Analyzing the Effect of Wind Speed Correlation at Wind Farms on ED Using Copula Method

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Along with increasing the wind power generation share in total generation capacity in power systems, maximum use of wind power generation capacity has been a major challenge for system operators. This is due to wind power generation is inherently uncontrollable and stochastic, and can notably affect the power systems operation. Therefore, the effect of wind power generations and especially their correlation on the power systems operation should be accurately studied and analyzed. Economic Dispatch (ED) is a proper tool to study the effect of wind power generations on the power systems operation. In this paper, initially, wind speed is modeled and forecasted for a specific time. Then, correlation among wind farm generations is modeled and simulated using Copula method. Finally, the effect of wind power generations and correlation among them on ED quantities is investigated. The simulation results show that wind power generations and correlation among them can notably affect the ED quantities such as operational cost, power units' generations and reserves, and wind generation curtailment. For instance, the absorbed wind power generation reduces and its curtailment increases. The simulations are implemented on the IEEE 30 buses test system with different load levels and different numbers, capacities and correlation intensities of wind farms installed in it. To solve the optimization problem of ED, the GA-RDPSO is proposed and used. The capability of this algorithm in finding the optimal solution for the ED problem is compared with the well-known optimizing algorithms of GA, PSO, RDPSO.

Keywords: *Economic Dispatch (ED), Wind power plant, Correlation, Wind uncertainty, Wind speed forecasting.*

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Nomenclature

a_i, b_i, c_i	Cost coefficients of thermal unit i
c_i^{UP}, c_i^{DN}	Reserve costs at up and down reserve limits of thermal unit i at t
c	Scale factor
$C_{i,t}^{g}$	Fuel cost of thermal unit i at t
$C_{i,t}^{r}$	Reserve cost of thermal unit i at t
i	Index of power unit
k	Shape factor
NG	Number of thermal units
NW	Number of wind farms
$P_{i,t}$	Production of thermal unit i at t
$P_{j,t}^{w}$	Production of wind farm j at t
$P_{i,min}, P_{i,max}$	Minimum and Maximum generation limits of thermal unit i
$P_{j,t}^{LB}, P_{j,t}^{UB}$	Allowed intervals of thermal unit i at t
$P_{l,t}$	Power system load at t
$\underline{\hat{P}}_{j,t}^{w}, \hat{\overline{P}}_{j,t}^{w}$	Predicted intervals of wind farm i at t
$\tilde{P}_{j,t}^{w} A_{j,t}^{w}$	Wind generation uncertainties
$PF_{l.min}, PF_{l,max}$	Limits of wind generation uncertainties
$R_{i,t}^{UP}, R_{i,t}^{DN}$	Up and down reserve limits of thermal unit i at t
t	Time step
$\Delta P_{i,max}^{UP}$	Incremental boundary of thermal unit i at up limit
$\Delta P_{i,max}^{DN}$	Decrement boundary of thermal unit i at down limit
$\Delta R_{i,t}^{UP}$	Incremental boundary of reserve capacity of thermal unit i at t
ω	Output power (MW) of the wind turbine
ω_r	Rated capacity (MW) of the wind turbine
v	Wind speed (m/s)
v_i	Cut-in speed (m/s) of the wind turbine
v_o	Cut-out speed (m/s) of the wind turbine

1. Introduction

The ever-increasing uses of energy and supplying the required energy for life is one of the important aspects of modern life. The exhaustion of fossil fuel-based energy, especially crude oil, requires the use of other energy resources to replace it. Along with food and water crises, experts believe that the future crisis that threatens human life is the energy crisis [1].

Today, electrical energy has become so important that human life is unimaginable without electricity and its wide network that feeds large and small complexes with many branches and buses. Due to the great importance of electrical energy, all efforts are made to supply the demanded electrical energy at the lowest cost and from renewable and pollution-free resources. In line with this, the authors of [2] analyzed the solar energy development trends in Iran and assessed the impact of climate variability on the performance of photovoltaic systems in the four main climatic regions of the country. Shirazi et al. in [3] focused on the efficiency and energy extraction of a solar photovoltaic system through the use of a solar tracker and bifacial panels. Wherein, the improvement in the basic elements of a solar photovoltaic system and power plant is discussed. Consequently, by performing mechanical calculations and modeling, the structure weight of the photovoltaic plant is reduced to the lowest possible value [3]. The paper [4] assessed the advantages and disadvantages of the floating PV on wetlands. In which, the reduced water evaporation and algal growth, along with challenges such as equipment corrosion and impact on aquatic ecosystems are considered [4].

