PAR/PST location and sizing in power grids with wind power uncertainty

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Abstract — **This paper presents a new stochastic programming model for PAR/PST definition and location in a network with a high penetration of wind power, with probabilistic representation, to maximize wind power penetration. It also presents a new optimization meta-heuristic, denoted DEEPSO, which is a variant of EPSO, the Evolutionary Particle Swarm Optimization method, borrowing the concept of rough gradient from Differential Evolution algorithms. A test case is solved in an IEEE test system. The performance of DEEPSO is shown to be superior to EPSO in this complex problem.**

Keywords – Wind power integration, Differential Evolution, Evolutionary Particle Swarm Optimization, PAR location

I. Introduction

This paper presents a model and a new solving strategy for the problem of locating and sizing PAR/PST FACTS devices in a transmission network, given a power system with high penetration of wind power.

PAR stands for Phase Angle Regulator and PST for Phase Shifting Transformer. In practice, both are devices used to control the flow of active power in meshed three phase transmission grids. Because the power through a line is roughly proportional to the sine of the angle between voltages at the sending and receiving ends of a line, its control may re-route power through alternative paths, preventing overloads and giving better use to the transmission capacity available. This comes at a high capital cost per device but it may be compensated by avoiding costly line reinforcements or allowing a more flexible operation with higher security and reduced operation costs.

The need for PARs may be especially felt in systems with distributed wind power generation. Wind is a source of uncertainty, temporal but geographical. Its variation at different locations may cause important changes in the network line flows - and line reinforcements become required. However, it is possible that a careful investment in PARs may avoid such expense because of the added flexibility in managing the grid flows.

Given a set of load as well as wind power scenarios, a system operator may need to curtail wind generation (at a cost) and replace it by conventional generation (at a cost) or, in more severe cases, to curtail load (at the highest cost of power not supplied). The suitable location of PAR devices and their optimal dimensioning (in terms of the maximum angle they may inject in a line) may serve to reduce or eliminate such curtailment.

The location of PAR devices in a network is a complex mixed-integer programming problem in a fixed scenario of load and generation. Optimizing the dimension of each PAR (in terms of the maximum admissible angle) leads to a non-linear objective function. The variation in load and the uncertainty in wind power, under the form of scenarios, leads to a stochastic non-linear mixed-integer programming problem. One approach to solving such type of problems is using a meta-heuristic.

This paper presents a new meta-heuristic formulation denoted DEEPSO, built as an Evolutionary Particle Swarm Optimization (EPSO) borrowing concepts from Differential Evolution. EPSO itself is already a hybrid between Particle Swarm Optimization and Evolutionary Programming. The advantage of hybrid algorithms is that each "pure" method exhibits some characteristics that push the search for the optimum in a globally right direction. By suitably blending methods, a more robust and general method may be derived.

The paper reports the modeling of the PAR/PST sizing and their location optimization for systems with high wind power penetration, together with a comparison in performance of the new DEEPSO algorithm with the benchmarked EPSO tool. The novelties of the model are its stochastic formulation, the representation of wind power, the balancing of trade-offs between PAR/PST angle capacity and the operation costs and the efficient solution by the new DEEPSO algorithm - providing much more robust results than the classical EPSO.

II. PAR Location and Sizing in Power Grids

A. *Modeling a PAR*

The objective function of the optimal sizing and location of PARs in a transmission system is related to the costs of installing the devices. The capital cost of each PAR may be modeled as being composed of a fixed cost plus a non-linear variable cost which is a function of the maximum angle that the PAR may inject. Some candidate locations in the power network must be specified and, in each location, a tentative device allocation may be defined. This forms a possible solution to the problem, which must be evaluated by solving the power flow equations in all scenarios considered and deciding if and how much power must be curtailed and of what nature: wind generation or load.

Furthermore, each scenario may have a probability of occurrence associated. The problem becomes of the type of stochastic optimization..

