Metaheuristic Approach for Online Optimal Reactive Power Management in Near-Shore Wind Power Plants

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***Abstract*— Mean-variance mapping optimization (MVMO) is an emerging metaheuristic optimization algorithm, whose evolutionary mechanism performs within a normalized search space. The most remarkable aspect of this mechanism resides in the application of a special mapping function to generate new values of the optimization variables based on their statistical significance throughout the search process. This paper concerns the feasibility of the MVMO to tackle the problem of online optimal reactive power management in near-shore wind power plants. The main challenges reside in the restricted computing budget and mix-integer nature of the problem. To this aim, MVMO is configured to evolve a single solution throughout the search process, and a new mapping function is proposed to improve the global search capability. Numerical tests on a benchmark system proposed by the IEEE Working Group on Modern Heuristic Optimization as well as a real world wind power plant demonstrate the effectiveness of MVMO.**

***Index Terms*-- Metaheuristic Optimization, Reactive Power Control, Wind Power Plant, On-Load Tap Changer, Mean-Variance Mapping Optimization**

I. INTRODUCTION

Northwestern Europe is heavily investing in the development of offshore wind power projects. As of this writing, a total of 6 wind power plants were grid connected throughout 2016, which entails approximately 1.5 GW of additional net installed grid connected capacity (which entails an average size of a grid-connected offshore wind power plant of about 380 MW, 12% more than the previous year) [1]. Currently, offshore wind power plants are required to provide reactive power support in both, steady-state operation, and during voltage dips. Particularly, for the steady-state operating regime, the grid code requirements are alternatively defined either in terms of the power factor, the amount of reactive power to be injected, or the voltage at the point of common coupling (PCC) [2].

Traditionally, the management of reactive power sources has been designed to perform in an uncoordinated manner (i.e. meeting local targets as seen at the terminal bus of each device). This approach is conservative, and although the reactive power requirement at PCC can be achieved without major drawbacks, the coordinated management of reactive power sources is essential to simultaneously achieve different operational objectives, i.e. minimum losses and higher efficiency. The coordinated approach is feasible nowadays with the adoption of modern technologies for data acquisition and communication.

As suggested in a previous paper by the authors [2], the coordinated management can be defined as an optimization problem, which possesses a mix-integer, discontinuous, multimodal (i.e. multiple local optima), and non-convex nature. These properties prevent the application of classical optimization algorithms, which, on the other hand, require a formulation of the problem that is based on a simplified (e.g. linearized equations) of the model of the system. Thus, recent research efforts have been devoted to the application of metaheuristic optimization algorithms, which attempt to determine a near-to-optimal (i.e. sufficiently good solution) without resorting to significant simplifications (i.e. keeping the non-linear equations) of the model of the system. In addition, these methods allow dealing with lack of information [3]. Current state-of-the art on the use of metaheuristics for optimal reactive power management reveals approaches based on pioneering algorithms like genetic algorithm [4], particle swarm optimization [5], differential evolution [6], and ant colony optimization [7], as well as emerging algorithms like Cuckoo search [8]. Despite of these achievements, stagnation in local optimum and reducing the computational effort remain as important challenges to be overcome.

It is worth emphasizing that the above-mentioned features make metaheuristic optimization a very attractive option for the development of optimization-based strategies for the operation and planning of offshore wind power plants. This paper addresses the optimal and coordinated reactive power management of offshore wind power plants by using the mean-variance mapping optimization algorithm, denoted henceforth as MVMO.

Unlike the majority of existing and popular metaheuristic algorithms, MVMO can be configured to evolve a single solution (single parent-offspring approach) throughout the search process. This is an advantage in terms of computing effort (i.e. less amount of problem evaluations), but might increase the risk of premature convergence. Nevertheless, this challenge is addressed in this paper by exploring the use of a new mapping function, which aims at improving the ability of MVMO to automatically switch between search exploration (i.e. generating diverse solutions in an attempt to cover the whole search space) and search exploitation (i.e. intensifying the search in a specific region of the search space), thus improving the global search capability of the algorithm. A first case study is built upon a benchmark system proposed by the IEEE Working Group on Modern Heuristic Optimization to ascertain the effectiveness of MVMO towards application in daily operation of near-shore offshore wind power plants, where variability of operating conditions is of concern. This also involves a comparative study with an powerful metaheuristic algorithm. A second case study based on a real-world wind power plant corroborates the suitability of MVMO for larger wind power plants with different topology.