Wind energy is a clean, free and readily available renewable energy source. In this regard, wind turbines are used to absorb wind power and convert it into electricity. Electricity generation through wind energy plays a very important role for the planet Earth in providing energy in a clean and sustainable way. Turbines or windmills convert the kinetic energy of the wind into electrical energy. The rotating blades of these turbines transfer the kinetic energy of the wind to the generator. Wind speed always changes and in consequence the energy produced by a wind turbine varies continuously. In wind farms, many turbines are connected to each other, and connecting several wind farms to form an energy network creates a more stable and reliable source of electrical energy [5].

Based on GreentechLead report, as can be seen in figure 1, the share of wind energy from the total generated electric energy in the world is significantly increasing. It is predicted that this share will reach to 12% in 2028 [6]. The installed capacity of wind generation in the world from 2013 to 2022 is shown in figure 2 [6]. The most important reasons for increasing attention to wind energy are: increasing the cost of fossil fuels, trying to reduce greenhouse gases, increasing the capacity of wind turbines and reducing the investment required to install them.

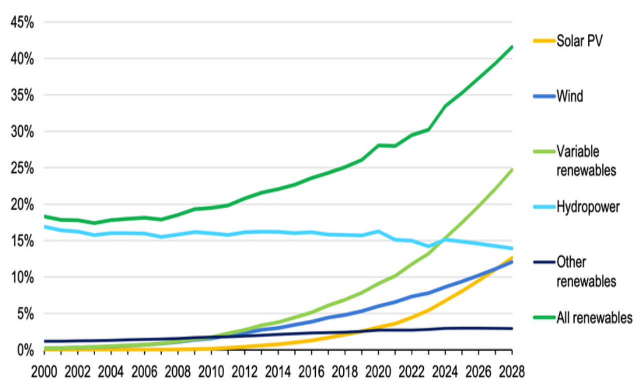


Fig. 1. The share of wind energy from the total generated electric energy in the word [6].

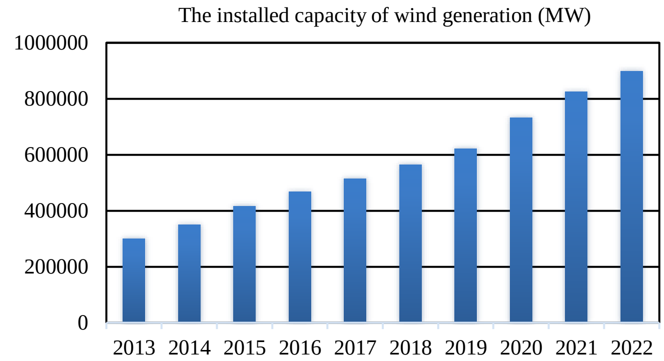


Fig. 2. The installed capacity of wind generation [6].

Increasing installed wind power capacity in power systems forces the system operators to make maximum use of wind power generation. This leads to operational challenges in power systems; wind power generation strongly affects the Economic Dispatch (ED) quantities such as operational cost, units' generations and reserves, wind generation curtailment. This is due to wind power generations are stochastic and uncontrollable, and there is usually correlation among generations of wind farms.

So far, many researches have been done on the effect of wind power generations on the power systems. In these researches, ED as a practical tool to optimize the power systems operations to reduce the operational costs is frequently used.

Authors of [7], presented an assessment model to estimate the uncertainty level of wind power generation. This is to find strategies for decreasing the impact of wind power on the grid. The results from their research will increase the safety and reliability of power grids with uncertain levels of wind power and promote the widespread use of wind power. The paper [8] presents a two-step method to predict the incoming wind conditions (wind speed and direction) of a wind turbine, considering the mutual influence of topography and wake, the impact of mesoscale meteorological conditions, and the time-varying characteristics. In reference [9], the impact of wind power uncertainty on power system operation is analyzed using a proposed hybrid metaheuristic optimization algorithm. This algorithm is based on bat algorithm and combines chaotic map and random black hole model together. Economic Dispatch in Cogeneration Systems (EDCS) to the optimal scheduling of heat and power of generation units and wind power generation is studied in [10]. It is shown that the inclusion of wind power achieves a more economical solution for EDCS with a reduction of up to 8%. In paper [11], a two-stage data-driven adjustable robust optimization (ARO) model is presented to realize an optimal day-ahead ED strategy for microgrid considering uncertainties of wind generation and electric vehicles. The simulation results illustrate the solution robustness, economic benefit, flexible adjustment capability and uncertainty depiction ability of the presented model.