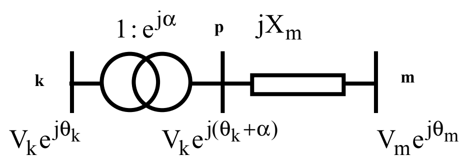

Fig. 1. Equivalent circuit for a PAR

The equivalent circuit for a PAR is in Fig. 1. Its effect is to force to a power flow from node k to node m:

$$P_{pm} = \frac{\theta_p - \theta_m}{X_{km}} = \frac{(\theta_k - \alpha) - \theta_m}{X_{km}} = \frac{\theta_k - \theta_m}{X_{km}} - \frac{\alpha}{X_{km}} \qquad (1)$$

This is equivalent to having a series reactance X_{km} plus a power injection, which will be a load in node k and a generation in node m. This allows a network power flow model to be written, as a function of α.

Given a specific set of N candidate locations to install a PAR and considering a generation system composed only of conventional units, the allocation and sizing of PAR is defined by the following

$$\min J_k = \sum_{i=1}^{N} u_i (A + B(\alpha_i^{Max})^2) + \text{Penalties} \qquad (2)$$

where u_i is a binary variable representing the installation of a PAR on location i, A and B are cost constants and α_i^{Max} is the maximum angle introduced by the device at location i. The constraints are the usual power flow equations of the DC model, incorporating eq. (1), plus limits on generation and on line flows and limits on the PAR angles:

$$\alpha_i^{min} \le \alpha_i \le \alpha_i^{max} \qquad (3)$$

These constraints may be transformed into penalties, in eq. (2), when adopting a meta-heuristic as the solver. Finally, the penalty term will include if necessary the cost for load curtailment, which is usually modeled as fictitious generators by the loads with generation cost equal to the usually high cost of power not supplied.

The objective function is further modified when in the presence of wind power, because there is also the possibility to spill wind (disconnect wind generation) if necessary, to assure the network security described by the constraints. This may be represented as a negative load which is supplied at the cost associated with wind curtailment (compensation to wind power producers).

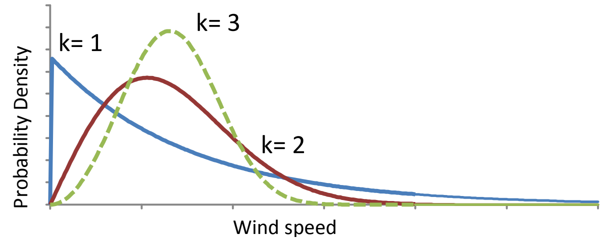

Fig. 2. Illustration of the Weibull p.d.f. for three values of the parameter k. Wind speed uncertainty is usually represented by a function with parameter k close to 2.

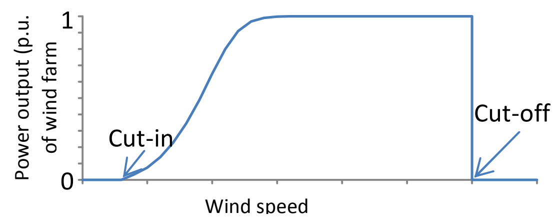

Fig. 3. Illustration of a wind-to-power curve from a wind power turbine

B. *Modeling wind power*

For the purpose of planning PAR location, one will take in account the wind availability in yearly terms, with a wind speed distribution given by a Weibull function (see Fig. 2). A curve fit to historical wind speed data may be composed with a function representing the wind-to-power model of a wind farm, extrapolated from the characteristics of wind power turbines - Fig. 3.

The probabilistic output power model for a wind farm is built by replacing the Weibull distribution with an approximation in discrete steps. This allows one to associate a step k in power output with a probability of occurrence p_k. A stochastic optimization model may be built where a solution is evaluated in all S scenarios:

$$\min J = \sum_{k=1}^{S} p_k J_k \qquad (4)$$

The value J_k represents a cost in each scenario k as given by expression (2). The constraints, in each scenario, are the usual constraints referred to in Section II.A.

III. THE DEEPSO OPTION – A NEW ALGORITHM

A. *Towards a successful hybrid*

The optimization solver used is denoted DEEPSO. It is an improvement of proven successful EPSO. The basic version of this algorithm was presented in 2002 [1][2]. The EPSO algorithm then received further improvement [3] and the latest version is available from [4], where examples and a source code are made public. Independent benchmarking experiments have demonstrated a net advantage of EPSO over other meta-heuristics, such as PSO (Particle Swarm Optimization) or Genetic Algorithms (e.g. see [5][6]).

