Artificial Immune Systems and Differential Evolution Based Approaches Applied to Multi-Stage Transmission Expansion Planning

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Abstract— **Transmission expansion planning (TEP) is a complex optimization task to ensure that the power system will meet the demand in an adequate quality level to customers along the planning horizon, while minimizing investment, operational, and interruption costs. Optimization approaches based on metaheuristics have demonstrated a good potential to find high quality solutions. Their success is related to the ability to avoid local optima by exploring the basic structure of each problem. Numerous advantages can be linked to these tools: a simple software complexity, an ability to mix integer and non-integer variables, and a faster time-response. This paper presents a performance comparison between two optimization tools based on Artificial Immune Systems and Differential Evolution to solve the multi-stage TEP problem. The proposed methodology includes the search for the least cost solution, bearing in mind investments and operational costs related to ohmic transmission losses. The multi-stage nature of the TEP is also taken into consideration. Case studies on a small test system and on a real sub-transmission network are presented and discussed.**

Keywords - Multi-stage transmission expansion planning, artificial immune systems, differential evolution, metaheuristics.

I. INTRODUCTION

The main objective of the multi-stage transmission expansion planning (TEP) is to decide where, when and what transmission reinforcements should be placed in the power network to ensure an adequate level of energy supply to customers, taking into account the load growth and new generator capacities. In a competitive energy market, TEP is a complex optimization task to ensure that the power system will meet the forecasted demand along the planning horizon, while minimizing investment, operational and interruption costs. This practice is the only rational response to conflicting customer and regulatory demands [1, 2].

Owing to today's power network dimensions, random behavior of transmission and generation equipment, load growth uncertainties, new generator source types and locations, market aspects, etc., the TEP problem has become combinatorial, stochastic, and highly complex. Even considering only deterministic aspects, it is very difficult to find the optimal solution for TEP problems, since it requires the use of combinatorial algorithms. If uncertainties and chronological aspects are added to these problems, the optimal solution becomes almost inaccessible.

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The chronological aspect refers to the multi-stage nature of the TEP problem. It requires the consideration of multi-time periods, determining possible sequences (i.e. stage-by-stage) of transmission reinforcements. To circumvent the multi-stage nature, simplified studies (also known as static analyses) determine, for just one stage, where new transmission facilities should be installed. Even so, the search for the optimal solution is still combinatorial. Several works can be found in the literature to solve TEP problems [2-16]. However, only a few works have considered the multi-stage nature of the TEP problem [7, 9, 12, 15, 16].

Optimization approaches based on metaheuristics [5-17] have demonstrated an enormous potential of finding high quality solutions. Several tools have been proposed in the last decade to solve TEP problems, e.g.: Simulated Annealing (SA) [5]; Tabu Search (TS) [6, 7, 15]; Genetic Algorithms (GA) [8, 9]; Greedy Randomized Adaptive Search Procedure (GRASP) [10, 11]; Evolution Strategies (ES) [12, 15]; Differential Evolution (DE) [13]; Particle Swarm Optimization (PSO) [14]; Ant Colony Optimization (ACO) [15]; and Artificial Immune Systems [16].

This work presents a performance comparison between two optimization tools based on the AIS and DE metaheuristics to solve the multi-stage TEP problem. Other heuristics such as the one used in GRASP [10, 11], are also used to construct better quality initial populations. The TEP problem includes the search for the least cost solution, bearing in mind investments and operational costs related to ohmic transmission losses. Also, the multi-stage nature of the TEP will be considered. The paper is organized as follows: Section 2 shows the formulation of the multi-stage TEP problem; Section 3 presents the AIS and DE metaheuristics and how to adapt then to the problem; Section 4 shows the application and performance comparison of the optimization tools to solve case studies involving a 6-bus system and a real sub-transmission network; and, finally, Section 5 presents the final conclusions and future works.

