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Dynamic Electric Dispatch for Wind Power Plants: A New Automatic Controller System Using Evolutionary Algorithms

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Abstract: In this paper, we use an evolutionary swarm intelligence approach to build an automatic electric dispatch controller for an offshore wind power plant (WPP). The optimal power flow (OPF) problem for this WPP is solved by the Canonical Differential Evolutionary Particle Swarm Optimization algorithm (C-DEEPSO). In this paper, C-DEEPSO works as a control system for reactive sources in energy production. The control operation takes place in a daily energy dispatch, scheduled into 15 min intervals and resulting in 96 operating test scenarios. As the nature of the optimization problem is dynamic, a fine-tuning of the initialization parameters of the optimization algorithm is performed at each dispatch interval. Therefore, a version of the C-DEEPSO algorithm has been built to automatically learn the best set of initialization parameters for each scenario. For this, we have coupled C-DEEPSO with the `irace` tool (an extension of the iterated F-race (I/F-Race)) by using inferential statistic techniques. The experiments carried out showed that the methodology employed here is robust and able to tackle this OPF-like modeling. Moreover, the methodology works as an automatic control system for a dynamic schedule operation.

Keywords: offshore wind power; optimization; energy efficiency; energy resources; clean energies

1. Introduction

To meet the ambitious goals of the Paris agreement [1] to prevent, or at least minimize, climate change, there is a global need for sustainable energy supply. Part of this energy supply must be produced by renewable sources. Market-driven policies are increasingly focused on promoting the use of wind and solar generation [2]. The production of energy and electricity from wind sources can be carried out both on the ground (onshore) and in wind farms installed in the ocean (offshore). Locations for the construction of offshore wind power plants (WPPs) are usually a few hundred kilometers away from the nearest coast, which requires long-distance cables in the ocean [3]. Being quick to install, especially when compared to other energy sources, great efforts to develop onshore and offshore wind farms are being made [4,5]. Figure 1 shows a simplified scheme of offshore wind energy production.

Generally, wind power generation occurs in three phases, as follows:

1. Wind turbines: the blades turn a shaft inside the wind unit. Power energy is produced via a rotational generator (which uses the conversion of magnetic energy into electric);
2. Offshore substation: the transformer equipment transforms the power for distribution and delivery to the onshore substation and;
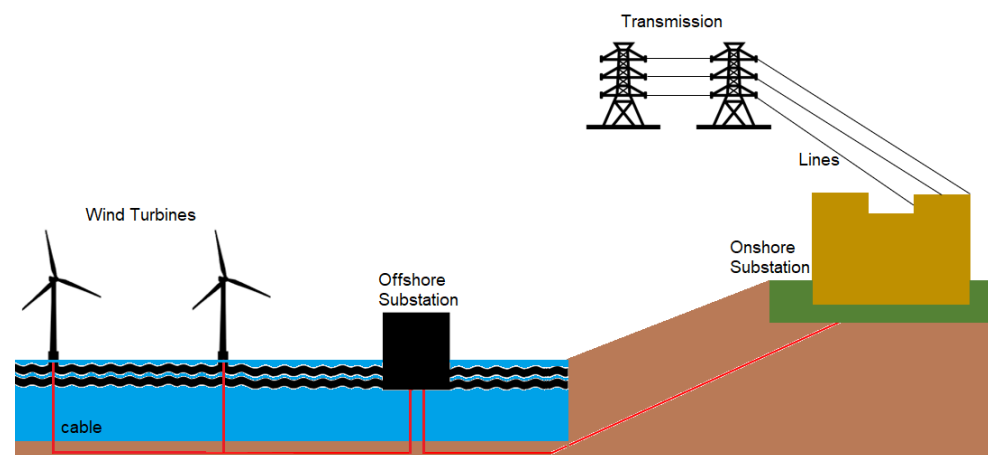3. Lines and grid: power transmission and distribution to consumers.

Figure 1. Example of a generic offshore wind power generation scheme.

Active and reactive power dispatch problems are common in the power production area, usually known as optimal power flow (OPF) [6]. Generally, OPF problems have a large dimensional space, and due to their multi-modality, nonlinearity, and non-convexity characteristics, these problems are considered large-scale optimization problems [7]. Solving an OPF consists of finding the more appropriate setups for the controller system (active power and voltages), transformers taps, shunt reactors, and capacitors values [8]. This work addresses an OPF-like problem: a wind power generation problem. We propose an optimal dispatch WPP controller, in which appropriate parameter settings of the algorithm are obtained automatically over time so that its performance is optimized. Several methods and techniques for solving OPF problems have been proposed in the state-of-the-art literature. The advantages and disadvantages associated with the most used methods for solving OPF problems can be found in the works of [6,9,10]. We summarize this information in Table 1.

Table 1. Methods used to solve electrical dispatch in optimal power flow problems.

Method	Description	Advantages	Disadvantages	Works
Linear	Usage of linear or	Convergence is fast	Inaccuracy due	[11]
Programming	piecewise linear cost functions and usage of DC power flow instead of AC power flow, which provides a linear relation between injections and line flows	and guaranteed; less computational effort; easy handling of inequality constraints	to linearization of cost funtions and nonlinear constraints	[12]
Quadratic	Usage of a quadratic	It does not require	Computation cost	[13]
Programming	objective function, all constraints are linear	linearization of functions	can be significantly high	[14]
Meta-heuristics	Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant Colony Optimization (ACO) are the most applied meta-heuristics	No linearization is required; uses non-continuos, non convex, and non differentiable functions; easy implementation	The solution obtained is not guaranteed to be optimal	[15] [16] [17] [18] [19]

Specifically in wind energy production, it is possible to find recent related works in the literature. Kotur and Stefanov [3] proposed an optimal power flow control in a system with offshore wind power plants. Using the IEEE 14-bus system test system, the Interior Point Method was applied to solve the OPF-like problem. The authors concluded that the proposed approach was more efficient than a standard system controller. A mathematical modeling of wind generation was proposed in [4]. The general idea was to minimize costs of wind intermittency using Linear Programming techniques. Results showed that the applied methodology is suitable for quantifying the effects of the shape of the forecast error distribution and the coefficient costs of wind intermittency.

A wind farm control strategy was proposed to maximize the power reserve during de-loading operation while maintaining the total power delivered by the WPP at the point of common coupling (PCC) [20]. The problem was solved by the AEOLUS SimWindFarm (SWF) Simulink toolbox [21]. Sakipour and Abdi [22] proposed a study based on wind power generation testing nine evolutionary algorithms, as Grey Wolf Optimizer (GWO), Artificial Bee Colony (ABC), GA, PSO, and among others. The goal was to find an efficient microgrid configuration using storage systems into a wind farm. Results showed that the GWO performed better, increasing the remaining expected life of batteries in the system.

Self-Adaptive Evolutionary Programming (SAEP) was proposed in [23] to minimize the wind power generation costs. Obtained solutions validated the proposed methodology. Gwabavu and Raji [24] presented a dynamical control system based on model predictive control applying Quadratic Programming to solve the OPF problem. The results showed that the proposed method can reduce grid-connected wind power fluctuations and limit system faults in power generation. Joseph et al. [25] proposed the use of a PSO method to maximize the system loadability within stability margins. Results showed that PSO improved the load carrying capacity when compared to the controller system installed in the plant. Bai et al. [26] applied the ABC algorithm to minimize the production costs on a WPP. A comparison of results between ABC, GA, and PSO was performed, and ABC showed better average results.