The Differential Evolution approach was proposed in [7][8] and has been gaining the favor of an interested community. It presents nowadays a number of variants; a comprehensive survey may be found in [9].

The idea behind the new DEEPSO is that some noise could be added to the EPSO search by embedding a DE operator in the global mechanism particle movement. This noise, in the DE sense, is influenced by local macro-gradients so there should be a push of the search in a generally right direction.

DEEPSO is, therefore, a new meta-heuristic variant being born as a hybrid of DE-EA-PSO. There is no deductive demonstration of its superiority over other options but illustration and convincing by example. In this paper, devoted to the optimization of the location and sizing of PAR/PST FACTS devices in transmission systems, it will be shown that DEEPSO outperforms the best EPSO version.

B. The EPSO basics

The PSO [10] depends on a *movement rule* that generates new individuals or particles, in the search space, from a set of known alternatives, called a swarm (the same as population). The basic movement rule, producing a new particle **X** for iteration (k+1) is based on

$$\mathbf{X}^{(k+1)} = \mathbf{X}^{(k)} + \mathbf{V}^{(k)} \tag{5}$$

where **V** is called the particle velocity and is defined by

$$\mathbf{V}^{(k+1)} = \mathbf{A}\mathbf{V}^{(k)} + \mathbf{B}(\mathbf{b}_i - \mathbf{X}^{(k)}) + \mathbf{C}(\mathbf{b}_G - \mathbf{X}^{(k)}) \tag{6}$$

where $\mathbf{b}_G$ is best point so far found by the swarm and $\mathbf{b}_i$ is the best past ancestor in the direct life line of the particle, with $\{\mathbf{b}_i, i = 1,..., \text{no. particles}\} = \mathbf{P}_b$ forming the set of the historical past best ancestors of each particle. Of course, $\mathbf{b}_G \in \mathbf{P}_b$.

A, B, C are diagonal matrices of parameters or weights whose values are defined in the beginning of the process. In a classical formulation, the parameter **A** is affected by a decreasing value with time (iterations), while the initial parameters **B** and **C** are successfully multiplied by random numbers sampled from a uniform distribution in [0,1].

From eq. (5) and (6) we conclude that a new particle $\mathbf{X}^{(k+1)}$ is formed as a combination of four other points:

- Its direct ancestor $\mathbf{X}^{(k)}$
- The ancestor $\mathbf{X}^{(k-1)}$ of its ancestor $\mathbf{X}^{(k)}$
- A (possibly) distant past best ancestor $\mathbf{b}_i$
- The current global best of the swarm $\mathbf{b}_G$.

We can give a different aspect to the rule in (6):

$$\mathbf{X}^{(k+1)} = (1 + \mathbf{A} - \mathbf{B} - \mathbf{C})\mathbf{X}^{(k)} - \mathbf{A}\mathbf{X}^{(k-1)} + \mathbf{B}\mathbf{b}_i + \mathbf{C}\mathbf{b}_G \tag{7}$$

In this expression, the sum of the parameters multiplying the four contributors to generate the offspring is equal to 1. This allowed one to identify this expression with an intermediary recombination in EA with 4 parents and a special rule to determine who the parents are (they are not randomly selected).

This interpretation is meaningful for the hybridization with DE. It means that an *enlarged population* is being considered, including not only the active particles but also the immediate ancestors and the set of the past best ancestors. The process keeps a memory of the space visited.

In the EPSO algorithm, the parameters in (6) are subject to mutation and selection in an attempt to discover the best suited weights that may drive the search with a higher progress rate.

The mutation of any parameter A,B,C (represented by w in the following) is ruled by multiplicative Lognormal random numbers such as in $w_i^* = w_i\,[\log N(0,1)]^\tau$ or by additive Gaussian distributed random numbers such as in $w_i^* = w_i + \sigma N(0,1)$. The learning parameter (τ or σ) must be fixed externally. The recombination operator is defined by the set (A,B,C). The scheme results in an adaptive recombination operator.