II. TRANSMISSION EXPANSION PLANNING PROBLEM

Different from most of works that perform a static planning, the present paper solves the TEP problem considering the chronology of the reinforcements. The interest is not only to define what reinforcements should be placed in the electric power network and their corresponding locations, but also when they will be added along the planning horizon to ensure an adequate level of energy supply to customers. At the end, the best expansion plans must be selected in order to minimize the present value costs involved in the objective function.

A. TEP Problem Formulation

The first step, considering the mathematical formulation of the TEP problem, is to define the representation of the solution matrix S^k (also named sequence), which corresponds to the candidate plan k, as follows:

$$S^k = \begin{bmatrix} s_{11}^k & s_{12}^k & \cdots & s_{1l}^k & \cdots & s_{1n}^k \\ s_{21}^k & s_{22}^k & \cdots & s_{2l}^k & \cdots & s_{2n}^k \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ s_{t1}^k & s_{t2}^k & \cdots & s_{tl}^k & \cdots & s_{tn}^k \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ s_{y1}^k & s_{y2}^k & \cdots & s_{yl}^k & \cdots & s_{yn}^k \end{bmatrix} \tag{1}$$

where n indicates the number of possible network branches allowed to receive reinforcements, y corresponds to the number of stages along the planning horizon, and s_{tl}^k refers to the total number of reinforcements at stage t and branch l in relation to the base system network configuration. If only one stage is considered (static problem), one has the following solution vector:

$$S_t^k = \begin{bmatrix} s_{t1}^k & s_{t2}^k & \cdots & s_{tl}^k & \cdots & s_{tn}^k \end{bmatrix} \tag{2}$$

During the optimization process, the selection of the candidate plans is carried out taking into account the whole horizon, aiming at minimizing the present value of the objective function.

In order to build a sequence, the maximum number of reinforcements in each branch must be satisfied. In addition, it is important to ensure a coordination scheme of the added reinforcements. For example, reinforcements inserted in stage t must be mandatorily included in the following stages t+1, t+2,..., y. These constraints are defined as follows:

$$\begin{aligned} s_{tl}^k &\le N_{lmax} \quad \forall l \in \{1,...,n\}; \quad \forall t \in \{1,...,y\} \\ s_{tl}^k &\le s_{(t+1)l}^k \quad \forall l \in \{1,...,n\}; \quad \forall t \in \{1,...,y\text{-}1\} \end{aligned} \tag{3}$$

where N_{lmax} refers to the maximum number of reinforcements allowed in branch l.

Every time that a candidate plan k is obtained, an evaluation is performed through a linear programming (LP) based on a DC power flow model, as described next:

Minimize:

$$z = \alpha^T r \tag{4}$$

subject to:

$$g + r + B\theta = d \tag{4a}$$

$$0 \le g \le g_{max} \tag{4b}$$

$$0 \le r \le d \tag{4c}$$

$$|f| \le f_{max} \tag{4d}$$

where α refers to the load shedding penalty vector; r is the load not-supplied vector; g is the generation bus vector; B represents the susceptance matrix; θ is the voltage angle vector; d is the load vector; g_{max} refers to the generation limit bus vector; f is the power flow vector; and f_{max} represents the power flow limit vector.

This LP is applied to each stage t of the planning horizon and can be efficiently solved by the interior point method. The Lagrange multipliers associated with the constraint (4a) are of high interest, since they can assist in the construction process of better quality initial sequences in the metaheuristic tools, as it will be commented in the Section III.C. These multipliers measure the benefit in terms of load not-supplied index concerning changes on the branches by the addition of new reinforcements. Denoting π^d as this Lagrange multiplier vector, the benefits can be estimated by [10]:

$$\pi_{ij}^d = (\theta_i - \theta_j)(\pi_i^d - \pi_j^d) \tag{5}$$

where π_{ij}^d is the Lagrange multiplier associated with the branch susceptance connecting buses i and j.

The proposed heuristic function also considers the investment costs associated with the new reinforcements, and it will assist the metaheuristics in finding better quality sequences. It is defined as follows [15]:

$$\eta(i,j) = \frac{\pi_{ij}^d}{Cinv_l} \tag{6}$$

where $Cinv_l$ is the unit investment cost for the reinforcements added in branch l that connects buses i and j.