Seok and Chen [27] proposed an intelligent wind power plant coalition formation model solved by mathematical programming to achieve profit growth. The authors concluded that the model is especially applicable to heterogeneous WPPs. According to Helmi et al. [28], improving the efficiency of distribution networks is a challenging goal for both large networks and microgrids connected to the public grid. In this context, the Harris Hawks Optimization (HHO) was proposed to minimize power losses of three IEEE systems: 33-bus, 85-bus, and 295-bus. Results showed that HHO performed better than Cuckoo search algorithm (CSA) and PSO for minimizing the losses of systems tested. An optimal network configuration in an active distribution network reduces power loss, improves voltage profile as well as system efficiency and reliability [29]. Thus, the Water Cycle algorithm (WCA) was proposed to reduce the losses of the IEEE 33-bus and IEEE 69-bus systems. WCA outperformed other optimization techniques such as CSA, Harmony Search Algorithm (HSA), and Fireworks Algorithm (FWA). Similar approaches to minimize system loss in wind power plants were proposed in Packiasudha et al. [30] using the Cumulative Gravitational Search Algorithm (CGSA). The minimization of system losses in wind farms was also solved via deterministic algorithms as seen in the works of Huang et al. [31] and Sakar et al. [32].

Pham et al. [33] proposed an optimization method, the Mean-Variance Mapping Optimization (MVMO), to solve the reactive optimal control to WPPs, taking into account the minimization of losses. MVMO was applied to solve the problem using the IEEE 41-bus system as test scenario (available in [34]). Obtained results showed that a fine-tuned MVMO version generated adequate solutions for the OPF-like problem. It is important to say that the IEEE 41-bus system model considers that there is no uncertainty associated with the decision variable values. For dealing with uncertainty in the variables, more complex approaches, such as stochastic or robust optimization methods, are needed. In [35,36], stochastic and a robust approaches were proposed to minimize network losses.

In this work, we solve a dynamic OPF-like problem representing the reactive power dispatch in wind power plants. We propose an integration between the Canonical Differential Evolutionary Particle Swarm Optimization algorithm (C-DEEPSO) [37] and `irace` [38] as an automatic control system to provide the electric dispatch for WPPs. C-DEEPSO, a hybridization between the particle swarm algorithm and the differential evolution algorithm, was proposed in 2018. The algorithm takes advantage of swarm intelligence methods and the canonical genetic operators of evolutionary computation techniques. Since its proposal, C-DEEPSO has been successfully applied to diverse power systems problems. In general, power system problems such as OPF (optimal power flow) and SCOPF (security constrained optimal power flow) are hard problems to solve, having a high number of distinct optimization variables to optimize and various constraints to deal with. It is well-known that algorithms for solving these types of problems demand a careful design. Motivated by the performance superiority of C-DEEPSO and its variants when applied to such problems (see [37,39–44]), C-DEEPSO presents good features and is a viable and competitive method for solving the OPF-like problem in WPP.

However, the C-DEEPSO performance is related to the choice of its main parameters: the weight mutation and the particle communication. Using the `irace` package as an internal C-DEEPSO mechanism to automatically fine-tune the parameters, we propose a framework capable of establishing an automated controller to carry out the daily electrical dispatch. In the experimental design, 24 h are discretized into 15 min intervals, totalizing 96 test scenarios. The proposed approach finds the best parameter setting yielding the optimal decision variables for each test scenario. Since the daily electrical dispatch problem is solved by breaking it down into 96 sub-problems in a recursive manner, the proposed approach can be seen as a dynamic way of tackling the OPF-like problem in WPP. To the best of our knowledge, this innovation has not yet been found in the state-of-the-art literature. More specifically, this paper presents the following contributions:

- A new electric dispatch controller with automatic adjustment to solve OPF-like problems in WPP;
- A novel framework to fine-tune the parameters of the C-DEEPSO algorithm. For this, the `irace` package is coupled to the internal mechanism of C-DEEPSO;
- A new approach to compare stochastic algorithms is performed via an application of post hoc tests using the DSCtool in order to validate the statistical robustness of the results;
- An in-depth performance assessment of C-DEEPSO + `irace` compared to two different algorithms, DEPPSO and MVMO, when solving the OPF-like problem applied to WPPs;
- Obtained results indicate a competitive performance favoring C-DEEPSO in terms of efficiency and accuracy when applied to the OPF-like problem;
- A projection analysis is conducted indicating reduction of the system energy losses around 2.35 MWh per day.

The rest of the paper is structured as follows. Section 2 presents Materials and Methods: the reactive power optimization applied to WPPs; the C-DEEPSO algorithm and the optimal adjustment control are proposed. Section 3 describes the experiments and results. Section 4 carries out a discussion about the obtained results. Finally, Section 5 includes an overall conclusion and future work.

2. Materials and Methods

2.1. Optimal Power Flow Modeling for Reactive Electric Dispatch

In a competitive environment, the active/reactive power dispatch problem can be formulated considering an alternating current representation and solved using the OPF model. Usually, consumers depend on a reliable and secure supply of electricity. Thus, the study of OPF plays an important role in the energy management system in which the entire system operation is supervised at each time interval. Generally, an OPF problem can be formulated minimizing losses in the power production. In addition to this, a variety of

formulations that take other features into account has also gained attention in the energy area, such as minimizing costs and pollutant emissions.

Traditionally, OPF is a non-linear, mixed-integer, and difficult-to-solve optimization problem being considered as an NP-hard problem [45]. OPF has equality and inequality constraints that need to be satisfied during the optimization process. Equality and inequality constraints are related to power balance at each node and power flow equations and the operational limits (such as line flows, voltages, and security constraints) [6,9]. This work used as an OPF-like model the well-known IEEE 41-bus system benchmark problem, which characterizes a reactive electrical dispatch problem for an offshore WPP [33].

2.1.1. Optimal Power Flow Formulation

The formulation of OPF for reactive power dispatch aims to minimize the total losses (in MWh) of the energy system. Table 2 displays the terms used in the mathematical model.

Table 2. Description of all terms in the mathematical model.

Term	Description
P_{loss}	Total losses of the energy system (in MWh)
NL	Total number of lines in system
G_k	Conductance of line K
U	Voltage magnitude of lines in (in kV): sending end (i); receiving end (j)
δ	Angle of the bus voltages (in degrees)
P_i	Active power injected (in MW)
Q_i	Reactive power (in MVar)
θ	Voltage angle (in degrees)
U_i^{min}, U_i^{max}	Bus voltage magnitude in limits minimum and maximum (in kV)
S_{ij}	Apparent power flow injection (in MVA)
T_k	Tap change limits
Q_k	Number of capacitor/reactor banks
NB	Number of buses

Equation (1) describes the objective function adopted in the IEEE 41-bus system:

$$min\ P_{loss}\ (in\ MWh) = \sum_{K=1}^{N_L} G_K[U_i^2 + U_j^2 - 2U_iU_j\cos(\delta_i - \delta_j)], \tag{1}$$

in which the term N_L represents the total number of lines in the system. G_K is the conductance of the line K; U_i and U_j are the magnitudes of the sending end and receiving end voltages of the line. The terms δ_i and δ_j are angles of the bus voltages.

To solve this OPF problem, the optimization algorithm is used as an automatic control to provide an efficient functioning of the WPP according to the input of the reactive power condition of the system. Reactive power is susceptible to failures and losses that must be minimized. Adjustments to minimize losses can be done at the so-called VAR points. The VAR points are inputs to command wind turbines. The input schedules of wind turbines are operated by the WPP control system by allocating the necessary reactive power equally to each generator in the farm.

This optimal reactive power dispatch problem must comply with a group of hard constraints, when the case set conditions for the variables must necessarily be satisfied, or soft set, in which case some variable values can suffer penalization if the conditions are not satisfied. The following set defines the constraints linked to the OPF studied in this work:

- Active (in MW) and Reactive (in MVar) power balance

$$P_i = P_i^{gen} - P_i^{load} = \sum_{j=1}^{n} U_i U_j [G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j)], \tag{2}$$

$$Q_i = Q_i^{gen} - Q_i^{load} = \sum_{j=1}^{n} U_i U_j [G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j)], \tag{3}$$

in which P_i is the active power injected, Q_i is the reactive power, U_i is the voltage magnitude, and θ_i is the voltage angle.

- Bus voltage (in kV)

$$U_i^{min} \leq U_i \leq U_i^{max}, \tag{4}$$

in which U_i corresponds to the bus voltage magnitude vector and its corresponding limits (min and max).

