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Optimal Management of Reactive Power Sources in Far-offshore Wind Power Plants

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Abstract—This paper introduces a new approach for the optimal management of reactive power sources, which follows a predictive optimization scheme (i.e. day-ahead, intraday application). Predictive optimization is based to the principle of minimizing the real power losses, as well the number of On-load Tap Changer (OLTC) operations for 24 time steps ahead. The mixed-integer nature of the problem and the restricted computing budget is tackled by using an emerging metaheuristic algorithm called Mean-Variance Mapping Optimization (MVMO). The evolutionary mechanism of MVMO is enhanced by introducing a new mapping function, which improves its global search capability. The effectiveness of MVMO (i.e. fast convergence and robustness against randomness in initialization and factors used in evolutionary operations) and the achievement of optimal grid code compliance are demonstrated by investigating the case of a far-offshore wind power plant, interconnected with HVDC link.

Index Terms—optimal reactive power management, mean-variance mapping optimization, on-load tap changer

I. INTRODUCTION

Offshore wind is a competitive power source and increasingly attractive investment with various benefits for the electric power generation. Europe is considered as the front-runner in this field, where during the year 2015 new offshore capacity of 3.02 GW was connected to the grid [1]. According to wind energy scenarios for 2030, offshore wind installations amount to 66 GW [2]. However, the high penetration of the wind power into the energy systems holds many technical/operational challenges. Offshore wind power plants are required to provide reactive power support during both the steady-state as well as during AC fault conditions [3].

Nowadays, the Transmission System Operators (TSO) of each country have defined Grid Code Requirements in order to ensure the safe, secure and reliable operation of power systems. Traditionally, the reactive power sources in the synchronous transmission systems are designed for operation in an uncoordinated manner, i.e. meeting local targets as seen at the terminal bus of each device. Although the reactive power requirement at the point of common coupling (PCC) can be achieved without major drawbacks, the aforementioned traditional approach is quite conservative (i.e. it does not entail efficient and optimal management of the reactive power sources) [4]. Since it is highly related to the way how the active and reactive power flow through a given grid topology, the optimal reactive power management is a particular form of optimal power flow (OPF) and a subject of remarkable research, which has immense significance on the security and economical operation of the power systems (e.g. by minimizing losses and ensuring fulfillment of technical constraints) [5], such as the control and optimization for operation of wind power plants [6].

This paper proposes an approach that involves coordinated management of reactive sources based on an OPF formulation that accounts for non-linear power flow equations. The benefit brought is minimum power losses and reduction of stress or disturbances for the controllable devices, i.e. transformers, simultaneously [4]-[7]. In order to solve this problem mathematically, various optimization algorithms that have been developed so far could be applied in principle, since the existing technologies for data communication and acquisition render the coordinated management as a feasible task. However the classical optimization algorithms, such as gradient-based algorithms, described in [8]–[10], struggle with non-linearity and non-convexity of the problem, which is also characterized by discontinuity and multimodal landscape [11]. Conclusively, the classical optimization tools are not flexible to be applied in a complex search space and are sensitive to the initial points as well [12].

Classical heuristic optimization algorithms, like genetic algorithms, particle swarm optimization, differential evolution, and evolutionary strategies, constitute alternative tools to tackle the above indicated optimization problems. Nevertheless, the effectiveness of these algorithms is highly dependent on finding proper parameter settings and usually entails significant algorithmic modifications. In addition, due to their population based search framework, these algorithms are not suitable for online applications, in which it is crucial to find optimal solutions within very reduced computing
The remainder of this paper is organized as follows. Section II gives an overview of the proposed optimization approach and describes the MVMO-based procedure. In Section III, a test case is developed and evaluated. Finally, conclusions and outlook for future work are presented in Section IV.

II. PROPOSED APPROACH

Fig. 1 depicts schematically the structure of the proposed approach. The optimization is performed for a given scenario, which includes a set of future operating points on a 24-hour time horizon [7]. The predicted wind speed for the considered time period results directly from a Neural Network (NN) [18], which, due to their conceptual simplicity, can be easily adapted without significant modifications.

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 strategically 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. The remainder of this paper is organized as follows. Section II gives an overview of the proposed optimization approach and describes the MVMO-based procedure. In Section III, a test case is developed and evaluated. Finally, conclusions and outlook for future work are presented in Section IV.

A. Optimization problem statement

Considering the total real power losses and the operation cost of the OLTC on a 24-hour time horizon, the formulation of the objective function is multi-objective and is given by the following equation, in which the problem is treated as single objective due to the use of the weight coefficients.

Minimize

\[ OF = \sum_{t=1}^{24} \left( w_1 \cdot P_L,t + w_2 \cdot OLTC_{cost,t} \right) \]  

subject to,

\[ v_{min} \leq v \leq v_{max} \]  

\[ i \leq i_{lim} \]  

\[ s \leq s_{lim} \]  

where, \( t \) stands for the time index and \( P_L,t \) constitutes the hourly real power losses. The system operating constraints given by (2)-(4) constitute the inequality constraints on the dependent variables, such as the voltage magnitude of the buses, the current through the cables, line and transformer flow limits, respectively.

