} - P_c^{(G)}) \quad j = 1, ..., N_p \] (12)

where \( P_a, P_b \) and \( P_c \) are randomly chosen vectors \( \in \{1, ..., N_p\} \) and \( a \neq b \neq c \neq j \). \( P_a, P_b \) and \( P_c \) are selected a new for each parent vector. The scaling constant \( F \) is an algorithm control parameter used to control the perturbation size in the mutation operator and improve algorithm convergence.

4) Crossover

The crossover operation generates trial vector \( (P_j^\prime) \) by mixing the parameter of the mutant vector with the target vector \( P_j \), according to a selected probability distribution.

\[ P_{i,j}^{(G)} = \begin{cases} P_{i,j}^{(G)}, & \text{if} \eta_i' \leq C_s \text{ori} = q \\ P_{i,j}^{(G)}, & \text{otherwise} \end{cases} \] (13)

Where \( j = 1, ..., N_p \) and \( i = 1, ..., D \); \( q \) is randomly chosen index \( \in \{1, ..., N_p\} \) that guarantees that the trial vector gets at least one parameter from the mutant vector; \( \eta_i' \) is a uniformly distributed random number within \([0,1]\) generated a new for each values of \( j \). Crossover constant \( C_r \) is an algorithm parameter that control the diversity of the population and aids the algorithm to escape from local optima. \( P_{i,j}^{(G)}, P_{i,j}^{(G)} \) and \( P_{i,j}^{(G)} \) are the \( i^{th} \) parameter of the \( j^{th} \) target vector, mutant vector, and trial vector at generation \( G \), respectively.

5) Selection

Finally, the selection operator determines the population by choosing between the trial vectors and their predecessors (target vectors) those individuals that presents fitness or are more optimal according to

\[ P_{j}^{(G+1)} = \begin{cases} P_j^{(G)}, & \text{if} P_j^{(G)} \leq f(P_j^{(G)}) \\ P_j^{(G)}, & \text{otherwise} \end{cases} \] (14)

The objective of deregulated power market is to minimize the costs of power production for the system subject to power balance constraints, generation limits and market clearing price.

6) Stopping criteria

There are various criteria available to stop a stochastic optimization algorithm. Some examples are tolerance, number of function evaluations and number of iterations. In this paper, to compare with the previous results, maximum number of iterations is chosen as the stopping criterion. If the stopping criterion is not satisfied, the above procedure is repeated from step 2 with incremented \( G \) value. Otherwise, \( P_{j}^{(G+1)} \) is the optimum generation schedule and \( f(P_j^{(G+1)}) \) is the minimum generation cost of auction dispatch problem.

V. SIMULATION RESULT

This section presents the computation results on three test systems, which were performed to evaluate the performance of the proposed algorithm. An auction based dispatch problem in deregulated power market including 3 and 8 sellers from the
literature have investigated. In order to simulate the market-clearing price of various demands in both concave and convex cost functions considering deregulation. To verify the performance of the purposed algorithm, 3 and 8 sellers system are repeatedly tested 50 times by differential algorithm. The program was written in MATLAB 7.01 and executed on Pentium-IV, 1.5GHz with 512 RAM. The result of market clearing price of the purposed DE method with power balance constraints only for those obtained in recent studies present in the literature and with, as maintained above all constraints for that of GA, DE methods

Test Case I

This case study consist 3 sellers system, are shown in table I. The data shown in Table I also available in [10]. The final demand is 850MW. The population size, Np, is set 9. The maximum generation is 100. The crossover factor, CR, is set 1 and the scaling factor is 0.95. The obtained result for 3-sellers system using the predetermined parameters are given in Table II and the results are compared with those from GA[10]. It shows that the DE has succeeded in finding global solution achieved with a high probability (i.e. 90 times among 100 trials) always satisfying the equality and inequality constraints. The robustness of the DE regarding to the population size and initial group. In Table III, the effect parameters are illustrated, where 100 random trials are performed for each parameter set. Among 9 sets of parameter in Table III, Case 9 shows the best performance in terms of the number of hits to be global solution, which was performed 90 times among 100 trials. Table IV shows the convergence rate of 3 sellers system. The convergence characteristics of convex cost function are shown in figure 1.