The complete EPSO algorithm includes also the addition of adaptive noise to the location of $\mathbf{b}_G$. This is achieved by a forth parameter or weight in the form of a diagonal matrix $\mathbf{w}_G$ was introduced, such that

$$\mathbf{b}_G^* = \mathbf{b}_G\,(1 + \mathbf{w}_G\,N(0,1)) \tag{8}$$

This weight $\mathbf{w}_G$ is also subject to adaptive mutations of the kind referred to above. Finally, in the most recent and efficient version, the Communication Factor **P** was introduced, creating a Stochastic Star communication topology among the swarm. The recombination (or movement) rule for EPSO becomes

$$\mathbf{X}^{(k+1)} = \mathbf{X}^{(k)} + \mathbf{V}^{(k)} \tag{9}$$

$$\mathbf{V}^{(k+1)} = \mathbf{A}\mathbf{V}^{(k)} + \mathbf{B}(\mathbf{b}_i - \mathbf{X}^{(k)}) + \mathbf{P}[\mathbf{C}(\mathbf{b}_G^* - \mathbf{X}^{(k)})] \tag{10}$$

where **P** is a diagonal matrix affecting all dimensions of an individual, containing binary variables of value 1 with probability p and value 0 with probability (1-p); the p value (communication probability) controls the passage of information within the swarm and is 1 in classical formulations (the *star*). The value of p must be tuned for each problem[13] but either values around 0,75 or around 0,2 are good options, depending on the case.

Given a population with a set of particles, the general scheme of EPSO became:

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REPLICATION - each particle is replicated (cloned) r
  times [usually r = 1]
MUTATION - all r particles have their A,B,C and wG
  parameters mutated
REPRODUCTION - each of the r+1 particles (original and
  clones) generate an offspring through recombination,
  according to the particle movement rule (9) and (10)
EVALUATION - the offspring have their fitness
  evaluated
SELECTION - by stochastic tournament or other
  selection procedure, the best child from each
  ancestor survives to form a new generation.
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C. Differential Evolution

DE is an evolutionary algorithm where the process works by producing a competing population, built from the current one by adding to it some fraction of the difference between two randomly sampled points $\mathbf{X}_{r1}$ and $\mathbf{X}_{r2}$. Then, having a second population generated, a recombination process with the original population produces descendants upon which a selection procedure acts to produce a new generation. This selection is elitist and one-on-one based, meaning that each parent competes for survival directly with its single offspring and the best is retained.

There are many variations to this scheme. This paper refers especially to the one that was denoted DE2 in [7], DE/rand-to-best/1 in [8] and DE/target-to-best/1 in [9], where the generation of a new individual may be written as

$$\mathbf{X}^{(\mathbf{k+1})} = \text{Recombination} < \mathbf{X}^{(\mathbf{k})}, \mathbf{V}^{(\mathbf{k+1})} > \qquad (11)$$

$$\mathbf{V}^{(k+1)} = \mathbf{B}(\mathbf{X}_{r1}^{(k)} - \mathbf{X}_{r2}^{(k)}) + \mathbf{C}(\mathbf{b}_G^* - \mathbf{X}^{(k)}) \qquad (12)$$

A notation slightly distinct from the usually seen in the DE literature is adopted here to enhance the similarities of (11) and (12) with (9) and (10). The canonic version of DE makes $\mathbf{C} = \mathbf{0}$; the canonic DE/target-to-best/1 version makes $\mathbf{B} = \mathbf{C}$. The DE formulations include particular recombination processes that are not discussed here. In the selection operator, each parent competes only with its offspring – another point of similarity with EPSO.

D. The DEEPSO enhancement

The EPSO scheme is a truly self-adaptive process acting on the recombination operator. The DE scheme cannot be classified as self-adaptive and the claims such as in [12] that an adaptive mechanism could be added refer to processes of a non-evolutionary nature. The success of the DE scheme seems to be related to the advantages of sampling the local macro-gradient of the objective function by picking up two random individuals from the population and using their difference. The same may be said of the PSO movement equation, which picks up the current position and the particle past best to take their difference. The insertion of the DE scheme into the EPSO movement equation is thus a natural variant to be experimented. As such, this paper presents a new hybrid (DEEPSO), which takes advantage of the positive characteristics of the original algorithms.