The bounds of decision variables refer to the wind turbines \( Var \) settings and the transformers tap change limits. They define the search space for the optimization algorithm and are described by the following equations:

\[ q_{WTG}^{min} \leq q_{WTG} \leq q_{WTG}^{max} \]  

\[ tap_{Tr,min} \leq tap_{Tr} \leq tap_{Tr,max} \]  

The hourly operation cost denoted by \( OLTC_{cost,t} \) is stated as follows:

\[ OLTC_{cost,t} = w_3 \cdot |tap_t - tap_{t-1}| \]  

where \( tap_t \) stands for the discrete tap positions at hour \( t \) and \( t-1 \), and \( w_4, w_5 \) are the weight coefficients corresponding to cost values, which were set to \( w_1 = 80, w_2 = 10, \) and \( w_3 = 1 \).

B. MVMO

MVMO belong to the family of evolutionary optimization algorithms and can be applied in multi-objective mixed integer and non-linear problems. Remarkably, it can be configured to perform to evolve a single solution throughout the optimization process or as a population-based; the first option is chosen in this paper, since it is intended for online application. The proposed methodology, based on MVMO as solver, for the formulated optimal reactive power management is described in Fig. 2 [4]. The procedure starts with the initialization of the parameter settings, such as the archive size, the selection method for evolution of optimization variables, and the maximum number of iterations. The searching space of all variables is confined in \([0,1]\) and therefore the real min/max have to be normalized to this interval. Therefore, during every iteration step, it is guaranteed that the solution vector does not violate the required boundaries [7].

Remarkably, MVMO bases its evolutionary mechanism on a special mapping function that extracts the statics successful behavioral pattern of the evolved solutions as described by...
mean and shape variables. This information is used to transform a variable $x_i^*$ varied randomly with unity distribution to another variable $x_i$. Besides, after each fitness evaluation, a solution archive is filled and continuously updated throughout the search. The archive stores and ranks the most successful solutions achieved so far [19]. The evolutionary loop is performed until a specified termination criterion is met (e.g., maximum number of function evaluations) [12]. The different stages of MVMO-based procedure are presented in the following paragraphs.

1) **Initialization** – The initial candidate solution is randomly generated between the boundaries as follows:

$$x_i^\text{init} = x_i^\text{min} + \text{rand} \left( x_i^\text{max} - x_i^\text{min} \right), \quad i = 1, 2, \ldots, D \quad (8)$$

The index $i=1, 2, \ldots, D$ concerns with the problem dimension, so D is the number of decision variables. In this case, in which the optimization is performed in a predictive manner, after the first hour of the day, the initial candidate solution for the subsequent hours is generated by the best solutions obtained from the previous hour.

2) **Fitness Evaluation & Local Search** – Before the fitness evaluation is performed, the decision variables are de-normalized from the interval [0, 1] to the original [min, max] boundaries. The normalized range, within which MVMO performs, ensures there is no violation of bound constraints. Finally, after the termination criterion is satisfied, which is specified in this paper as a predefined number of fitness evaluations, the search process stops. Alternatively, in case that there is no improvement of fitness over successive fitness evaluations, then the process can be also terminated. In order to intensify the search once MVMO has found an attractive region, local search strategy, e.g., subordinating other classical or heuristic algorithms, can be added into the fitness evaluation stage.

3) **Solution archive** – The solution archive, where the $n$ best individuals obtained so far by MVMO are stored, serves as the knowledge base for guiding the algorithm’s searching direction. The size of the solution archive remains constant for the entire process and is set in the initialization stage. The filling of the archive obeys to a descending order of fitness over the iterations as presented in Fig. 3 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 those already stored in the archive. Since the fitness improves over the iterations, the stored solutions in the archive keep changing.

The mean and shape variables are computed after every update of the archive for each optimization variable as follows:

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

$$s_i = -\ln(v_i) \cdot f_s \quad (10)$$

where, the variance is calculated only for different variables in the archive by using (10).

$$v_i = \frac{1}{n} \sum_{j=1}^{n} (x_i(j) - \bar{x}_i)^2 \quad (11)$$

At the beginning $v_i$ is set to 1, since $\bar{x}_i$ corresponds with the initialized value of $x_i$. The computed shape variable $s_i$ 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 $s_i$. 