Once sequence k is found, for a specific planning horizon composed of y stages, the objective function of the multi-stage TEP problem can be described by:

$$Min\ f(S^k) = \sum_{t=1}^{y} \frac{(\sum_{l=1}^{n} Cinv_l m_{tl}^k + Closs_t^k + \alpha^T r_t)}{(1+e)^{h(t)}} \tag{7}$$

where $f(S^k)$ represents the total cost function in present value terms, associated with sequence k; e indicates the discount rate; $h(t)$ corresponds to a function that informs the numerical difference between the year of stage t and the base year; $Cinv_l$ was already defined in (6); $m_{t\,l}^k$ refers to the number of reinforcements located at stage t and branch l of sequence k, i.e. $m_{tl}^k = s_{tl}^k - s_{(t\text{-}1)\,l}^k$ (if t represents the initial stage, then $m_{tl}^k = s_{tl}^k$); α and r_t are the same as defined in (4); and $Closs_t^k$ represents the operational costs associated with ohmic losses at stage t of sequence k, which is described in the next section.

B. Ohmic Transmission Losses

In order to include the operational costs associated with the ohmic transmission losses in the optimization process, a special DC flow model is used. Basically, the losses are calculated using the voltage angle vector obtained by the LP solution of a given configuration. Afterwards, these losses are distributed as loads, where terminal buses i and j receive half of the ohmic losses found in the circuit that connects these buses. Again, a new LP is solved considering this new increased load and a new voltage angle vector is found. This corresponds to the solution for a given configuration.

The amount of losses associated with the circuit between buses i and j can be approximated as:

$$P_{ij} = (r_{ij} \times f_{ij}^2) \tag{8}$$

where r_{ij} is the resistance of the circuit and f_{ij} is the active power flow, and all quantities are in pu. The total operational ohmic losses cost (*Closs*) is given by [15]:

$$Closs = 8736 \times C_{kWh} \times LF \times \sum_{\forall_{ij}} P_{ij} \tag{9}$$

where C_{kWh} represents the loss unit cost in US$/kWh; LF is the loss factor, which modulates the load curve and the value 8736 aims at converting the incremental loss costs into annualized costs.

III. Optimization Approaches Based on Metaheuristics

A. Artificial Immune Systems – AIS

The AIS metaheuristic intends to capture some principles of the Natural Immune System (NIS). One of the main algorithms presented in the literature is the CLONALG [18], which is based on the following concepts: reproduction, hypermutation, selection and receptor editing. In the reference [16], an adapted CLONALG algorithm is presented to solve the TEP problem, where the sequence S^k, described by (1), corresponds to each antibody of the immune system. In addition, each element $s_{t\,l}^{k}$, which refers to the reinforcement options, corresponds to a position of this antibody.

The role of the reproduction operator is to clone antibodies, i.e. to perform identical copies. As discussed in [16], it is more interesting to select all antibodies of the parent population to generate clones if the optimization process aims at locating multiple optima; the objective of the TEP problem is to identify the set of best sequences and not only the best one. In addition, when the number of copies provided by each antibody is the same, a better exploration of the search space may be reached when the hypermutation operator is used [18].

Since n_{Ab} is the number of antibodies (sequences) and n_{clo} is the number of clones generated by each antibody S^k, after the application of this operator, there will be $G^{n_{Ab}}$ groups consisted of the original antibody S^k and its respective clones $Cl^{k,u}$:

$$\begin{aligned} & G^k = \{S^k, Cl^{k,u}\}, \text{ where } Cl^{k,u} = S^k \\ & \forall k \in \{1,2,...,n_{Ab}\}\ ;\ \forall u \in \{1,2,...,n_{clo}\} \end{aligned} \tag{10}$$