The DEEPSO algorithm is equal to EPSO in its development sequence; however, the movement rule should now be expressed by:

$$\mathbf{V}^{(k+1)} = \mathbf{A}\mathbf{V}^{(k)} + \mathbf{B}(\mathbf{X}_{r1}^{(k)} - \mathbf{X}_{r2}^{(k)}) + \mathbf{P}[\mathbf{C}(\mathbf{b}_G^* - \mathbf{X}^{(k)})] \qquad (13)$$

where $\mathbf{b}_G^*$ is given by (8). $\mathbf{X}_{r1}^{(k)}$ and $\mathbf{X}_{r2}^{(k)}$ should be any pair of distinct particles already visited. These particles should be ordered such that, for minimization,

$$f(\mathbf{X}_{r1}^{(k)}) < f(\mathbf{X}_{r2}^{(k)}) \qquad (14)$$

These particles may be sampled in different ways, which define distinct variants for DEEPSO: they may be extracted from the set $\mathbf{P}_C$ of particles in the current generation or the set $\mathbf{P}_b$ of historical past best particles. The DEEPSO model defines that $\mathbf{X}_{r2}^{(k)}$ equal to $\mathbf{X}^{(k)}$ so only $\mathbf{X}_{r1}^{(k)}$ is sampled.

To complete the model, the sampling of $\mathbf{X}_{r1}^{(k)}$ $(= \mathbf{b}_{r1}^{(k)})$ among $\mathbf{P_b}$ may repeated for each component of $\mathbf{V}$ to be calculated, instead of sampling a single particle with all its components. This means that one is, in fact, calculating $\mathbf{X}_{r1}^{(k)}$ from a uniform recombination of all the particles in $\mathbf{P}_b$. The equations regulating DEEPSO are, therefore,

$$\mathbf{X}^{(k+1)} = \mathbf{X}^{(k)} + \mathbf{V}^{(k)} \qquad (15)$$

with $\mathbf{V}^{(k)}$ calculated in four DEEPSO versions:

1. **<u>DEEPSO Sg</u>** (sampling in the same generation):

$$\mathbf{V}^{(k+1)} = \mathbf{A}\mathbf{V}^{(k)} + \mathbf{B}(\mathbf{X}_{r1}^{(k)} - \mathbf{X}^{(k)}) + \mathbf{P}[\mathbf{C}(\mathbf{b}_G^* - \mathbf{X}^{(k)})] \qquad (16)$$

with $\{\mathbf{X}_{r1}^{(k)}, \mathbf{X}^{(k)}\}$ ordered according to (10) and $\mathbf{X}_{r1}^{(k)}$ sampled once from the current generation.

2. **<u>DEEPSO Sg-rnd</u>**: the same but with $\mathbf{X}_{r1}^{(k)}$ re-sampled in the current generation for each component of $\mathbf{V}$.
3. **<u>DEEPSO Pb</u>** (sampling from the past bests):

$$\mathbf{V}^{(k+1)} = \mathbf{A}\mathbf{V}^{(k)} + \mathbf{B}(\mathbf{b}_{r1}^{(k)} - \mathbf{X}^{(k)}) + \mathbf{P}[\mathbf{C}(\mathbf{b}_G^* - \mathbf{X}^{(k)})] \qquad (17)$$

with $\{\mathbf{b}_{r1}^{(k)}, \mathbf{X}^{(k)}\}$ ordered according to (10) and $\mathbf{b}_{r1}^{(k)}$ sampled once from $\mathbf{P}_b$.

4. **<u>DEEPSO Pb-rnd</u>**: the same but with $\mathbf{b}_{r1}^{(k)}$ re-sampled among $\mathbf{P}_b$ for each component of $\mathbf{V}$.

This last version proved to be the best performing in many case studies, including in clustering with the fuzzy c-means algorithm and in power system unit commitment (a mixed-integer problem with combinatorial nature).