The rest of the paper is structured in the following sequence: Section II overviews the MVMO-based solution procedure. The case studies as well as the numerical results are presented in Section III. Finally, concluding remarks and outlook for future research work are provided in Section IV.

II. MVMO-BASED PROCEDURE

Fig. 1 outlines the algorithmic steps of the MVMO-based solution procedure. The blocks of the figure encompassed with light blue background highlight the steps involved in the evolutionary mechanism of MVMO, whereas the block with yellow color refers to the evaluation of the optimization problem (objective function and constraints).

The algorithm parameter settings, the model of the offshore wind power plant, and the reactive power requirement at the PCC are inputs. The procedure starts with the generation of an initial solution, which constitutes a vector comprising random samples of the optimization variables, each one drawn within the corresponding [min, max] bounds.

Due to the normalized search space, where the evolutionary mechanism of MVMO performs, the sampled values are transformed to the range [0, 1]. The aforementioned normalized range ensures that there is no violation of bound constraints. The optimization variables are de-normalized only in the stage where the optimization problem is evaluated.

The core of the procedure is contained in the inner loop of the flowchart, in which, problem evaluation for a given (proposed) solution and updating of a solution archive (i.e. memory of the success achieved by evolving the solution throughout the search process) is followed by creation of a new solution (i.e. offspring generation) based on the best ranked solution in the archive (i.e. parent) and by applying the mapping function to generate new values for a set of selected optimization variables (i.e. mutation operation). The procedure ends once the termination criterion, defined as a maximum number of function evaluations, is met. In case that there is no improvement of fitness over successive fitness evaluation, then the process can be also terminated. In order to intensify the search once MVMO has found an attractive region, local strategy, e.g. subordinating other classical heuristic algorithms, can be added into the fitness evaluation stage. Detailed description of the evolutionary mechanism of MVMO can be found in [9].

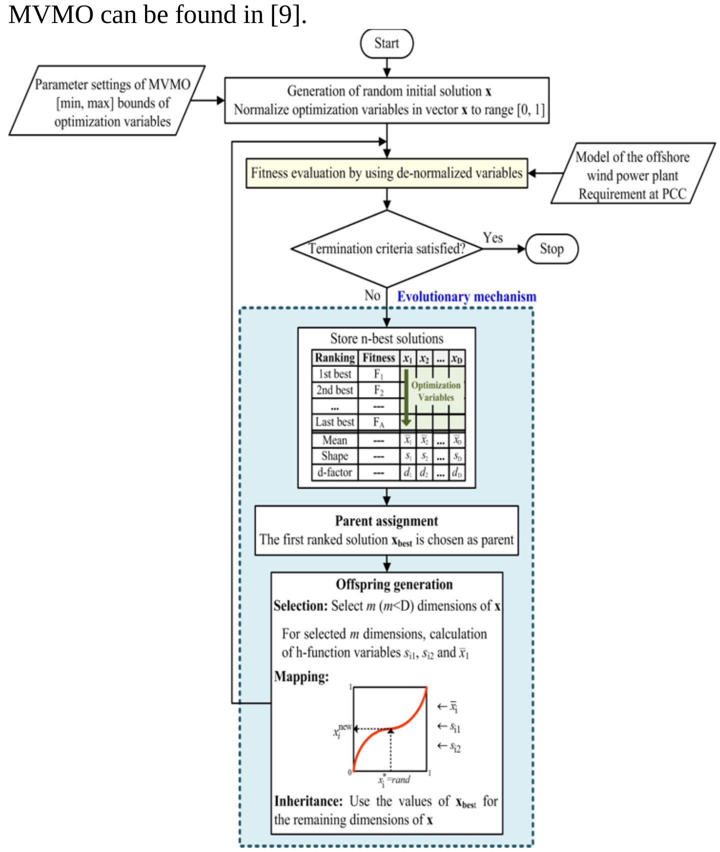

Fig. 1. MVMO-based procedure for optimal reactive power management

A. *Optimization problem statement and fitness measure*

The optimization task aims at minimizing the total transmission losses in the system subjected to technical constraints as shown below in (1) to (6):