The paper [12] presents a new flexibility-based risk-limiting dynamic economic load dispatch solution incorporating wind power. By the suitable economic trade-off between system flexibility level and risk of load shedding and wind power curtailment, the best reduction in these two unwanted risks is obtained. The authors of paper [13] proposed a method to stabilize the fluctuation of wind power using energy storage system (ESS) to reduce wind power uncertainties in ED. In paper [14], based on fuzzy random theory, a model to address uncertainties of load and wind power in ED is proposed. The papers [15, 16] use neural networks to address uncertainties of load and wind power. Compared to traditional dispatch models, the proposed model leads to less power generation cost.

The well-known and frequently-used optimization tools to solve the ED problem in power systems are the GA [17, 18], the PSO [19, 20] and the RDPSO [21]. However, as compared in the table 1 and tested in the simulation section, these algorithms are unable in finding the best solution for the ED problem in the presence of wind speed correlation at wind farms.

Table 1- Comprehensive comparison of the proposed method with the most related methods.

Method	Correlation modeling	Best solution
GA [17, 18]	No	No
PSO [19, 20]	No	No
RDPSO [21]	No	No
Proposed GA-RDPSO	Yes	Yes

The aim of this paper is to analyze the effect of wind speed correlation at wind farms on ED using Copula method. Also, the GA-RDPSO is proposed to compute ED. The main contributions of this paper can be summarized as below:

- The wind speed is modeled and forecasted for a time horizon (the next 24 hours) using a Recurrent Neural Network (RNN) known as Long Short-Term Memory (LSTM).
- Correlation among wind speeds and wind farms' generations is modeled and simulated using Copula method.
- The effect of stochastic behavior of wind power generations and correlation among them on the main operational quantities of power systems is studied for the next 24 hours. This is done by performing ED along with the Copula method on the considered power system.
- To solve the optimization problem of ED, the GA-RDPSO is proposed and used. The capability of this algorithm in finding the optimal solution for the ED problem is compared with the well-known optimizing algorithms of GA, PSO, RDPSO.

The simulations are implemented on the IEEE 30 buses test system with different load levels and different numbers and capacities of wind farms installed in it. The rest of this paper is organized as: in section 2, related concepts and mathematical formulations of considered ED are stated. Simulation results and discussion are provided in section 3. In section 4, the future studies and limitations are presented, and the concluded points from this paper are summarized in section 5.

2. Related concepts and mathematical formulations

2.1. Wind speed forecast using a Long Short-Term Memory (LSTM) network

A Long Short-Term Memory (LSTM) network as a reliable and accurate tool is used to forecast wind speed at wind farms locations in this paper. The LSTM is a type of Recurrent Neural Network (RNN) used to model time data. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell. Forget gates decide what information to discard from a previous state by assigning a previous state, compared to a current input, a value between 0 and 1. A (rounded) value of 1 means to keep the information, and a value of 0 means to discard it. Input gates decide which pieces of new information to store in the current state, using the same system as forget gates. Output gates control which pieces of information in the current state to output by assigning a value from 0 to 1 to the information, considering the previous and current states. Selectively outputting relevant information from the current state allows the LSTM network to maintain useful, long-term dependencies to make forecasts, both in current and future time-steps [14, 15].

Hourly wind speed during a year as previous long-term time-series data is used to train the LSTM network in this paper. Then, wind speed is forecasted based on this data using the LSTM network. Forecasted hourly speeds for the next month are depicted in figure 3. For the sake of comparison, the actual speeds are depicted, too. Also, the rate of forecasting error per hour is plotted in figure 4. The values of the forecasting indicators are MAE = 0.3477 m/s, RSME = 0.5154 m/s, MAPE = 4.0489 %. Therefore, the LSTM model can forecast wind speed with acceptable accuracy. This accuracy is enough and suitable for modeling wind speed at wind generation farms.