<table>
<thead>
<tr>
<th>Case</th>
<th>Scaling Factor (F)</th>
<th>Crossover Constant (CR)</th>
<th>Minimum Cost</th>
<th>No. Of Hits to Global</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.5</td>
<td>0.2</td>
<td>8195.35</td>
<td>10</td>
</tr>
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<td>2</td>
<td>0.55</td>
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<td>8194.7</td>
<td>30</td>
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<tr>
<td>3</td>
<td>0.6</td>
<td>0.4</td>
<td>8194.5</td>
<td>28</td>
</tr>
<tr>
<td>4</td>
<td>0.65</td>
<td>0.5</td>
<td>8194.4</td>
<td>80</td>
</tr>
<tr>
<td>5</td>
<td>0.7</td>
<td>0.6</td>
<td>8194.4</td>
<td>75</td>
</tr>
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<td>6</td>
<td>0.75</td>
<td>0.7</td>
<td>8194.4</td>
<td>75</td>
</tr>
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<td>7</td>
<td>0.8</td>
<td>0.8</td>
<td>8194.4</td>
<td>75</td>
</tr>
<tr>
<td>8</td>
<td>0.85</td>
<td>0.9</td>
<td>8194.4</td>
<td>85</td>
</tr>
<tr>
<td>9</td>
<td>0.95</td>
<td>1</td>
<td>8194.35</td>
<td>90</td>
</tr>
</tbody>
</table>

Table III: Effects of Parameters in DE Performance

<table>
<thead>
<tr>
<th>Methods</th>
<th>Best Time (Secs)</th>
<th>Best Cost ($/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA[10]</td>
<td>1</td>
<td>8194.4</td>
</tr>
<tr>
<td>DE</td>
<td>0.28</td>
<td>8194.35</td>
</tr>
</tbody>
</table>

VI CONCLUSION

Differential evolutions have been applied to solve auction formulation in deregulated power system and their
performance is examined on three test cases of deregulated power system. Investigation reveals that DE performs much better than GA in terms of convergence rate, solution speed, and quality of solution and success rate in smaller as well as larger system. Investigation also reveals that the superiority of DE over its counterpart becomes more prominent in case of larger systems. The proposed algorithm combines the powerful searching mechanism of DE with the mathematical foundations for global optimization. The proposed algorithm can solve the problem efficiently and accurately.

TABLE V 8SELLERS TEST SYSTEM

<table>
<thead>
<tr>
<th>No. Of Units</th>
<th>Lower Limit (MW)</th>
<th>Upper Limit (MW)</th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>20</td>
<td>100</td>
<td>100</td>
<td>7.92</td>
<td>-0.001562</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>100</td>
<td>100</td>
<td>7.92</td>
<td>-0.001562</td>
</tr>
<tr>
<td>3</td>
<td>20</td>
<td>100</td>
<td>100</td>
<td>7.92</td>
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<tr>
<td>4</td>
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<td>100</td>
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<td>8</td>
<td>20</td>
<td>100</td>
<td>100</td>
<td>7.92</td>
<td>-0.001562</td>
</tr>
</tbody>
</table>

TABLE VI 8SELLERS CONTRACTED DEMANDS

<table>
<thead>
<tr>
<th>No. Of Units</th>
<th>GA Methods [10]</th>
<th>DE Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unit1 (MW)</td>
<td>20 20 20 100</td>
<td>70</td>
</tr>
<tr>
<td>Unit2 (MW)</td>
<td>100 100 100 100</td>
<td>20</td>
</tr>
<tr>
<td>Unit3 (MW)</td>
<td>100 20 20 100</td>
<td>100</td>
</tr>
<tr>
<td>Unit4 (MW)</td>
<td>20 20 100 20</td>
<td>20</td>
</tr>
<tr>
<td>Unit5 (MW)</td>
<td>20 20 100 100</td>
<td>20</td>
</tr>
<tr>
<td>Unit6 (MW)</td>
<td>100 20 100 100</td>
<td>100</td>
</tr>
<tr>
<td>Unit7 (MW)</td>
<td>70 20 20 70</td>
<td>20</td>
</tr>
<tr>
<td>Unit8 (MW)</td>
<td>20 70 20 70</td>
<td>100</td>
</tr>
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</table>

TABLE VII RESULTS OF TEST CASE II (8 SELLERS SYSTEMS)

<table>
<thead>
<tr>
<th>Methods</th>
<th>Best Time (Secs)</th>
<th>Best Cost ($/h)</th>
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</thead>
<tbody>
<tr>
<td>GA [10]</td>
<td>1.0</td>
<td>4307</td>
</tr>
<tr>
<td>DE</td>
<td>31.75</td>
<td>4306.98</td>
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</tbody>
</table>

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VII REFERENCES


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