Minimize

$$OF = P_{L,t}\ ,\ t = 1,2,\ldots,n \tag{1}$$

subject to

$$\mathbf{p}(\mathbf{v},\boldsymbol{\theta}) - \mathbf{p_g} = \mathbf{p_d} \tag{2}$$

$$\mathbf{q}(\mathbf{v},\boldsymbol{\theta}) - \mathbf{q_g} = \mathbf{q_d} \tag{3}$$

$$\mathbf{v_{min}} \le \mathbf{v} \le \mathbf{v_{max}} \tag{4}$$

$$\mathbf{i} \le \mathbf{i_{lim}} \tag{5}$$

$$\mathbf{s} \le \mathbf{s_{lim}} \tag{6}$$

where, t stands for the time index and $P_{L,t}$ constitutes the hourly active power losses. The equality constraints given by (2) and (3) account for nodal balance of active and reactive power balance, respectively. The set of inequality constraints given by (4)-(6) concern with acceptable ranges of buses' voltage magnitudes, the current limit of transmission branches (lines, cables, and transformers), and the branch power flow limits, respectively.

The vector of decision variables is denoted by **x**, and its elements, i.e. x_i, refer to the wind turbines Var settings and the transformers tap change limits. The bounds of decision variables define the search space for the optimization algorithm, and are described by the following equations:

$$q_{WTG}^{min} \le q_{WTG} \le q_{WTG}^{max} \qquad (7)$$

$$tap_{Tr,min} \le tap_{Tr} \le tap_{Tr,max} \quad (8)$$

It worth mentioning that a static penalty scheme is selected to determine the fitness measure associated to each **x** generated throughout the optimization search process. The fitness measure is the sum of the value of the objective function (e.g. total active power losses) and a penalization due to violation of technical constraints (e.g. line thermal limit). The penalization is computed as the product of a penalty factor, which is chosen as a high value (e.g. 1e7), and the sum of the constraint violations.

B. Solution archive

The solution archive, where the *n* best individuals obtained so far are stored, serves as the knowledge base for guiding algorithm's searching direction. The size of the archive is set in the initialization stage of the MVMO-procedure and remains constant for the entire process.

The filling of the solution archive obeys to a descending order of fitness of the n-best solutions found over the iterations as presented in Fig.2, and consequently the overall best found so far is always the first ranked solution. Once the archive is full, an update is conducted only if the solution fitness evaluation revealed that the new solution is better than these already stored. Finally, as the stored solutions in the archive keep changing over the iterations, the fitness is continuously improving.

After every update of the archive for each optimization variable x_i, the mean $\bar{x}_i$ and variance v_i are calculated by the following equations, respectively.

$$\bar{x}_i = \frac{1}{n}\sum_{j=1}^{n} x_i(j) \qquad (9)$$

$$v_i = \frac{1}{n}\sum_{j=1}^{n} (x_i(j) - \bar{x}_i)^2 \qquad (10)$$

where, the variance is calculated only if the new generated variable of an optimization variable differs from the previous one. The shape variable s_i in the archive is computed by using (11).

$$s_i = -\,ln(v_i)\cdot f_s \qquad (11)$$

At the beginning v_i is set to 1, since $\bar{x}_i$ corresponds with the initialized value of x_i. The shape variable computed s_i is one of the mapping function inputs with strong influence on its geometric characteristic shape. For this reason, the scaling factor f_s, which allows controlling the form of the mapping function and the search process, is involved in the calculation of s_i.

Ranking	Fitness	x_1	x_2	...	x_D
1st best	F_1				
2nd best				Normalized Optimization Variables	
. . .	F_2				
Last best	F_A				
Mean	---	$\bar{x}_1$	$\bar{x}_2$	...	$\bar{x}_D$
Shape	---	s_1	s_2	...	s_D
d-factor	---	d_1	d_2	...	d_D

Fig. 2. Solution archive

C. Generation of a new solution

Recalling Fig. 1, the best ranked solution is chosen as parent to generate a new solution. Basically, *m* out of D dimensions (i.e. optimization variables) of the parent are chosen by using a random-sequential scheme, and subsequently undergo mutation operation based on the so-called mapping function.