- Branch apparent power flow (in MVA)

$$S_{ij}^{min} \leq S_{ij} \leq S_{ij}^{max}, \tag{5}$$

in which S_{ij} (MVA) is the apparent power flow injection at the sending end of the transmission circuit connecting bus *i* to bus *j*. S_{ij}^{min} and S_{ij}^{max} are the maximum and the minimum limits of apparent power flow.

- Transformer tap

$$T_k^{min} \leq T_k \leq T_k^{max}, \tag{6}$$

in which T_k corresponds to the vectors of transformer discrete tap change limits (minimum and maximum). The term T_k also means the tap setting position of the On-Load Tap Changer (OLTC).

- Shunt VAR

$$Q_k^{min} \leq Q_k \leq Q_k^{max}, \tag{7}$$

in which Q_k are capacitor/reactor banks discrete variables.

The penalization of the fitness value of infeasible solutions is a useful approach for treating constraints [42,46–48]. Therefore, to meet the constraints, we use the fitness function (f_p) provided in the Equation (8):

$$f_p = \begin{bmatrix} 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} max(0, Pg_{REF} - \overline{Pg_{REF}})^2 + max(0, \underline{Pg_{REF}} - Pg_{REF})^2 \\ \sum_{i=1}^{NB_{PQ}} [max(0, U_i - \overline{U_i}) + max(0, \underline{U_i})]^2 \\ \sum_{i=1}^{NC} [max(0, |S_{ij}| - \overline{S_{ij}}) + max(0, |S_{ji}| - \underline{S_{ij}})]^2 \\ \sum_{i=1}^{NB_{REF+PU}} [max(0, Q_i - \overline{Q_i}) + max(0, \underline{Q_i} - Q_i)]^2 \end{bmatrix}. \tag{8}$$

in which *REF* is the voltage magnitude, *NB* is the number of buses, and *NC* is the number of circuits in the network.

2.1.2. Offshore Wind Power Plant (WPP)

The plant's components, in general, have to be well organized for the functioning of point of common coupling (PCC). The PCC corresponds to the point in which the generating facility's local electric power system connects to the utility's electric system and measures the system losses. Therefore, the task of the proposed WPP optimizer system is to control set points of each generator and the active or passive reactive power compensation

equipment, so that control conditions at the PCC are attended. In this work, a version of the WPP modeling (IEEE 41-bus test system) is used to test the robustness of the proposed approach to solve the problem of optimal reactive power dispatch addressed. Figure 2 shows the control scheme of a WPP—a typical topology system. The data about the test network is provided in Appendix A.
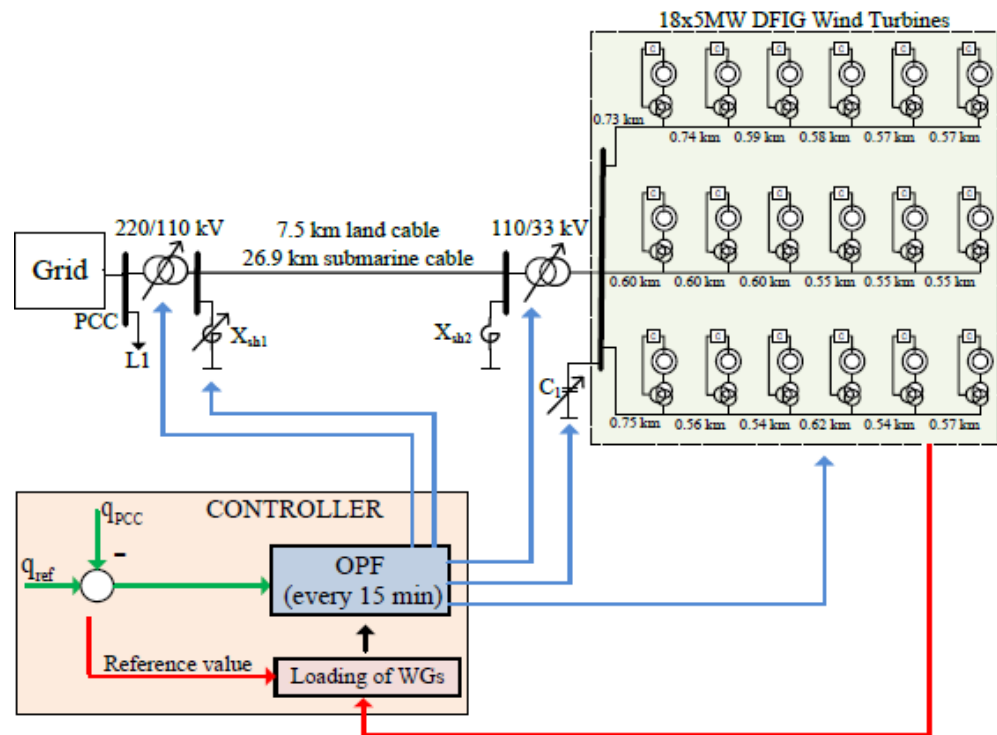

Figure 2. WPP control scheme layout inspired on [49].

From the scheme detailed in Figure 2, the reactors X_{sh1} and X_{sh2} are adjusted continuously; C_1 is the capacitor, and it provides support to assist reactive power. The $L1$ term is the active power indicating the load generated by the plant. The reactive power (q_{ref}) is provided until it reaches the power of common coupling (q_{PCC}) by the controller. Here, the difference between q_{ref} and q_{PCC} for normal is a constraint in which q_{PCC} is the actual reactive power injection at the PCC. The OPF addressed here is considered a mixed-integer problem and is over-contrained. The problem has 22 optimization variables, comprising 18 continuous variables associated with the wind generator reactive power set-points, 02 discrete variables associated with the stepwise adjustable on-load transformers' tap position, and 02 continuous variables defining the adjustment of shunts (X_{sh1} and X_{sh2}). Table 3 describes the characteristics of the IEEE 41-bus test system and the respective description of the problem taking into account the mathematical formulation described in Section 2.1.1.

2.2. The C-DEEPSO Algorithm

The Canonical Differential Evolutionary Particle Swarm Optimization (C-DEEPSO) [37] is a single-objective algorithm based on the EPSO (Evolutionary Particle Swarm Optimization) [50] and Differential Evolution (DE). C-DEEPSO is an improvement of DEEPSO (see [51,52]). C-DEEPSO has been successfully applied to several optimization problems in power systems, such as: minimization of costs in power production [53], active power dispatch in large scale grids [37], cascade operation in hydropower plants [39], study of energy generation via renewable sources and energy storage systems [41], hybrid microgrid systems operation [43], minimization of active power losses [40], control optimization in hydraulic power plants [44], and pattern classification [54].

Table 3. IEEE 41-bus test system characteristics.

		IEEE 41-Bus Test System	
Description of test system			
		Generators	18
		Linked cable	1
	Transfomers	Fixed tap: T1	33
		Fixed tap: T2	13
Description of the optmization problem		Continuous variables	18
	Optimization variables	Discrete variables	2
		Continuous and stepwise variables	2
		Constraints system	123

C-DEEPSO working mechanisms depend on mutation cycle, recombination, and selection procedures. The idea is to generate a new offspring population such that the overall fitness of the swarm is refined. mboxC-DEEPSO uses a memory archive (Memory B) to use the information archived from previous generations in order to refine the search process. For improving the search assimilation, the movement equation adopted is described by Equations (9) and (10):

$$V_t = w_I^* \times V_{t-1} + w_A^* \times (X_{best} + F \times (X_{t-1} - X_r)) + w_C^* \times \mathcal{C} \times (X_{gb}^* - X_{t-1}), \qquad (9)$$

$$X_t = X_{t-1} + V_t, \qquad (10)$$

in which V_t is the velocity of the particle, and X is the current solution. X_{best} is the best solution, and X_{gb} the global best solution. The term t means the current generation. $\mathcal{C}$ is a $n \times n$ diagonal matrix that helps the algorithm to escape to a better search region (see [39]). Inertia (w_I), assimilation (w_A), and communication (w_C) are the weights used. X_r is obtained via uniform combination of current and memory populations. Here, we used inspiration from DE algorithm. The *DE/best/1* operation is performed inside C-DEEPSO when X_{t-1} is better than X_r. In C-DEEPSO, the weights associated with inertia, assimilation, and communication are changed accordingly to Equation (11):

$$w^* = w + \tau \times \mathcal{N}(0,1), \qquad (11)$$

in which τ represents the mutation rate. C-DEEPSO uses a Gaussian Distribution ($N(0,1)$) to move slightly the current solution in the search space.