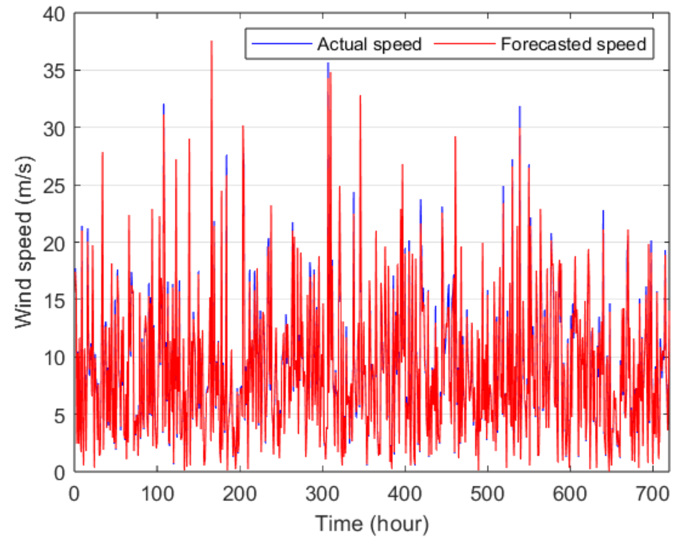


Fig. 3. Wind speed forecasting using the LSTM network.

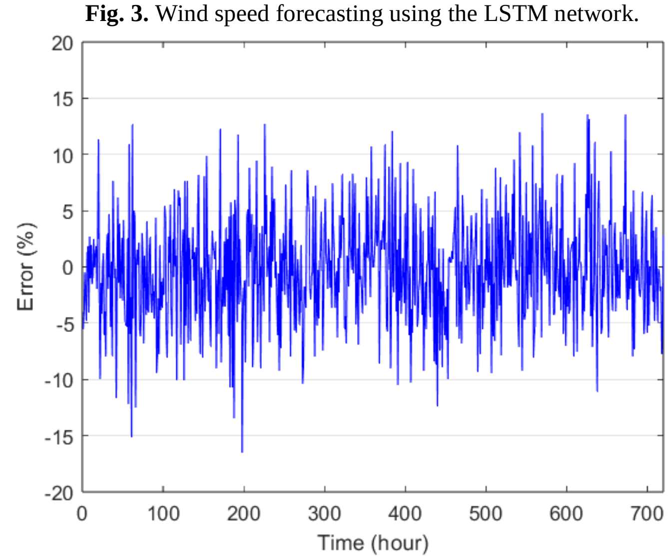


Fig. 4. Forecasting error of the LSTM network.

2.2. Wind power generation modeling

Generated power by a wind turbine depends on the wind speed at the turbine site. This power varies from zero to the rated capacity of the wind turbine. Wind speed is usually modeled using the Weibull probability distribution function (pdf), as equation (1).

$$f(v) = (k/c)(v/c)^{(k-1)}e^{-(v/c)^k}, 0 < v < \infty \quad (1)$$

where, v, k, and c are in respect the wind speed (m/s), shape factor and scale factor.

In the literature, the well-known model of equation (2) is frequently used to model the power generated by a wind turbine. This model is used in this paper, too.

$$\omega = \begin{cases} 0, & for\ v < v_i\ and\ v > v_o \\ \omega_r (v - v_i)/(v_r - v_i), & for\ v_i \le v \le v_r \\ \omega_r, & for\ v_r \le v \le v_o \end{cases} \quad (2)$$

where, ω, ω_r, v_i, v_o and v_r are respectively the output power (MW), the rated capacity (MW), cut-in speed (m/s), cut-out speed (m/s) and rated speed (m/s) of the wind turbine.

2.3. Modeling of correlation among wind farms generations using a Copula method

Wind speeds and consequently wind farms' generations have correlations with each other, usually. This correlation is considerable when wind farms are geographically and climatically close together, and can affect power systems operations and ED quantities. An important task in this regard is the proper modeling of this correlation and inserting it in power systems operation calculations. In this paper, the famous Copula method as a proper and accurate tool is used to consider this correlation in the ED calculations.

In probability theory and statistics, a Copula is a multivariate cumulative distribution function (cdf) for which the marginal probability distribution of each variable is uniform on the interval [0, 1]. Copulas are used to describe/model the dependence (inter-correlation) between random variables. There are generally two Copula function clusters: the Ellipse Copula clusters and Archimedean Copula clusters. More details about these Copula functions can be found in [22].