Given a uniform random number x_i^* sampled within the interval [0, 1], the new value of each selected dimension x_i is determined based on the mapping function. Both the input and output of the mapping function are always between the range [0, 1]. For each selected dimension, this function accounts for its mean and variance in order to generate a new value. The variation of the shape of the mapping function depends on these parameters, thus allowing to control the shift from search exploration (curved shape) and search exploitation (flattered shape). A new mapping function is used in this paper:

$$\begin{array}{ll}
\underline{if \quad x_r^* < 0.5} & \underline{if \quad x_r^* \ge 0.5} \\
s_1^* = s_1 / \left(1-\bar{x}\right) & s_2^* = s_2 / \bar{x} \\
h_m = \bar{x} - \dfrac{\bar{x}}{\left(0.5\cdot s_1^* + 1\right)} & h_m = \dfrac{\left(1-\bar{x}\right)}{\left(0.5\cdot s_2^* + 1\right)} \\
h_f = \bar{x}\cdot\left(1-e^{-x_r^*\cdot s_1^*}\right) & h_b = \left(1-\bar{x}\right)/\left(\left(1-x_r^*\right)\cdot s_2^* + 1\right) + \bar{x} \\
h_c = \left(\bar{x}-h_m\right)\cdot 2\cdot x_r^* & h_c = h_m \cdot 2\left(1-x_r^*\right) \\
x_i^{new} = h_f + h_c & x_i^{new} = h_b - h_c
\end{array} \qquad (12)$$

where $\boldsymbol{x_i^{new}}$ is the new value of the selected dimension $\boldsymbol{x_i}$, $\bar{\boldsymbol{x}}$ denotes mean value of the selected variable $\boldsymbol{x_i}$. $\boldsymbol{s_1^*}$ and $\boldsymbol{s_2^*}$ are named as shape factors and oscillate around the entropy measure as given in (10), which is a function of the variance $\boldsymbol{v_i}$ of the selected variable. Both $\bar{\boldsymbol{x}}$ and $\boldsymbol{v_i}$ are computed from stored values in the solution archive [9].

III. CASE STUDIES

A. Application to a test system

The layout of the test near-shore wind power plant, radially connected through an AC link to the PCC, is shown in Fig. 3. Detailed description of the system can be found in [10].

The objective is to minimize the total active power transmission losses while fulfilling constraints associated to nodal balance of power, nodal voltages, allowable branch power flows, and difference between q_{ref} (grid requirement) and q_{PCC} (actual reactive power injection at the PCC). The problem has 22 optimization variables, comprising 18 continuous variables associated to wind generator reactive power set-points, 2 discrete variables associated to stepwise adjustable on-load transformers' tap positions, a discrete variable defining the stepwise adjustment of the capacitor C_1, and a continuous variable defining the adjustment of reactor X_{sh1}. The computing budget is restricted to 1000 problem evaluations (i.e. 1000 AC power flow calculations).

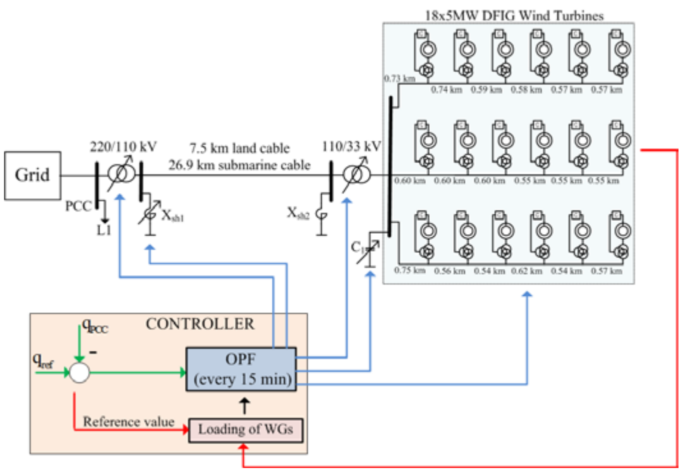

Fig. 3. Scheme for optimal reactive power management in offshore wind power plant

Challenging conditions are created by defining reactive power requirements as abrupt stepwise changes of q_{ref} throughout 24 hours (divided in 15 min intervals) as shown in Fig. 4. The figure also illustrates the variability of active power output of the plant.