The global best solution X_{gb} is mutated in order to attract the current individual as next as possible to a attracting promising bay of solutions. The current individual is then slightly moved in the search space using a Gaussian Distribution. The term X_{gb} is mutated using the Equation (12):

$$X_{gb}^* = X_{gb}[1 + \tau \times \mathcal{N}(0,1)]. \qquad (12)$$

C-DEEPSO pseudo-code is shown in Algorithm 1, in which NP is the population size, MB is the memory archive size, and G means generations used. The terms P and τ are the communication probability and is the mutation rates, respectively.

Algorithm 1: C-DEEPSO algorithm.

1　**begin**
2　　SET *NP*, *MB*, *P*, *G*, and τ;
3　　EVALUATE *NP*
4　　UPDATE X_{gb} and *MB*;
6　　**while** *stopping criterion is not satisfied* **do**
8　　　**for** *all particles of swarm* **do**
9　　　　CALCULATE X_r using $S_g P_b$-*rnd*;
10　　　　COPY X_t;
11　　　　MUTATE weights using Equation (11) ;
12　　　　MOVE X_t and its copy using Equation (9);
13　　　　EVALUATE X_t and its copy;
14　　　　SELECT X_{best} to be part of the new *NP*
15　　　　　(*t = 2 tournament with uniform probability distribution*);
16　　　**end**
17　　　UPDATE X_{gb} and *MB*;
18　　**end**
19　**end**

2.3. Optimal Adjustment Control Proposed: C-DEEPSO Integrated with `irace` Package

The electrical dispatch referring to one day (24 h) has been discretized into 15 min intervals, resulting in 96 test scenarios to be solved. Our proposal is to perform the dynamic dispatch of the system performing the automatic adjustment of the C-DEEPSO algorithm. To achieve this goal, we have integrated the `irace` package within the C-DEEPSO algorithm to automatically adjust the rates of its main operators: mutation and communication. This measure is in line with good practices for carrying out fine-tuning of parameters to evolutionary algorithms.

The fine-tuning process is a methodology that is applied to find the best configurations of parameters considering a set of possible values for the parameters for each problem. We have performed the fine-tuning process using `irace` tool [38]. The `irace` is an *R* package that is able to automatically configure an algorithm when its performance depends on the choice of the parameter settings.

As the OPF problem is both dynamic and a *blackbox* problem (IEEE 41-bus system), we have created an interface between `irace` and the Matlab script implementing the C-DEEPSO algorithm. This interface calls C-DEEPSO, runs it only one time in the problem requested by the `irace`, and returns the best fitness value. The `irace` package then makes a series of statistical comparisons using hypothesis tests (to check, for instance, mean differences). In our experimental design, we are looking for the best rates for Communication and Mutation Probability parameters for each test scenario.

The `irace` iterates, for each one of the 96 scenarios, all the possible configurations of mutation probability and communication rate and compares them, excluding the ones that are proven statistically worse. In the end of the iterations, the `irace` returns a dataframe with all tested configurations (ordered as tested) and a list of the best configurations, called elite configurations. This dataframe, called `irace.Rdata`, also has a list of rejected configurations that are proven statistically worse than the elite configurations. Figure 3 exemplifies the proposed optimal controller in action. The previous (or classical) optimized control is composed by an optimization algorithm (A), such as DEEPSO, MVMO, or other, that solves the OPF problem (B) and finds an optimized solution (C). In our proposed optimized control, we conduct a process that finds the best parameter configuration for C-DEEPSO algorithm before running it on the OPF-like problem, to obtain the optimized solutions via C-DEEPSO for solving the electric dispatch in a WPP.
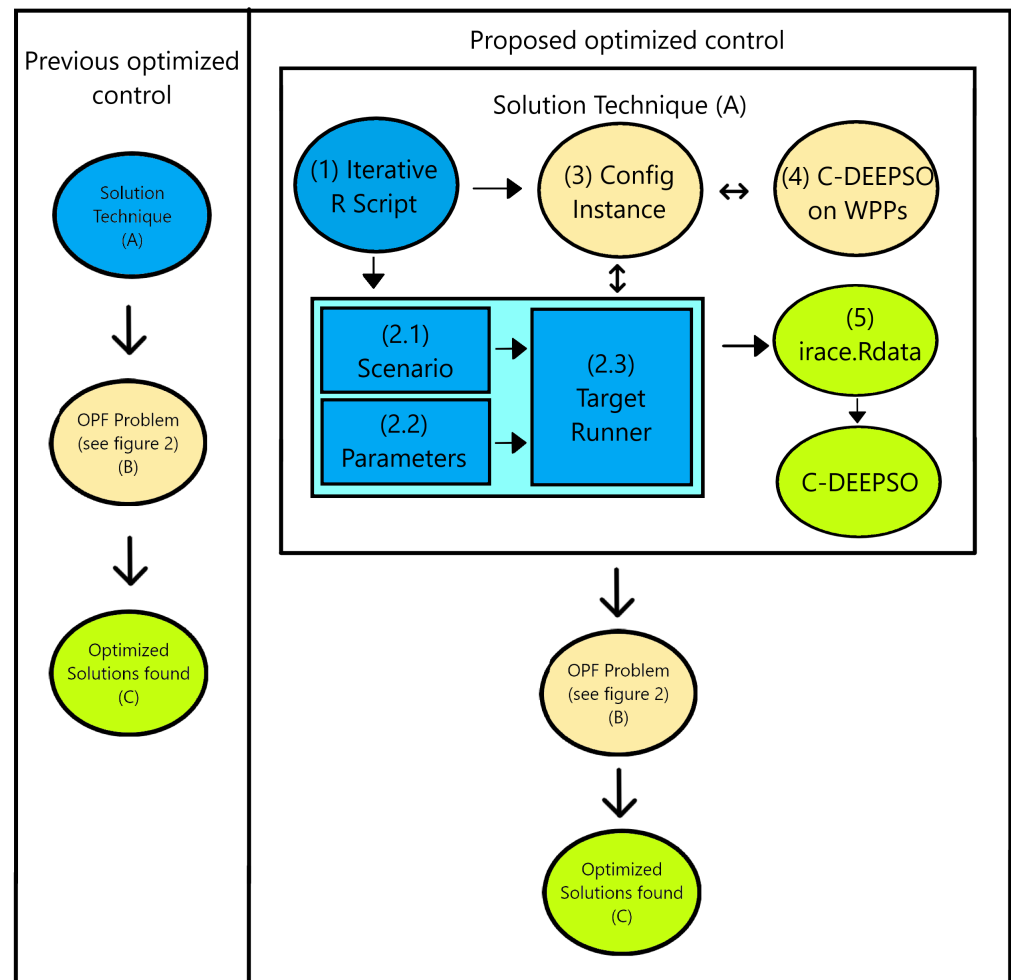
Figure 3. Proposed optimized control: the iterative *R* Script (1) is responsible for iterating the instances of the WPP problem and calling `irace` (2). The `irace` uses three main files: the scenario (2.1), where we set the number of times the algorithm should run, the hypothesis test we want to use, and the confidence we want in our results; the parameters (2.2), where we set what parameters we want to find the best values in the fine-tuning process; and the target runner (2.3), which is responsible for running the algorithm and performing the tests to find out the best parameters values. There is also one Config Instance Matlab script (3) that creates an interface between the `irace` and the C-DEEPSO (4), running C-DEEPSO for the WPP problem instance (from iterative *R* script) with the `irace` parameters. In the end, the `irace` returns a data structure called `irace.Rdata` (5) with the results.