Let us assume, there are stochastic variables represented by $x_i\ (i = 1,2,\dots,N)$. The cdf of x_i can be connected using Copula function to get the joint distribution, as equation (3):

$$H(x_1, x_2, \dots, x_N) = C(F_1(x_1), F_2(x_2), \dots, F_N(x_N)) \quad (3)$$

where, $F_i(x_i)$ is cdf of x_i, $C(.)$ is the Copula function and $H(.)$ is the joint distribution of $x_1, x_2, \dots, x_N$. So, the joint cdf $h(.)$ can be written as equation (4):

$$h(x_1, x_2, \dots, x_N) = \frac{\partial C(u_1, u_2, \dots, u_n)}{\partial u_1 \partial u_2 \dots \partial u_n} \prod_{i=1}^{n} \frac{F_i(x_i)}{\partial x_i} \quad (4)$$

where, u_i denotes $F_i(x_i)$, for simplicity [23].

In a power system, Copula joint distribution among wind generation farms can be modeled as the following steps:

Step 1- calculate $F_i(x_i)$ for each wind farm generation using the kernel density estimation method. That, x_i denotes the generation of wind farm $i\ (i = 1,2,\dots,N_w)$.

Step 2- transform $F_i(x_i)$ to a uniform distribution using cumulative integration.

Step 3- compute the joint Copula functions of multi wind farms generations. In this paper, the maximum likelihood estimation method is used to estimate the needed parameters of the joint Copula functions.

Step 4- check the accuracy of the joint Copula function to make sure it best fits the actual correlation of wind farms generations.

In this paper, the multivariate Gaussian copula in matlab toolbox is used to model linear correlation among wind speed samples [24]. These generated wind speed samples are hypothetical and used in simulations as wind speeds at the sites of wind farms. Three levels of correlation: a) no correlation, b) with correlation factor of 0.5 and c) with correlation factor of 0.95 are considered in simulations; these correlation levels respectfully denote the states of "without correlation", "with semi correlation" and "with complete correlation" of wind speeds; these simulated states are near to reality for different geographical and climatical conditions of the sites of the wind farms.

2.4. The related ED optimization problem

The ED is the basic mechanism for determining the best cost-effective point of operation for all controllable devices connected to the power system according to their economic efficiency in real time [25]. In this paper, the aim of ED is to minimize the total operational cost of a power system, including the cost of thermal power units and wind farms in a time horizon. It is assumed that there is T intervals in the time horizon. The total cost includes the sum of hourly production of thermal units ($P_{i,t}$) and wind farms ($P_{j,t}^w$) at each time step ($t = 1,2,\dots,T$), in the schedule horizon. The flowchart of the related ED model is as figure 5. In which, at each time step, the ED is computed based on demand data and the forecasted (predicted) amounts of wind powers (pw) to minimize the objective function (5).

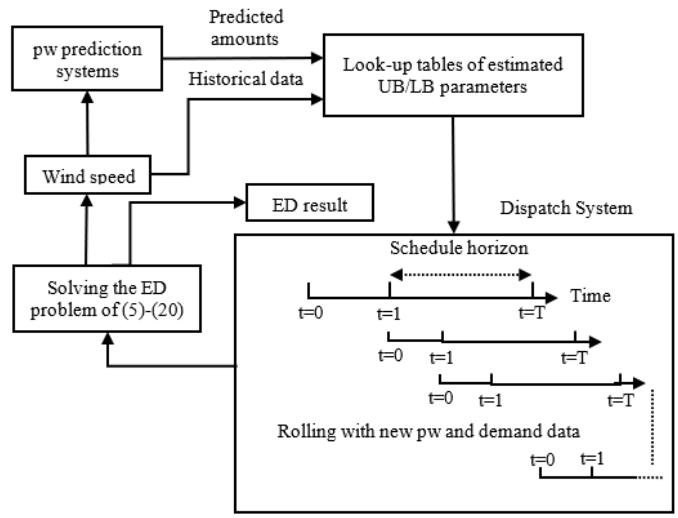


Fig. 5. The flowchart of the related ED model.