Fig. 5 shows the obtained values of the fitness function in the last evaluation done in the MVMO procedure. All constraints were satisfied at this stage (i.e. no penalty value affecting the fitness), so the value of the fitness corresponds with the value of the total active power transmission losses.

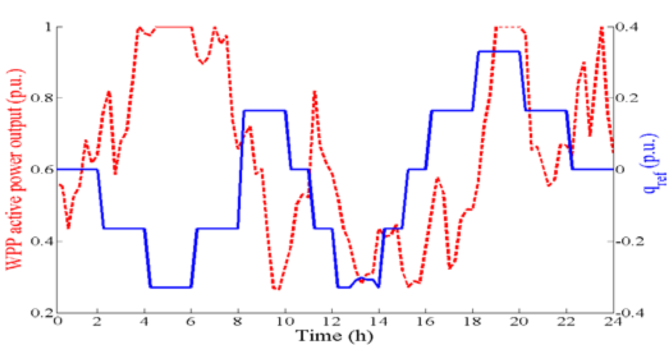

Fig. 4. Daily active power output profile and requirement at PCC (q_{ref})

The best, average, and worst fitness values obtained throughout each point of time are included in the figure. These values were computed by repeating the optimization 31 times (a number that is usually suggested for comparing statistics in competitions of evolutionary computation [11]). The closeness between best and worst values indicates a high degree of robustness of MVMO to find the optimum in all optimization repetitions, irrespectively of having random initialization and the fact that random factors are in used in the evolutionary mechanism. These results attest the suitability of MVMO as a powerful solver for online optimal control purposes.

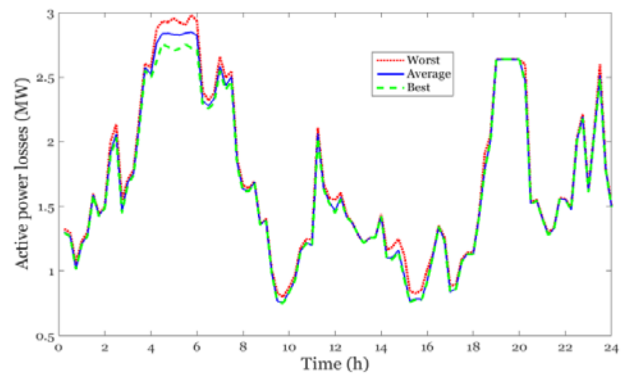

Fig. 5. Time series and bounds of the fitness function value

Table 1, presented in the following page, summarizes the statistics of the fitness value obtained for three hard-to-solve operating conditions (i.e. the highest difficulty to meet technical constraints), indicating the corresponding time of occurrence (cf. Fig. 3). The statistic measures obtained by using Differential Evolutionary Particle Swarm Optimization (DEEPSO) are comparatively depicted in the table. DEEPSO won the 2014 Competition on Optimal Power Flow problems, organized by the IEEE Working Group on Modern Heuristic Optimization [12]. Note that MVMO provides similar statistics for t=5h and t=20h, but outperforms in t= 12h. The latter time step corroborates the benefit of the improved evolutionary mechanism of MVMO, since it allows finding solutions that entail a considerable decreased value of transmission losses. In addition, it is worth highlighting that MVMO performs as a single parent-offspring algorithm (which is traditionally expected to have high probability of premature convergence and stagnation), whereas DEEPSO performs as a population based algorithm (which is traditionally expected to be more successful).

B. Application to a real system

The effectiveness of MVMO in solving computationally complex problems is also demonstrated in a real study case, in which the offshore wind power plant is also connected through an AC link to the PCC as shown in Fig. 6. The wind power plant under investigation, termed as the Borssele plant, is connected to the onshore Dutch transmission system. The plant consists of two zones, I and II, connected via a 22km HVAC cable. 100 fully-rated-converter wind turbines, each rated at 6 MW are used for the simulations.