3. Experiments and Results

The experimental part of this work is carried out under the observation of the daily electrical dispatch. Generally, when planning the electrical dispatch operation, the seasonality of the region in relation to the generating source must be taken into account. According to Arce et al. [55], the main stages of dispatch operation planning, taking into account seasonality, are: long (several-year horizon), medium (one-year horizon), short-term (one-week horizon), daily (one day), and in real time. In this work, we have chosen to carry out a study under the bias of daily planning of electrical dispatch operation in a wind power plant (WPP). This approach is justified by the fact of having in hand data for only one day testing in IEEE 41 Bus-System. The main rationale behind our choice has been the possibility of a performance comparison among the proposed approach and the two state-of-the-art approaches, DEEPSO and MVMO.

The electrical dispatch in WPPs discussed in this work is dynamic in nature. To handle its dynamicity, we use an integration between C-DEEPSO and `irace`, which works like an optimized automatic controller. The WPP system has 18 generators (5 MW) that are connected to the transformers (100 MVA) and the grid (220 kV) through a submarine cable (110 kV—around 30 km length). The transformers provide OLTC service and operate T1 (% kV with 33 taps and 220 kV to PCC) and T2 with 13 taps. There is no equality in the distances between the generators and the WPP main collector. Wind turbine terminals need to be maintained between 0.92 and 0.97 kV (which corresponds 920–970 V). The nominal voltage value is 0.95 kV (950 V). The system also has a shunt reactor adjusted with ON/OFF control (500 Ω) to adequate the excessive charging of the submarine cable.

The goal is to provide optimized sets of all VAR sources to meet the actual reactive power requirement at PCC including: the individual reactive power of each wind turbine, OLTC adjustments, and shunt reactor ON/OFF positions. The controller calculates the optimal adjustment in intervals of 15 min, in a total of 96 intervals, for which the reactive electric dispatch must be solved. Simulation has been done to show the reactive power control problem, which is defined by progressive changes in the necessary reactive power (q_{ref}). The experimental design contemplates over a period of one day (24 h discretized to in intervals of 15 min). Figure 4 shows a typical WPP output.
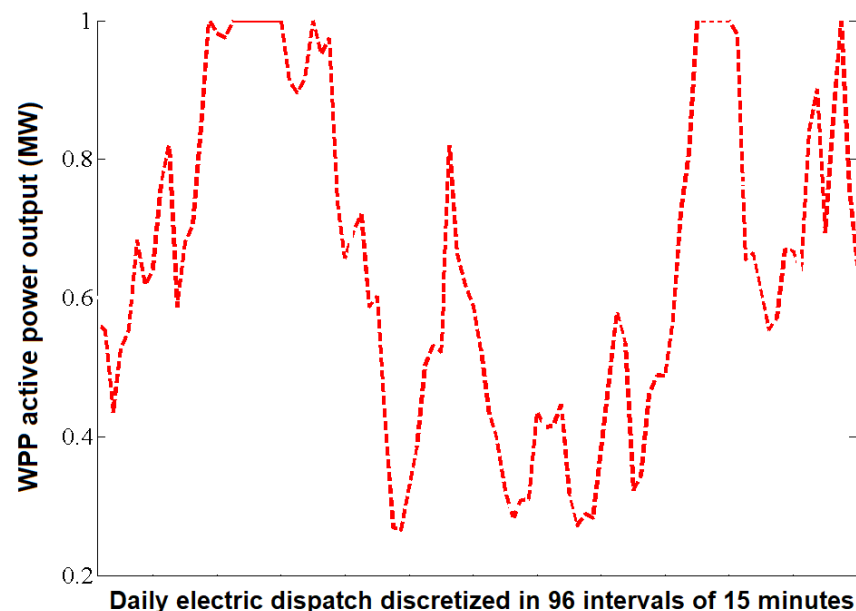
Figure 4. Day profile of active power dispatch for individual wind turbines.

A control strategy must be carried out to ensure system availability and to continuously meet reactive power (q_{ref}). Here, the adopted experimental design is used to show that C-DEEPSO is able to solve the OPF-like problem addressed, respecting the constraints. C-DEEPSO was runned 31 times in each one of the 96 intervals of power production. The computational simulation was done using an Intel i9 3.7 Ghz and 64 GB de RAM on Ubuntu 20.04.2.0 LTS Operating System computer. The code was implemented in Matlab using the MATPOWER package. The integration of R (4.1.1) and Matlab was done with a Python (3.7) script.

To validate our proposal, the performance of C-DEEPSO integrated with `irace` is compared to the performance of DEEPSO and MVMO algorithms. Since C-DEEPSO has been derived from DEEPSO, the comparison between those algorithms also aims to see if the improvements brought by C-DEEPSO are relevant. On the other hand, MVMO is the reference algorithm for this problem. DEEPSO and MVMO [33] results have been extracted from [34], where they were used in their best parameter configuration. Figure 5 shows the result obtained by each tested algorithm: C-DEEPSO + `irace`, DEEPSO, and MVMO.

The graph presents the range of all scenarios, emphasizing cases 14–31 in its expansion. C-DEEPSO shows the best result among the tested methods.
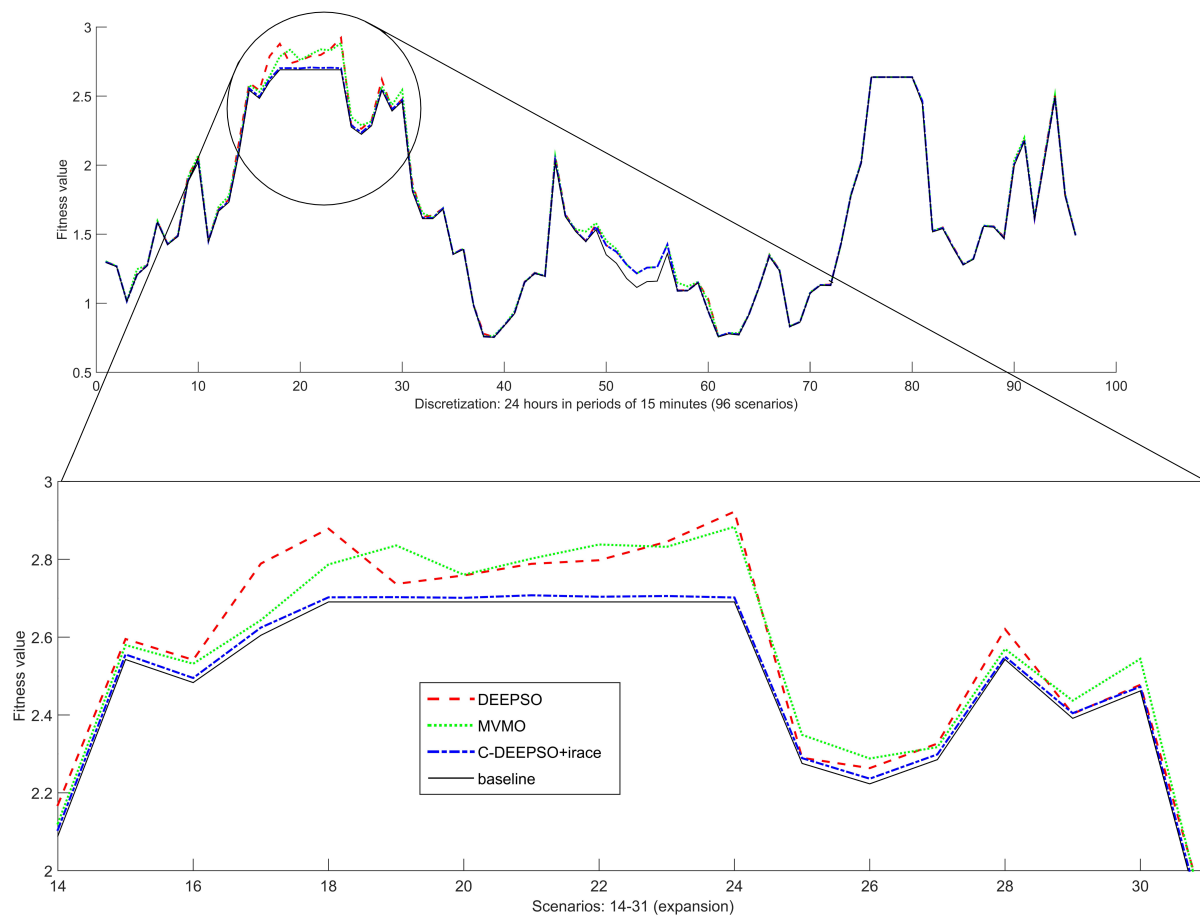
Figure 5. Algorithms results with an expansion graph (scenarios 14–31).