The hypermutation operator aims to achieve higher affinity antibodies in order to provide better quality antibodies. The hypermutation process consists of adding a perturbation Z_t^k to each clone $Cl_t^{k,u}$, at all stages t of the planning horizon, as shown as follows:

$$\widetilde{Cl}_t^{k,u} = Cl_t^{k,u} + Z_t^k \tag{11}$$

$$Z_t^k = \sigma \times \left[N_{t1}(0,1)\ \ N_{t2}(0,1)\ \ldots\ N_{tl}(0,1)\ \ldots\ N_{tn}(0,1) \right] \tag{12}$$

where $\widetilde{Cl}_t^{k,u}$ represents a new antibody, which is obtained through the mutation of clone $Cl_t^{k,u}$; σ is the mutation magnitude; and N_{tl} (0,1) corresponds to a Gaussian distribution with zero mean and unit variance. As it can be seen, the perturbation Z_t^k is continuous. Therefore, a rounding function must be applied to each position of the new antibodies, since the reinforcements are discrete variables.

After using the hypermutation operator, the strategy adopted by the selection process is to keep the n_b best antibodies, based on (7), from each group G^k (parent and its respective clones) to create a new group G^*. It is important to observe that if just the best clone is selected, all others will be disregarded and valuable information may be lost as mentioned in [18].

Avoiding a combinatorial explosion, all antibodies of the resulted group G^* are compared at each iteration. This step is represented by the receptor editing that selects the best antibodies of group G^* in order to minimize (7). In addition, it is not allowed the selection of identical antibodies. At the end, the best and distinct n_{ab} antibodies will evolve to the next generation, keeping the same size of the initial population. This process ensures a better quality and diversified population for the next generation, since there will not be identical antibodies.

In the original CLONALG [18], the receptor editing operator aims at substituting the lower affinity antibodies by new ones. The objective is to escape from local optima and provide a better exploration of the search space. The CLONALG proposed in this work achieves the same objective in assuring a selection of distinct antibodies for the next generation. In this case, it is unnecessary to substitute the lower affinity antibodies. Better performance is reached by this modified CLONALG algorithm when applied to TEP problems, as shown in [16].

B. Differential Evolution – DE

Contrary to GA, ES and AIS metaheuristics that follow a probability distribution function to perform a perturbation in the individuals, the DE is based on a weighted difference among individuals, i.e. arithmetical combinations. Basically, at each generation, the offspring population is obtained by application of mutation and recombination operators. Among a range of mutation rules [13] and considering the TEP problem, preliminary studies have pointed that best results can be achieved when the following mutation rule is applied to all t stages of the planning horizon:

$$X_t^k = Round[S_t^{r_1} + F(S_t^{r_2} - S_t^{r_3})] \tag{13}$$

where X_t^k corresponds to the mutated individual k; r_1, r_2, r_3 and k are indices randomly chosen, where $r_1 \neq r_2 \neq r_3 \neq k$; $S_t^{r_1}$, $S_t^{r_2}$, and $S_t^{r_3}$ are the respective selected individuals; F refers to the mutation factor; and *Round* is a function that returns a rounded integer number.

The recombination operator consists in exchanging information between the mutated and original individuals. The following equation shows how this operator works, considering all l branches and t stages of the planning horizon:

$$w_{t\,l}^{k} = \begin{cases} x_{t\,l}^{k} & \text{if } (rand_l \leq CR) \text{ or } (l = \gamma) \\ s_{t\,l}^{k} & \text{otherwise} \end{cases} \tag{14}$$

where $rand_l$ is a random variable that follows a uniform distribution (0,1); γ is randomly chosen among the eligible branches to receive reinforcements; CR refers to the recombination rate; and $w_{t\,l}^{k}$ corresponds to each position of the new individual after the application of the recombination operator.

Finally, the selection operator compares each new individual W^k obtained by the mutation and recombination operators with its respective original individual from the parent population S^k, as shown as follows:

$$S^{k\,(new)} = \begin{cases} W^{k} & \text{if } f(W^{k}) \leq f(S^{k}) \\ S^{k} & \text{otherwise} \end{cases} \tag{15}$$

where $S^{k\,(new)}$ refers to the individual k selected to the next generation; and f (.) corresponds to the evaluation of the objective function.