Table 1. Statistics of the fitness function value in hard-to-solve operating conditions

Statistics of active power losses (MW)	**Time= 5 h**		**Time= 12 h**		**Time= 20 h**	
	MVMO	**DEEPSO**	**MVMO**	**DEEPSO**	**MVMO**	**DEEPSO**
Best	2.7247	2.7042	0.8383	1.4493	2.6373	2.6373
Mean	2.8417	2.830	0.8461	1.5499	2.6373	2.6373
Median	2.8377	2.832	0.8397	1.4647	2.6373	2.6373
Worst	2.9822	2.955	0.9638	1.4581	2.6373	2.6373
Std.	0.0753	0.0629	0.0234	0.0211	5.0161E-08	7.4776E-08

The internal power transmission of each 300 MW zone of the wind farm is realized by the wind turbine transformers, each rated at 0.69/66 kV, multiple cables with different lengths and four step-up on-load tap-changing transformers of 6.7 MVA, at the offshore and onshore side, rated at 230/66/66 kV and 380/225/33 kV respectively.

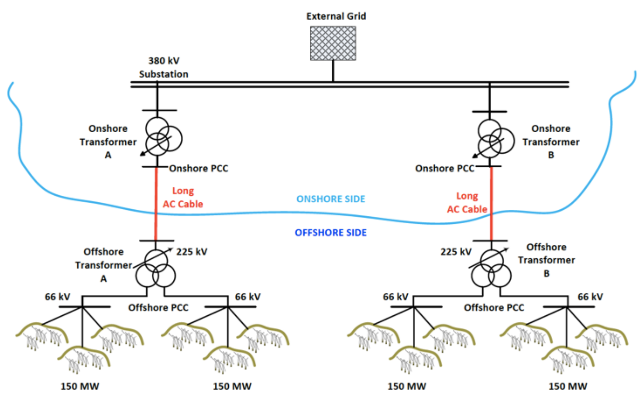

Fig. 6. Borssele wind farm layout with AC cable

In this case, the objective is to minimize the total operational cost of the wind farm for the next 24 hours, by suggesting the reactive power reference of each wind turbine as well as the optimal tap settings of the offshore and onshore transformers.

The problem has 104 optimization variables, comprising 100 continuous variables associated to wind turbine reactive power set-points and 4 discrete variables associated to stepwise adjustable on-load transformers tap positions.

The numerical results demonstrate that the proposed approach based on MVMO algorithm ensures compliance for the wind power plant without the need for additional hardware (i.e. STATCOM) as the compliance is ensured by means of optimal reactive power set-points per each wind turbine in each steady-state operation point.

In Fig.7, it is shown that the reactive power reference for each wind turbine, derived from the optimization, is according to the capability curve of the wind turbines, since all the values are within the predefined envelope. This is attributed to the fact that MVMO works with a normalized search space, which ensures that the bound constraints (e.g. feasible min-max values of wind turbine reactive power set-points) are never violated. This is an advantage with regard to other algorithms, since the algorithm does not require extra computing effort to repair solutions to lie within the [min, max] boundaries of the search space. Each set of points arranged in the same horizontal line refers to different value of wind speed.

In addition, it is observed in Fig. 8 that the reactive power absorption/injection at the onshore PCC is between the required boundaries, since the deviation is lower than the accepted +/- 0.1 p.u. (= +/- 30 MVar) according to the technical specifications defined by TenneT TSO.

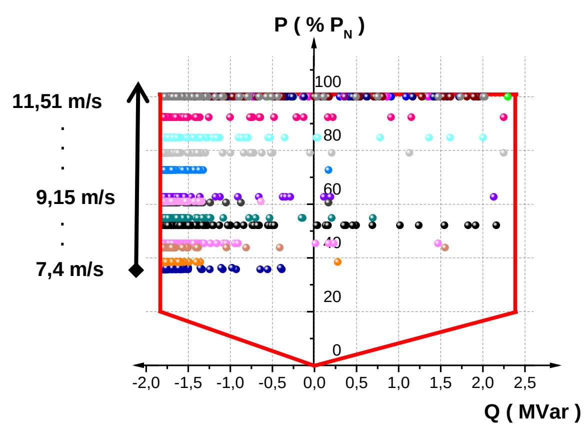

Fig. 7. Hourly reactive power set-points for every wind turbine.