The `irace` package implements the iterated racing methodology [38], a method for automatic configuration with steps: (1) sampling new configurations according to a particular distribution; (2) selecting the best configurations from the newly sampled ones by means of racing; and (3) updating the sampling distribution in order to bias the sampling towards the best configurations. Table 4 shows the algorithms' results in terms of average (AVR) and standard deviation (STD). The configurations of Mutation and Communication rates found by `irace` are also displayed. As can be seen in Table 4, C-DEEPSO coupled to `irace` obtained, after the iterated racing process, a specific set of parameters for each test scenario.

Results from 31 runs of each algorithm show that C-DEEPSO has the lowest average in 100% of cases tested. To show the efficiency of C-DEEPSO, we carried out a more complete statistical analysis. We used a new tool to perform a post hoc Kolmogorov–Smirnov test to perform a hypothesis test about mean differences, the DSCTool [56]. We compared the results of the algorithms in order to rank them for each of the problem instances using DSCTool. DSCTool is a statistical tool used to compare the performance of algorithms under different scenarios. We applied the DSCTool with the Kolmogorov–Smirnov test with 95% confidence to compare the results of C-DEEPSO against the MVMO and DEEPSO algorithms for all 96 instances of the WPP problem. The algorithms have been ranked as shown in Table 4. (Aiming to allow reproducibility and extension of our results, an online publicly repository is made available at https://github.com/jvcavancini/C-DEEPSO (accessed on 17 October 2021). It contains our proposed approach (C-DEEPSO

+ irace), the WPP model, and a .csv file containing the optimal decision variable values for each test scenario, corresponding to the median solution over the 31 runs.)

Table 4. Comparative result of the C-DEEPSO + `irace`, DEEPSO and MVMO algorithms. Legend: scenario (Sc.) is the number of each measured interval of energy production (96); significance (S.) with $\alpha = 5\%$ on Kolmogorov–Smirnov test ("+" reject null hypothesis of mean difference and "=" not reject the null hypothesis); optimal mutation rate found (Mut.); optimal communication rate found (Com.); mean (mean results of 31 runs); STD (standard deviation of 31 runs).

Sc.	S. (5%)	C-DEEPSO + `irace` Mut.	Com.	AVR	STD	DEEPSO AVR	STD	MVMO AVR	STD
1	(+)	0.70	0.50	**1.2961**	**0.0063**	1.3004	0.0065	1.2995	0.0021
2	(+)	0.30	0.40	**1.2670**	**0.0007**	1.2737	0.0068	1.2709	0.0025
3	(+)	0.50	0.20	**1.0137**	**0.0032**	1.0185	0.0091	1.0180	0.0062
4	(+)	0.90	0.50	**1.2061**	**0.0016**	1.2104	0.0067	1.2142	0.0125
5	(+)	0.10	0.30	**1.2745**	**0.0012**	1.2774	0.0049	1.2775	0.0030
6	(+)	0.40	0.40	**1.5893**	**0.0013**	1.5907	0.0024	1.5950	0.0030
7	(+)	0.60	0.90	**1.4272**	**0.0021**	1.4306	0.0039	1.4317	0.0034
8	(+)	0.50	0.40	**1.4864**	**0.0023**	1.4901	0.0027	1.4912	0.0018
9	(+)	0.70	0.50	**1.8886**	**0.0067**	1.9206	0.0251	1.9127	0.0177
10	(+)	0.60	0.70	**2.0370**	**0.0068**	2.0599	0.0210	2.0681	0.0248
11	(+)	0.90	0.80	**1.4493**	**0.0018**	1.4605	0.0192	1.4668	0.0288
12	(+)	0.20	0.10	**1.6732**	**0.0021**	1.6879	0.0092	1.6967	0.0202
13	(+)	0.10	0.10	**1.7389**	**0.0060**	1.7545	0.0092	1.7653	0.0197
14	(+)	0.60	0.80	**2.1052**	**0.0067**	2.1385	0.0232	2.1313	0.0158
15	(+)	0.60	0.50	**2.5555**	**0.0096**	2.5764	0.0157	2.5835	0.0178
16	(+)	0.70	0.30	**2.4950**	**0.0081**	2.5230	0.0226	2.5268	0.0157
17	(+)	0.70	0.40	**2.6245**	**0.0127**	2.7631	0.0632	2.7530	0.0497
18	(+)	0.70	0.30	**2.7023**	**0.0155**	2.8377	0.0498	2.8328	0.0653
19	(+)	0.60	0.40	**2.7028**	**0.0139**	2.8389	0.0547	2.8321	0.0596
20	(+)	0.90	0.30	**2.7010**	**0.0185**	2.8295	0.0629	2.8368	0.0379
21	(+)	0.50	0.10	**2.7075**	**0.0225**	2.8264	0.0541	2.8243	0.0522
22	(+)	0.70	0.30	**2.7038**	**0.0204**	2.8400	0.0420	2.8105	0.0433
23	(+)	0.80	0.40	**2.7057**	**0.0174**	2.8492	0.0521	2.8130	0.0604
24	(+)	0.90	0.30	**2.7018**	**0.0162**	2.8246	0.0604	2.8306	0.0384
25	(+)	0.50	0.70	**2.2891**	**0.0017**	2.3205	0.0267	2.3284	0.0260
26	(+)	0.90	0.80	**2.2363**	**0.0085**	2.2791	0.0185	2.2739	0.0227
27	(+)	0.90	0.50	**2.2987**	**0.0008**	2.3322	0.0199	2.3268	0.0164
28	(+)	0.70	0.50	**2.5500**	**0.0051**	2.5840	0.0246	2.5884	0.0252
29	(+)	0.90	0.70	**2.4046**	**0.0047**	2.4348	0.0256	2.4355	0.0167
30	(+)	0.60	0.70	**2.4728**	**0.0041**	2.5042	0.0195	2.5105	0.0216
31	(+)	0.90	0.90	**1.8216**	**0.0095**	1.8371	0.0133	1.8455	0.0319
32	(+)	0.50	0.30	**1.6190**	**0.0032**	1.6326	0.0126	1.6384	0.0242
33	(+)	0.40	0.70	**1.6158**	**0.0020**	1.6206	0.0055	1.6215	0.0022
34	(=)	0.10	0.80	**1.6868**	**0.0026**	1.6888	0.0039	1.6901	0.0024
35	(=)	0.30	0.90	**1.3567**	**0.0022**	1.3586	0.0032	1.3593	0.0035
36	(+)	0.70	0.80	**1.3935**	**0.0016**	1.3961	0.0032	1.3979	0.0039
37	(+)	0.90	0.90	**0.9846**	**0.0011**	0.9891	0.0080	0.9863	0.0023
38	(+)	0.50	0.90	**0.7589**	**0.0015**	0.7652	0.0154	0.7616	0.0024
39	(=)	0.40	0.80	**0.7549**	**0.0015**	0.7603	0.0126	0.7578	0.0031
40	(=)	0.30	0.90	**0.8379**	**0.0008**	0.8402	0.0071	0.8419	0.0053
41	(+)	0.40	0.40	**0.9269**	**0.0136**	0.9272	0.0073	0.9272	0.0039
42	(+)	0.80	0.50	**1.1522**	**0.0003**	1.1555	0.0052	1.1555	0.0023
43	(+)	0.90	0.70	**1.2172**	**0.0012**	1.2209	0.0065	1.2215	0.0044
44	(+)	0.80	0.40	**1.1964**	**0.0012**	1.2018	0.0099	1.1997	0.0022
45	(+)	0.70	0.80	**2.0350**	**0.0061**	2.0626	0.0186	2.0708	0.0257