![Figure 2. MVMO-based procedure for optimal reactive power management](image)

![Figure 3. Solution archive](image)
4) **Offspring generation** – To create a new solution, MVMO uses a random sampling strategy. In order to generate a new solution, in every iteration the solution with the best fitness so far is used. It is assumed that the distribution of the new variable $x_i$, doesn’t correspond with any of the well-known distribution functions. Given a random number $x'_i$ from the interval [0, 1], the new value of each selected dimension $x_i$ is determined based on the classical mapping function:

$$x_i = h_x + (1 - h_1 + h_0) \cdot x'_i - h_0$$  \hspace{1cm} (12)

where $h_x$, $h_1$ and $h_0$ are the inputs of the mapping function based on different inputs given by:

$$h_x = h(x = x'_i)$$  \hspace{1cm} (13)

$$h_1 = h(x = 1)$$  \hspace{1cm} (14)

$$h_0 = h(x = 0)$$  \hspace{1cm} (15)

Both input and output of the mapping function are always between the range [0, 1]. The definition of the transformation mapping h-function is the following:

$$h(x, s_1, s_2, x_i) = \bar{x}_i \cdot (1 - e^{-x \cdot s_{12}}) + (1 - \bar{x}_i) \cdot e^{-x \cdot s_{12}}$$ \hspace{1cm} (16)

As illustrated shown in the following figure, the h-function transforms the variable $x'_i$ varied randomly with unity distribution to another variable $x_i$, which is concentrated around the mean value calculated from the archive. The variation of $\bar{x}_i$ implies shifting of the curve between the original lower and upper boundaries of the search range, while the variation of $s_{1,1}$ and $s_{1,2}$ affects the bent shape of the curve, i.e. emphasized either exploration or exploitation.

When the accuracy need to be improved or more global search is required, the factor $f_g$ should be increased ($f_g > 1$) and decreased ($f_g < 1$), respectively. Therefore, $f_g$ can be used to change the shape of the function.

The above described mapping function does not ensure that the mutation of the optimization variable is performed equitably in both directions (towards min-max bounds). This can adversely affect the global search capability of MVMO (impacting the convergence speed). Thus, a new mapping function is used in this paper:

$$x_i = h_f + (1 - h_1 + h_0) \cdot x'_i - h_0$$ \hspace{1cm} (12)

where $h_f$, $h_1$ and $h_0$ are the inputs of the mapping function based on different inputs given by:

$$h_f = (1 - e^{-0.5 \cdot x'_i})$$  \hspace{1cm} (13)

$$h_1 = (1 - e^{-0.5 \cdot x_i})$$  \hspace{1cm} (14)

$$h_0 = (1 - e^{-0.5 \cdot x_i})$$  \hspace{1cm} (15)

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Considering the output wind speed data of the prediction model, the power produced by each wind turbine is calculated in the Python script by using the following equation:

\[
P_m = \frac{1}{2} \cdot (\pi \cdot R^2) \cdot \rho \cdot C_p \cdot v_m^3
\]

Finally, for performing the optimization on 24-hour time horizon, the calculated power is fed into the wind power plant model implemented in DigSILENT PowerFactory.

C. Optimization results

The wind scenario for the considered time period of 24-hours is the result of the implemented wind speed forecasting method. The wind profile, shown in the Fig.7, is used for the simulations.

In Fig. 8, the difference between the cumulative initial cost, calculated for zero reactive power reference at every wind turbine, and the optimum cost is estimated around 10.97 % for the 24-hour time horizon under investigation. The reactive power set-points for every generating unit derived from the optimization are according to the Grid Code Requirements indicated in [20], since all the values are within the predefined envelope presented in Fig. 9a. Although not shown here due to space constraints, it is worth indicating that the grid code requirement at PCC was also met when the turbines were set to have zero reactive power reference. The figure also evidences that the optimization results in reactive power contributions from each generator according to their individual capabilities and electrical distance. Moreover, it is also confirmed that the normalized search space of MVMO ensures that bound constraints (5) are never violated [4]. This is an advantage with regard to other algorithms, since MVMO does not require extra computing effort to repair solutions to lie within the [min, max] boundaries. Each set of points arranged in the same horizontal line refers to the different value of wind speed. Technical constraints (2)-(4) are handled based on static penalty scheme [21], which proved to be suitable for this problem.
The performance of MVMO for solving the mixed-integer nonlinear complex problem of predictive optimization, within a reduced number of allowed function evaluations, is presented in Fig. 6, where the algorithm converges almost before 300 iterations. The fast convergence behavior and the quick discovery of the optimum solution with minimum risk of premature convergence is revealed thanks to the well-designed balance between search diversification and intensification of MVMO, which is in agreement with results obtained with the test bed of the 2015 IEEE Competition on Computationally Expensive problems [23].

IV. CONCLUSIONS

The main goal of the approach presented in this paper is to minimize the wind power plant power losses, as well as the variations of the transformers tap positions, while the reactive power set-points of individual wind turbines in the power plant are utilizing an optimal reactive power management scheme. The scheme ensures grid code compliance with steady state reactive power requirements, while the operational cost of the wind power plant is also reduced. Finally, it is presented by means of numerical results on a real offshore wind power plant in Germany, that the application of MVMO and its new mapping function in the optimal coordination of reactive power sources in the wind power plant under investigation entails robustness and enhances performance in terms of convergence speed. The application of the presented approach to other wind power plant topologies and Grid Codes is currently under investigation.

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