For comparison purposes, regarding the robustness of the metaheuristic algorithm, the obtained values of the fitness evaluation in the last evaluation done in the MVMO procedure are presented in Fig.8. The fitness corresponds with the value of the 24-hour cumulative optimum cost of Borssele wind farm, since all the constraints were again satisfied at this stage (i.e. no penalty value affecting the fitness).

The worst, mean and best fitness values obtained, with regard to the cumulative initial cost are included in the figure. These values were computing by repeating the optimization 31 times. The cumulative initial cost is calculated while considering zero reactive power reference at every wind turbine. The small difference between best and worst values shows that the proposed MVMO-based solution approach is robust to randomness in initialization and evolutionary operations.

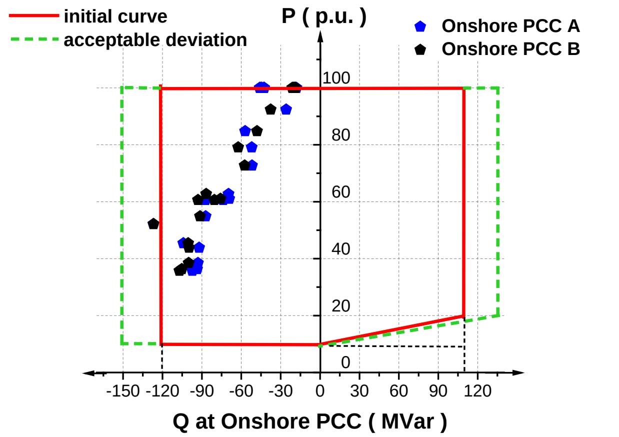

Fig. 8. Reactive power at the onshore PCC

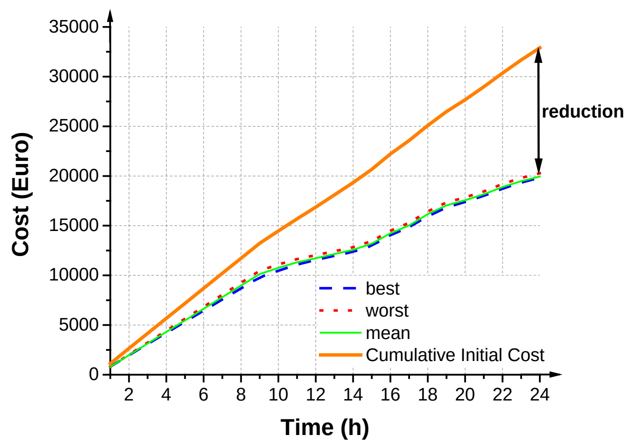

Fig. 9. Time series and bounds of the fitness function value.

IV. CONCLUSIONS

The application of MVMO for optimal coordination of reactive power sources in near-shore wind power plants was presented in this paper. Numerical results, including comparative analysis with a powerful stochastic solver of the current state-of-the art, demonstrate that MVMO constitute a competitive optimization solver, and the enhanced evolutionary mechanism of the algorithm entails a robust performance with respect to optimization repetition and random factors involved in the initialization (e.g. assuming that no initial solution is known) as well as the evolutionary mechanism of the algorithm. This is a very important aspect for any evolutionary algorithm to be applied in online applications in energy management systems.

Another advantage of MVMO resides in the use of a normalized search space, which on one hand helps in ensuring strict fulfillment of the min-max bounds of the optimization variables (i.e. equipment technical limits are respected), and, on the other hand, it avoids additional computational effort (additional calculations) to repair any unfeasible solution which can be outside the min-max search bounds as a result of the application of the evolutionary operations. The latter aspect is very common in most of existing evolutionary algorithms.

The first case study, based on a benchmark (prototype) wind power plant, illustrates the effectiveness of MVMO w.r.t. the results obtained by using a powerful stochastic solver of the current state-of-the-art, and also highlights the advantage of MVMO when dealing with extreme situations (e.g. due to exceptional operational requirements at the PCC) in which determining the optimal contribution from different reactive power sources is crucial to ensure compliance. The second case study corroborates the advantages of using MVMO in wind power plants of larger size. The application of the presented approach in far-offshore wind power plants (connected through HVDC links) is already under investigation. Future work will be directed to the feasibility of the solution in meshed offshore transmission grids.

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