Table 4. *Cont.*

		C-DEEPSO + irace				DEEPSO		MVMO	
Sc.	S. (5%)	Mut.	Com.	AVR	STD	AVR	STD	AVR	STD
46	(+)	0.60	0.10	**1.6322**	**0.0026**	1.6450	0.0100	1.6557	0.0256
47	(+)	0.90	0.60	**1.5231**	**0.0019**	1.5351	0.0109	1.5530	0.0339
48	(+)	0.80	0.30	**1.4491**	**0.0012**	1.4647	0.0211	1.4668	0.0220
49	(+)	0.50	0.80	**1.5546**	**0.0004**	1.5732	0.0143	1.5935	0.0382
50	(+)	0.90	0.50	**1.4189**	**0.0001**	1.4217	0.0040	1.4298	0.0155
51	(+)	0.80	0.90	**1.3725**	**0.0001**	1.3730	0.0006	1.3795	0.0097
52	(=)	0.80	0.90	**1.2804**	**0.0000**	1.2803	0.0000	1.2804	0.0001
53	(+)	0.70	0.80	**1.2160**	**0.0000**	1.2160	0.0001	1.2161	0.0001
54	(=)	0.70	0.90	**1.2579**	**0.0000**	1.2578	0.0000	1.2578	0.0000
55	(=)	0.60	0.90	**1.2610**	**0.0000**	1.2611	0.0000	1.2611	0.0000
56	(+)	0.60	0.70	**1.4257**	**0.0001**	1.4279	0.0029	1.4352	0.0164
57	(+)	0.80	0.50	**1.0896**	**0.0013**	1.1006	0.0192	1.1134	0.0098
58	(+)	0.80	0.70	**1.0940**	**0.0057**	1.1071	0.0241	1.1287	0.0379
59	(+)	0.40	0.30	**1.1506**	**0.0027**	1.1626	0.0252	1.1852	0.0330
60	(+)	0.90	0.50	**0.9422**	**0.0012**	0.9676	0.0411	0.9699	0.0126
61	(+)	0.90	0.40	**0.7590**	**0.0009**	0.7683	0.0195	0.7642	0.0098
62	(+)	0.90	0.60	**0.7825**	**0.0079**	0.7859	0.0103	0.7883	0.0133
63	(+)	0.90	0.50	**0.7726**	**0.0010**	0.7820	0.0185	0.7800	0.0126
64	(+)	0.90	0.50	**0.9194**	**0.0007**	0.9249	0.0168	0.9238	0.0095
65	(+)	0.90	0.90	**1.1182**	**0.0007**	1.1215	0.0043	1.1202	0.0024
66	(+)	0.90	0.50	**1.3421**	**0.0012**	1.3444	0.0022	1.3445	0.0014
67	(+)	0.40	0.90	**1.2360**	**0.0013**	1.2396	0.0048	1.2393	0.0013
68	(+)	0.40	0.70	**0.8317**	**0.0009**	0.8387	0.0145	0.8341	0.0036
69	(+)	0.50	0.70	**0.8642**	**0.0044**	0.8690	0.0106	0.8660	0.0021
70	(+)	0.50	0.80	**1.0739**	**0.0006**	1.0766	0.0045	1.0757	0.0015
71	(+)	0.50	0.70	**1.1317**	**0.0005**	1.1339	0.0031	1.1344	0.0041
72	(+)	0.70	0.70	**1.1299**	**0.0004**	1.1329	0.0034	1.1324	0.0028
73	(=)	0.50	0.10	**1.4195**	**0.0016**	1.4244	0.0035	1.4223	0.0021
74	(+)	0.90	0.60	**1.7804**	**0.0041**	1.7891	0.0250	1.7833	0.0038
75	(+)	0.80	0.80	**2.0113**	**0.0003**	1.2987	0.0018	2.0223	0.0030
76	(+)	0.90	0.50	**2.6373**	**0.0000**	1.2964	0.0010	2.6373	0.0000
77	(=)	0.20	0.20	**2.6373**	**0.0000**	1.2972	0.0018	2.6373	0.0000
78	(+)	0.30	0.40	**2.7373**	**0.0000**	1.2963	0.0010	2.6373	0.0000
79	(=)	0.80	0.30	**2.6373**	**0.0000**	1.2974	0.0020	2.6373	0.0000
80	(=)	0.30	0.40	**2.6373**	**0.0000**	2.6373	0.0000	2.6373	0.0000
81	(+)	0.70	0.20	**2.4610**	**0.0012**	2.4738	0.0373	2.4637	0.0070
82	(+)	0.80	0.80	**1.5201**	**0.0017**	1.5227	0.0030	1.5248	0.0022
83	(+)	0.40	0.50	**1.5445**	**0.0017**	1.5465	0.0030	1.5493	0.0020
84	(+)	0.60	0.90	**1.4070**	**0.0022**	1.4095	0.0026	1.4096	0.0013
85	(+)	0.10	0.90	**1.2795**	**0.0019**	1.2822	0.0035	1.2819	0.0012
86	(+)	0.60	0.90	**1.3203**	**0.0028**	1.3238	0.0033	1.3229	0.0018
87	(+)	0.10	0.50	**1.5585**	**0.0014**	1.5608	0.0025	1.5635	0.0014
88	(+)	0.10	0.90	**1.5526**	**0.0018**	1.5546	0.0022	1.5574	0.0020
89	(+)	0.40	0.50	**1.4724**	**0.0012**	1.4757	0.0034	1.4769	0.0017
90	(+)	0.20	0.70	**2.0066**	**0.0026**	2.0119	0.0068	2.0221	0.0063
91	(+)	0.80	0.70	**2.1807**	**0.0004**	2.1924	0.0126	2.1981	0.0053
92	(=)	0.30	0.60	**1.6123**	**0.0018**	1.6172	0.0024	1.6223	0.0032
93	(+)	0.80	0.90	**2.0554**	**0.0059**	2.0642	0.0102	2.0719	0.0052
94	(+)	0.60	0.90	**2.4899**	**0.0043**	2.5161	0.0236	2.5123	0.0071
95	(+)	0.60	0.80	**1.7829**	**0.0015**	1.7849	0.0036	1.7923	0.0050

Table 4. *Cont.*

Sc.	S. (5%)	C-DEEPSO + `irace`				DEEPSO		MVMO	
		Mut.	Com.	AVR	STD	AVR	STD	AVR	STD
96	(+)	0.80	0.40	**1.4976**	**0.0016**	1.5001	0.0022	1.5030	0.0028
		Total		38.01 (MWh)		38.80 (MWh)		40.35 (MWh)	

4. Discussion

We adopted an $\alpha = 5\%$ (significance level) to conduct the inference statistical test. In each power production interval (in a total of 96), if the Kolmogorov–Smirnov test finds a significant difference between the mean of algorithms, the DSCtool provides the ranking among of algorithm performances. Table 4 shows the signal of statistical test realized: (+) exists differences among the means of algorithms with confidence of 95%, and (=) null hypothesis of equality of means is rejected. In our analysis, 84 test cases (87% of them, respectively) show that there are differences among the algorithm means. However, in 12 out of 96 scenarios, or in 12.5% of the scenarios, the Kolmogorov–Smirnov test was unable to reject the null hypothesis.

Thus, we can say that C-DEEPSO + `irace` has results with greater robustness when compared to the others in 87% of cases. Observe that C-DEEPSO + `irace` shows a lower mean value and presents the maximum ranking in the Kolmogorov–Smirnov test, as shown in Table 4 with symbol (+). In the remaining 12 scenarios, the null hypothesis cannot be rejected, showing that there is no statistical significance in the difference of the algorithm means when compared to DEEPSO (indicated by the symbol (=) symbol in Table 4). To summarize, in 87.5% of the test cases, C-DEEPSO + `irace` is the most efficient algorithm when compared to DEEPSO. In 12.5% of the test cases, C-DEEPSO + `irace` and DEEPSO are tied in the first position. It is worthwhile to notice that, in all 96 scenarios, C-DEEPSO + `irace` shows a low average in comparison to MVMO (state-of-the-art algorithm). Therefore, we can say that MVMO is always classified in the third position for solving the OPF-like problem addressed in this work.