Therefore, this selection operator performs a pair comparison, which is different from the CLONALG selection operator, where the next generation is formed by the best individuals among the parent and offspring populations.

C. *Final Remarks*

Several works [6, 7, 9-12, 15, 16] discuss the importance of using a procedure to build initial good quality sequences, which contributes to a better performance of the metaheuristics. In these references, it is assured that there is a higher chance to find best plans when metaheuristics consider sequences of good quality as starting points for the search.

A strategy is to use the heuristic function given by (6) as the basic knowledge to build initial good quality sequences. Examples of procedures to build these initial sequences, bearing in mind the multi-stage TEP problem, are presented in [15, 16], which is named by *Intelligent Initialization*.

IV. Results

Case studies on a 6-bus system and on a real sub-transmission network are presented and discussed in the next sections. All CPU times refer to a *Pentium Core 2 Duo* processor (2.66 GHz). The programs were developed using the software MATLAB.

A. *6-bus System*

The 6-bus system has 3 generation and 3 load buses connected by 11 double transmission circuits. Figure 1 shows the unifilar diagram of this system. Considering the reference or starting year, the installed capacity is 260 MW and the load peak is 210 MW. All deterministic bus and circuit data can be found in [7, 12, 15].

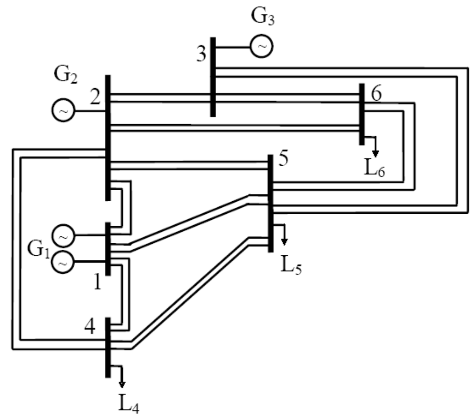

Figure 1. 6-bus System – Reference Year.

The system planning horizon consists of 8 years, where at each year the generating capacities and load are increased by 25%, in relation to the reference year. Therefore, installed capacity and the load will be 780 MW and 630 MW, respectively, at the end of the period of analysis (8th year). New transmission reinforcements can only be added to the existing branches and are limited to 3 reinforcements per branch. In order to calculate the present value of (7), it is used a discount rate (e) of 10%. In relation to the operational costs associated with the ohmic losses, the following parameters are used: C_{kWh} = 0.10 US$/kWh and LF = 0.6144.

Considering the proposed CLONALG algorithm, the following parameters are selected: number of clones generated by each antibody, n_{clo}=5; number of sequences selected from each group G^k, n_b=2; mutation magnitude applied to branches in the last stage of planning horizon, σ_1=0.3; mutation magnitude of the other stages, σ_2=0.6. The algorithm is interrupted after a maximum number of generations, n_{ger}^{max} =100. Regarding the DE metaheuristic, the following parameters are used: mutation factor, F=0.8; recombination rate, CR=0.9. The algorithm is interrupted after a maximum number of generations, n_{ger}^{max} =100 or if all individuals of the population become identical.

The final objective of the optimization approaches is to find the 25 best sequences that minimize the present value cost according to (7).

The performance of the metaheuristics is evaluated through the index that measures the quality of the best sequences found. The quality index, Iq (%), can be calculated as follows:

$$Iq(\%) = \frac{1}{n_{best}} \sum_{b=1}^{n_{best}} \frac{f(S^b) - f(S^{best})}{f(S^{best})} \times 100 \tag{16}$$

where n_{best} corresponds to the number of best sequences selected at the end of the optimization process; f *(.)* is the function that minimizes the costs in present value, given by (7); S^b indicates one of the best sequences stored after the end of the search; and S^{best} refers to the best sequence known for the problem, independently if it is not found in a given simulated case.