IV. PAR/PST LOCATION AND SIZING – CASE STUDIES WITH DEEPSO

The optimal location and sizing of PAR/PST devices, taking in account a high penetration of wind power, is scarcely referred to in the literature. Earlier publications such as [13] were mainly focusing on a fixed scenario and minimizing losses. More recent publications such as [14][15][16] were concerned with system loadability or congestion reduction; [17] introduces multiple load steps and load curtailment costs. However, neither the probabilistic modeling of the problem nor the high penetration of wind power have been addressed so far.

Such a stochastic optimization formulation requires solving an Optimal Power Flow (OPF) problem (here in its widely known DC version), for each scenario of load and wind power. In the objective function (2), two Penalty terms are added: for the disconnection of wind generation and for load curtailment. The first takes in account the limitations that the transmission system imposes in conveying wind power – this will likely be activated in scenarios of high wind generation. The second will be activated in cases of very low or null wind power injection. Thus a solution will be found with the following priority: first, with wind curtailment, if useful; then, with load curtailment, if necessary.

Because the exercise is on investment planning, one will consider all generation as available, therefore outages due to maintenance our repair are not considered. Certainly, outage scenarios may also be included in the model.

The OPF will act upon a system with a particular solution for the sizing and location of PARs, defined by a chromosome with a length N (this being the number of permissible locations for PAR devices), each component i being a proposal for α_i^{max} at location i. This chromosome will be fixed across all S scenarios to allow the evaluation of the objective function in (4). The OPF problem is solved under an objective function J_S of the type

$$\max J_S = \sum Pgw_f - V_{PNS} * \sum PNS_m \qquad (18)$$

where Pgw_f stands for the wind power generation at location f and PNS_m stands for the load curtailed at node m; V_{PNS} is the value associated to the MW curtailed.

The following studies were conducted on the IEEE RTS 24 bus system [18]. For the studies including wind power, suitable additions of wind farms were made.

A. *PAR location without wind power*

A first series of studies were conducted without wind power but with three load scenarios. The location of PAR devices was tested by successively adding more load to the system. Eight possible locations for the PAR devices were defined - they are registered in Table I.

The load increments applied are in Table II, obtained by multiplying the basic data by a load factor > 1. Fig. 4 summarizes the results obtained: if one keeps adding PARs up to 4 (in the best locations out of 8 alternatives), there is a corresponding benefit in avoiding load curtailment. At 1.19 times the base load one cannot avoid load curtailment (although it is minimized with the presence of 4 PST) and if the load is greater there is no possible benefit from adding any extra PAR.

B. *Wind power integration*

The conventional generation was replaced by wind generation, with progressive additions at nodes 18, 22, 16 and 15, keeping the total installed capacity. The capacity on some lines has been limited. Three load scenarios were taken in account, with distinct geographical distribution of the demand. A stochastic representation of wind power, as in II.B was adopted, defining 8 wind scenarios with distinct probabilities. The wind availability was taken as linearly correlated among wind farm locations, in this study, which is the most severe case, although the definition of scenarios allows for considering lower correlation values.

The stochastic model defined by Eq. (2) and (18) was repeatedly solved for 8 distinct levels of wind power injection at distinct locations. Some of the results are in Fig. 5; they show that a suitable location of PAR devices guarantees an increased penetration of wind power with a practically constant average wind generation curtailed, if conventional generation above 1260 MW is replaced by wind generation with a stochastic nature. However, when too much conventional generation is replaced (case of 1926 MW), then one cannot avoid episodes of load curtailment, even with the best location of PAR, because of cases of insufficient generation capacity (in moments of absence of wind combined with peak power).