Therefore, we consider that C-DEEPSO + `irace` is an effective method to solve the electric dispatch problem performing an optimal control of the WPP. C-DEEPSO minimizes the transmission losses. Furthermore, it complies with PCC power requirements ensuring the adjustment of all correlated variables. Observe that DEEPSO and MVMO use a single set of optimal parameters considering the whole time scenario. The novelty of the proposed approach is to treat the OPF-like problem in WPP as having a dynamic optimal set of parameters. Integrating `irace` with C-DEEPSO, the optimal parameters have been adjusted for each of the 96 test cases. This dynamic parameter configuration is responsible for the optimized performance of the proposed approach. C-DEEPSO has proved to be efficient and competitive for solving the problem in a dynamic way. Our algorithm works as a joint electrical dispatch control that learns from the system's input data at each measured time interval. `irace` identifies the best mutation and communication rates at each time interval, ensuring the robustness of the proposed system controller.

The total sum of losses is shown in Table 4 for each algorithm. The proposed approach presents a cumulative daily average value of 38.01 MWh per day, while DEEPSO and MVMO present 38.80 MWh and 40.35 MWh, respectively. As shown, the decrease in daily cumulative value is approximately 3% compared to C-DEEPSO and 6% in relation to MVMO. The statistical tests indicate these values show significant improvements. Considering C-DEEPSO + `irace` and the reference algorithm, MVMO, there is a difference of 2.35 MWh per day, favoring the C-DEEPSO + `irace`. In a monthly projection, we would have a total loss of 70.02 MWh per day, supporting the C-DEEPSO + `irace`.

5. Conclusions

Recent works have shown that wind and solar power have become viable energy sources in developing countries to serve as a sustainable way to produce electricity. The

electric dispatch problem in wind power plants can be expressed as an OPF-like problem, in which the goal is to minimize the cost losses of a WPPs. In this work, we used an integrated methodology to minimize reactive power losses in the transmission network in wind farms (OPF-like), coupling C-DEEPSO and `irace` package (in a fine-tuning methodology). The C-DEEPSO + `irace` incorporates a single-objective meta-heuristic, implementing some procedures of Swarm Intelligence and Evolutionary Computation. In the proposed approach, the daily dispatch (24 h) was discretized into 15 min intervals, totalizing 96 test scenarios. For each test scenario, `irace` finds the best parameter configuration for the mutation and communication rates and C-DEEPSO finds the optimal decision variables yielding the minimization of the power losses. The problem is solved in a recursive way and can be seen as an automatic controller for the problem. Using the IEEE 41-bus test system, the proposed algorithm was compared to two other algorithms: DEEPSO and MVMO. Both algorithms were at their best performance with the set of best parameters optimized by their proponents. The results indicated that the proposed C-DEEPSO + `irace` algorithm outperformed its competitors, being statistically superior when dealing with hard OPF-like problems in WPP.

Although being a very promising approach, the proposed methodology has some limitations that can be addressed in future works. The problem can be solved using long- or medium-term electrical dispatch planning. Different objective criteria such as the minimization of the overall costs can be applied for solving the problem. The `irace` can also be coupled with a multi-objective evolutionary algorithm for solving the OPF-like problem, taking into account the two or more objective functions simultaneously. Finally, the IEEE 41-bus system model considers that there is no uncertainty associated with the decision variable values; however, a robustness analysis is an important aspect to be analyzed.

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Appendix A. Data about the Test Network—IEEE 41-Bus System

Here, we provide the typical layout of an IEEE 41-bus System. Parameters of system components were taken from an offshore WPP in Germany. Tables A1 and A2 contain all power flow data used.

Table A1. Bus data.

Bus	Type	Pd	Qd	Gs	Bs	Area	Vm	Va	BaseKV	Zone	Vmax	Vmin
1	3	0	0	0	0	1	1	0	220	1	1.1	0.9
2	1	0	0	0.5208	−12.1	1	1	0	110	1	1.1	0.9
3	1	0	0	0	0	1	1	0	110	1	1.1	0.9
4	1	0	0	0.4586	−8.0667	1	1	0	110	1	1.1	0.9
5	1	0	0	0	9.8965	1	1	0	33	1	1.1	0.9
6	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
7	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
8	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
9	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
10	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
11	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
12	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
13	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
14	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
15	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
16	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
17	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
18	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
19	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
20	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
21	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
22	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
23	1	0	0	0.0049	0	1	1	0	33	1	1.1	0.9
24	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
25	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
26	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
27	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
28	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
29	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
30	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
31	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
32	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
33	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
34	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
35	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
36	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
37	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
38	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
39	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
40	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95
41	1	−5	0	0	0	1	1	0	0.95	1	1.05	0.95

Table A2. Branch data. Legend: ratio (R), maximum ratio (R_{max}), minimum ratio (R_{min}).

fbus	tbus	r	x	b	rateA	rateB	rateC	R	Angle	Status	R_{max}	R_{min}
1	2	0.0016	0.0640	0	200	200	200	1	0	1	1.149	0.851
2	3	0.0024	0.0104	0.0653	135	135	135	0	0	1	0	0
3	4	0.0136	0.0241	0.2115	135	135	135	0	0	1	0	0
4	5	0.0032	0.1654	0	100	100	100	1	0	1	1.13	0.87
6	24	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
7	25	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
8	26	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
9	27	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
10	28	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
11	29	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
12	30	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
13	31	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0

Table A2. *Cont.*

fbus	tbus	r	x	b	rateA	rateB	rateC	R	Angle	Status	R_{max}	R_{min}
14	32	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
15	33	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
16	34	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
17	35	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
18	36	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
19	37	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
20	38	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
21	39	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
22	40	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
23	41	0.0065	1.5282	0	5.5	5.5	5.5	1	0	1	0	0
5	6	0.0081	0.0279	0.0024	31.5	31.5	31.5	0	0	1	0	0
6	7	0.0023	0.0064	4.90×10^{-4}	28.5	28.5	28.5	0	0	1	0	0
7	8	0.0022	0.0062	4.73×10^{-4}	28.5	28.5	28.5	0	0	1	0	0
8	9	0.0052	0.0080	4.03×10^{-4}	20	20	20	0	0	1	0	0
9	10	0.0046	0.0070	3.51×10^{-4}	20	20	20	0	0	1	0	0
10	11	0.0048	0.0074	3.70×10^{-4}	20	20	20	0	0	1	0	0
5	12	0.0019	0.0067	5.76×10^{-4}	31.5	31.5	31.5	0	0	1	0	0
12	13	0.0025	0.0069	5.25×10^{-4}	28.5	28.5	28.5	0	0	1	0	0
13	14	0.0025	0.0069	5.25×10^{-4}	28.5	28.5	28.5	0	0	1	0	0
14	15	0.0046	0.0071	3.57×10^{-4}	20	20	20	0	0	1	0	0
15	16	0.0046	0.0071	3.57×10^{-4}	20	20	20	0	0	1	0	0
16	17	0.0046	0.0071	3.57×10^{-4}	20	20	20	0	0	1	0	0
5	18	0.0056	0.0193	0.0017	31.5	31.5	31.5	0	0	1	0	0
18	19	0.0030	0.0085	6.48×10^{-4}	28.5	28.5	28.5	0	0	1	0	0
19	20	0.0024	0.0068	5.17×10^{-4}	28.5	28.5	28.5	0	0	1	0	0
20	21	0.0049	0.0075	3.77×10^{-4}	20	20	20	0	0	1	0	0
21	22	0.0048	0.0074	3.70×10^{-4}	20	20	20	0	0	1	0	0
22	23	0.0048	0.0074	3.70×10^{-4}	20	20	20	0	0	1	0	0

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