This ED model minimizes the objective function (5) subjected to the equal and unequal constraints of (8)-(20). In (5), the terms $\sum_{i=1}^{NG} C_{i,t}^g$ and $\sum_{i=1}^{NG} C_{i,t}^r$ are the fuel cost of all thermal units and the total reserve cost of thermal units at time *t*, respectively. This objective function is to minimize the sum of these costs in the schedule horizon of one month. The values of $C_{t,i}^g$ and $C_{t,i}^r$ at the hour t are respectively calculated using (6) and (7).

$$\text{Min.} \sum_{t=1}^{T} \Delta t. \left(\sum_{i=1}^{NG} C_{i,t}^g + \sum_{i=1}^{NG} C_{i,t}^r \right) \quad (5)$$

$$C_{i,t}^g = a_i (P_{i,t}^2) + b_i (P_{i,t}) + c_i \quad \forall t, i \quad (6)$$

$$C_{i,t}^r = c_i^{UP} (R_{i,t}^{UP}) + c_i^{DN} (R_{i,t}^{DN}) \quad \forall t, i \quad (7)$$

Minimizing of the objective function (5) should be subjected to the following equal and unequal constraints of (8)-(20):

- The supply-demand balance of the power system, as (8):

$$\sum_{i=1}^{NG} P_{i,t} + \sum_{j=1}^{NW} P_{j,t}^w = P_{l,t} \quad (8)$$

- The uncertainty of wind powers should be within the Low/Up boundaries and supplied by system reserves as (9) and (10). Also, generations of thermal units should be within their Low/Up boundaries considering their reserves, as (11):

$$\sum_{j=1}^{NW} \left(P_{j,t}^w - \underline{\hat{P}}_{j,t}^w\right) = \sum_{i=1}^{NG} R_{i,t}^{UP} \quad \forall t, i, j \quad (9)$$

$$\sum_{j=1}^{NW}\left(\widehat{\overline{P}}_{j,t}^{w}-P_{j,t}^{w}\right)=\sum_{i=1}^{NG}R_{i,t}^{UP} \qquad \forall t,i,j \tag{10}$$

$$\begin{cases}P_{i,min}\le P_{i,t}\le P_{i,max}\\ P_{i,min}\le P_{i,t}\le P_{i,max}-R_{i,t}^{UP}\end{cases} \qquad \forall t,i \tag{11}$$

- The constraints of the increasing and decreasing rate of power units' generation while taking into account the reserve levels, as (12)-(14):

$$P_{i,t}-P_{i,t-1}\le \Delta P_{i,max}^{UP}.\Delta t \quad \forall t,i \tag{12}$$

$$\begin{cases}P_{i,t}-P_{i,t-1}+R_{i,t}^{UP}\le \Delta P_{i,max}^{UP}.\Delta t\\ -P_{i,t}+P_{i,t-1}\le \Delta P_{i,max}^{DN}.\Delta t\end{cases} \qquad \forall t,i \tag{13}$$

$$\begin{cases}P_{i,t}-P_{i,t-1}+R_{i,t}^{UP}\le \Delta P_{i,max}^{UP}.\Delta t\\ -P_{i,t}+P_{i,t-1}+R_{i,t-1}^{UP}\le \Delta P_{i,max}^{DN}.\Delta t\end{cases} \tag{14}$$

- The relationship between the assigned and used reserve capacities of each thermal generator, as (15):

$$0\le \Delta R_{i,t}^{UP}\le R_{i,t}^{UP} \qquad \forall t,i \tag{15}$$

- The lower and upper bounds of scheduled production of each wind farm per hour, as (16):

$$\underline{\hat{P}}_{j,t}^{w}\le P_{j,t}^{w}\le \widehat{\overline{P}}_{j,t}^{w} \qquad \forall t,j \tag{16}$$

- The relationship between the prediction intervals and the allowed intervals to produce a feasible solution, as (17):

$$\begin{cases}\widehat{\overline{P}}_{j,t}^{w}\le P_{j,t}^{UB}\\ \underline{\hat{P}}_{j,t}^{w}\le P_{j,t}^{LB}\end{cases} \qquad \forall t,j \tag{17}$$