TABLE I – CANDIDATE LOCATIONS FOR PAR DEVICES (LINE AND NODE CODES REFERRING TO THE NETWORK REPRESENTATION IN [18])

Loc. No.	Line	Loc. No.	Line	Loc. No.	Line
1	1-2	4	8-10	7	12-13
2	14-16	5	3-24	8	8-9
3	6-10	6	17-22		

TABLE II – LOADS LEVELS (BASE: 2850 MW)

Load Factor	Load (MW)	Load Factor	Load (MW)
1.1	3135	1.17	3334.5
1.15	3277.5	1.19	3391.5

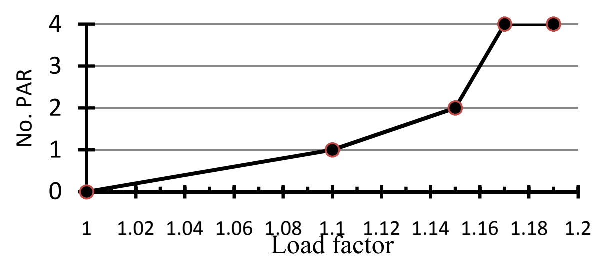

Fig. 4. Optimal number of PAR Transformers to be added to the system as a function of the load. Curtailment is null up to load factor = 1.17.

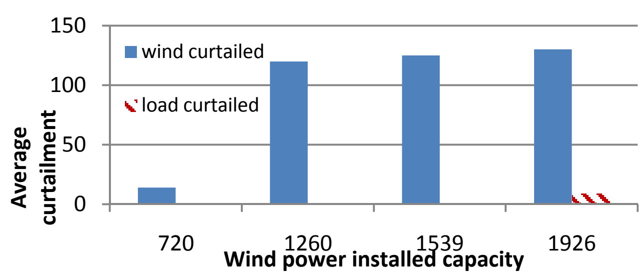

Fig. 5. Variation with average wind power curtailment with the increase in wind power penetration, taking in account the best insertion of PAR.

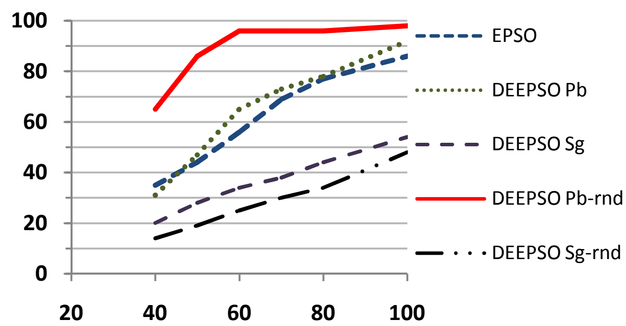

Fig. 6. Number of hits on the optimum (y-axis) vs. number of generations (x-axis) in 100 runs for EPSO and 4 DEEPSO variants.

C. Comparison DEEPSO-EPSO

The comparison in performance of the classical EPSO with variants of the new DEEPSO algorithm show a net advantage of DEEPSO (see Fig. 6). For the same stochastic problem, optimizing the number and size (max angle) of PAR in a choice of 8 locations in the system, 100 runs were made for each algorithm, with a swarm of 30 particles.

The figure counts how many times each algorithm reached the optimum. The DEEPSO Pb-rnd algorithm displays remarkable superiority: at 60 generations it had already reached a 96% efficiency in finding the optimum. In second place, we meet the DEEPSO Pb and the original EPSO algorithms with similar development.

V. Conclusion

Inserting PAR/PST FACTS devices in a network is a very attractive alternative against line reinforcement or new line building, when a network needs to be adapted to absorb a high penetration of wind power. The sizing and location of such devices in a network, to increase its capacity to deal with distributed wind power generation with probabilistic representation, is a mixed-integer stochastic combinatorial problem that requires an efficient algorithm to be solved.

This paper not only supplies a new model for this problem, which was not previously found in the literature, but also suggests, as a tool, a new algorithm that is built as an Evolutionary Particle Swarm Optimization (EPSO) with a Differential Evolution contribution – the **DEEPSO Pb-rnd**. The efficiency of the algorithm is far superior to the classic EPSO formulation and therefore it constitutes a new promising technique to deal with problems of this nature.

In systems with a growing penetration of wind power, the option for PST or PAR devices must be weighted to accommodate the uncertainty associated with wind power. Furthermore, the work reported in this paper is also seen as important for such systems because they demand stochastic models in order to provide a realistic representation of the wind penetration characteristic, replacing inappropriate capacity factor assessments.

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