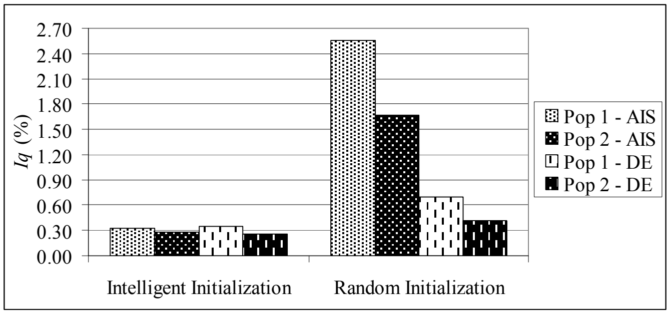

Figure 2. Initialization Process: Intelligent x Random.

TABLE I. POPULATION SIZE

	Intelligent Initialization		**Random Initialization**	
Metaheuristic	***Pop 1***	***Pop 2***	***Pop 1***	***Pop 2***
AIS	10	15	10	15
DE	100	200	50	100

Figure 2 shows the importance of considering an *Intelligent Initialization* process to provide good quality populations at the beginning of the search. The presented results correspond to a mean value after the simulation of 10 cases using different seeds randomly chosen. The tests considered different sizes for the population (Table I), which were selected in order to obtain a similar computational effort using both initialization process. In all situations, the *Intelligent Initialization* process contributed to better quality indices (i.e. smaller values) when compared with the results using a *Random Initialization*.

Considering the DE metaheuristic, a higher size population must be defined to avoid a premature convergence, since the selection operator allows that identical individuals evolve to the next generation. This problem is accentuated when the initial population is obtained by the *Intelligent Initialization* process, which generally consists of individuals with a lower number of reinforcements as compared with the initial population provided by a *Random Initialization*.

A performance comparison between the AIS and DE metaheuristics using the *Intelligent Initialization* process is shown in Fig. 3. The simulation results refer to the following population sizes: AIS {5; 10; 15; 20; 25} and DE {50; 100; 150; 200}. The points represent the mean values for the quality index and CPU time, after the simulation of 10 cases. A linear approximation is used to estimate the quality index along the time scale for both metaheuristics. From this linear approximation, it is possible to estimate the population size needed to reach a specific quality index and its respective CPU time. From Fig. 3, one can observe that there is an improvement in the quality index as the population size and, consequently, the CPU time are increased. Comparing the performance of the metaheuristics, one can conclude that the AIS is better than the DE along almost all time period. For example, considering the AIS, it is needed only 33 min. to reach an index of 0.326%, which represents a population size of 10. To achieve the same quality index, the DE would need about 70 min., which represents a population size of 115.

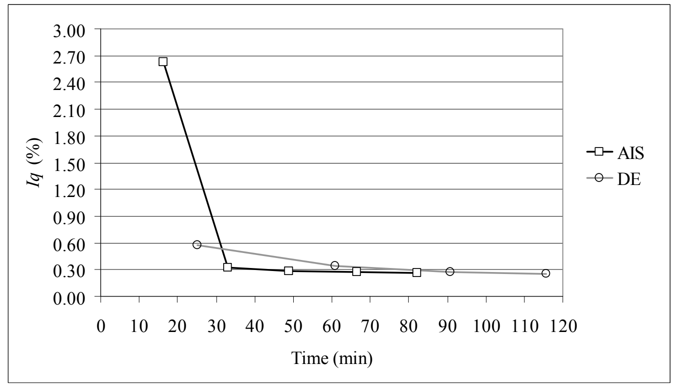

Figure 3. 6-bus System Performance Comparison.

TABLE II. BEST SEQUENCE FOR THE 6-BUS SYSTEM

Year	**Reinforcements Added**							**Annual Costs (10^6 US$)**		
	1-4	***1-5***	***2-4***	***2-5***	***2-6***	***3-5***	***3-6***	***Inv.***	***Ohmic Losses***	***Total***
8	0	0	1	0	0	0	1	80.00	7.50	87.50
7	1	0	0	1	0	0	0	45.00	7.29	52.29
6	0	1	0	0	1	1	0	65.00	6.41	71.41
5	1	0	0	0	0	0	0	25.00	5.80	30.80
4	0	1	0	0	0	0	1	60.00	4.99	64.99
3	1	0	0	0	0	0	0	25.00	4.36	29.36
2	0	1	0	0	0	0	0	20.00	3.49	23.49
1	0	0	0	0	0	0	0	0.00	2.79	2.79
0	0	0	0	0	0	0	0	0.00	2.34	2.34
Total Present Value (10^6 US$)								188.92	28.90	217.82

Table II presents the best sequence found for the 6-bus system, which has a total present value cost of US$ 217.82 millions. The annual costs related to the investments and ohmic losses, as the reinforcements added along the planning horizon, are also shown.

B. *Real Sub-transmission Network*

A real sub-transmission network, which belongs to CEMIG (State Energy Company of Minas Gerais), located in the North Region of Minas Gerais, Brazil, was used as the second case study. This sub-transmission system is composed by 12 buses, including 6 loads, 1 interconnection and 1 generation bus. The peak load of this subsystem is 780.05 MW and the maximum local generating capacity 226.76 MW. The remaining power is supplied by the interconnection bus. There are 20 transmission circuits operating with two voltage levels: 138 kV and 345 kV.

An expansion horizon of 10 years is considered, and the loads in this area will be assumed to grow with an average rate of 5% per year. For sub-transmission reinforcing purposes, all possible interconnections among the 138 kV buses are considered. A maximum of three transmission lines per branch is accepted. Even for this small sub-transmission network, a total of 3.29×10^{38} reinforcement sequences are, in principle, eligible for this TEP problem. The same parameters presented in the previous section are used to solve the multi-stage TEP problem for the real sub-transmission network.

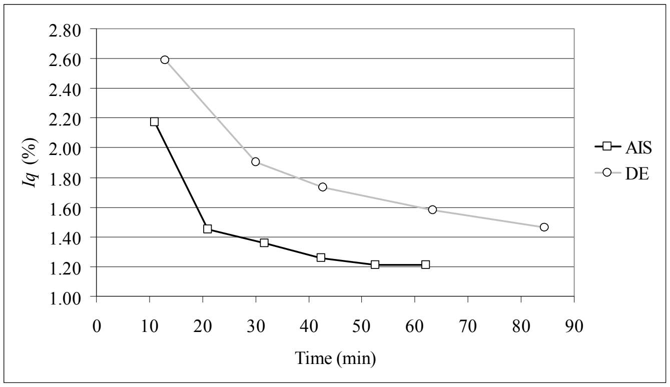

Figure 4. Real Sub-transmission Network Performance Comparison.

Figure 4 shows the performance comparison between the metaheuristics using the *Intelligent Initialization* process to build a good quality initial population. The simulation results refer to the following population sizes: AIS {5; 10; 15; 20; 25; 30} and DE {100; 200; 300; 400; 500}. The points represent the mean values for the quality index and CPU time, after the simulation of 10 cases.

From the Fig. 4, one can observe that the AIS achieved far better performance than the DE along all the time period. While the DE metaheuristic need 30 min. to reach a quality index of 1.90%, which represents a population size of 200, the AIS would need at about only 15 min. to achieve the same quality index, which would correspond to a population size of 8.

V. Conclusion

This work presented a performance comparison between two optimization approaches based on the metaheuristics Artificial Immune Systems (AIS) and Differential Evolution (DE), to solve the multi-stage transmission expansion planning (TEP) problem. The final objective was to find the best sequences that minimize the present value cost of investments and ohmic transmission losses.

The performance of the metaheuristics was evaluated through the index *Iq* (%), which measures the quality of the best sequences found. From the case studies involving a small test system and a real sub-transmission network one could conclude that the AIS reached smaller indices, i.e. found better sequences, than the DE. In addition, better results were achieved when an initial good quality population was defined through a process named by *Intelligent Initialization*.

A more comprehensive study comparing also the Tabu Search, Evolution Strategies, Particle Swarm Optimization and Ant Colony Optimization metaheuristics to solve large network configurations are among the future researches to be carried out.

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