- Three important sets of constraints subject to wind generation uncertainties, expressed as (18)-(20):

$$PF_{l.min}\le \sum_{i=1}^{NG}S_{l,i}P_{i,t} + \sum_{j=1}^{NG}S_{l,i}\tilde{P}_{j,t}^{w}A_{j,t}^{w}\le PF_{l,max}, \qquad \forall t,l \tag{18}$$

$$\sum_{i=1}^{NG}P_{i,t}+\sum_{i=1}^{NG}\Delta R_{i,t}^{UP}+\sum_{j=1}^{NW}\tilde{P}_{j,t}^{w}A_{j,t}^{w}\ge P_{l,t}, \qquad \forall t \tag{19}$$

$$\sum_{i=1}^{NG}P_{i,t}+\sum_{i=1}^{NG}\Delta R_{i,t}^{DN} +\sum_{j=1}^{NW}\tilde{P}_{j,t}^{w}A_{j,t}^{w}\ge P_{l,t},\forall t, A_{j,t}^{w}=1, \quad \forall t,j \tag{20}$$

2.5. The proposed optimization algorithm

As mentioned, the GA-RDPSO algorithm is proposed to solve the ED optimization problem. The capability of this algorithm in finding the optimal solution for this ED problem is compared with the well-known optimizing algorithms of Genetic Algorithm (GA) [17, 18], Particle Swarm Optimization (PSO) [19, 20], Repulsion-Based Particle Swarm Optimization (RDPSO) [21]. The details of these algorithms and their optimization approach are presented in the mentioned references.

The flowchart of the proposed GA-RDPSO as a two-level combination of GA (gray blocks) and RDPSO (white blocks) is shown in figure 6. It is obvious that the problem of (5)-(20) is a two-level optimization problem: in the first level, the binary GA optimizes the status of on and off generation units. Because, the binary GA is the most efficient in solving binary optimization problems in comparison to other heuristic algorithms. At the second level, the RDPSO algorithm solves the ED problem with the units determined in the first level by GA. The fitness function for the RDPSO algorithm is the same as the ED cost. Of course, the GA needs a fitting function to move towards optimality, too. To this aim, the final calculated objective function of the RDPSO is used as a fitness function for the GA algorithm.

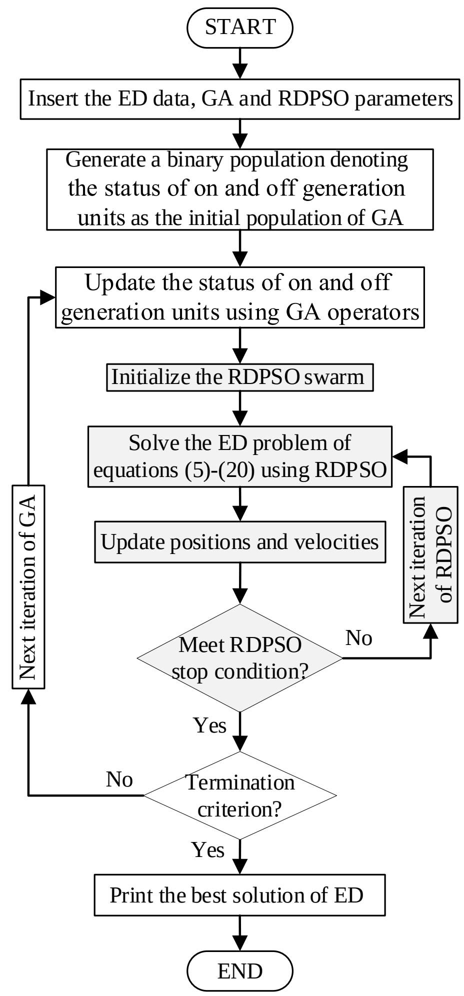


Fig. 6. The flowchart of the proposed GA-RDPSO.

Table 2- The setting parameters of GA, PSO, RDPSO and the proposed GA-RDPSO algorithms.

Algorithm	Parameter
GA	Population = 100, Iteration = 100 Cross Over % = 70, Mutation% = 30
PSO	Population = 100, Iteration = 100 Inertia Weight = 1, Damping = 0.99 C1 = 2, C2 = 1
RDPSO	Population = 100, Iteration = 100 Inertia Weight = 1, Damping = 0.99 C1 = 1, C2 = 2
Proposed GA-RDPSO	Similar to the setting parameters of GA and PSO

For the sake of comparison, all simulation conditions and setting parameters of these algorithms are chosen the same. The setting parameters of these algorithms are provided in table 2.

3. Simulation Results

The simulations are implemented on the IEEE 30 buses test system [26] in matlab environment using matpower package [27]. The studied system includes 30 buses, 41 branches and 6 conventional generation buses. The generation units are at buses 1, 2, 5, 8, 11 and 13, respectively named by p1, p2, p3, p4, p5 and p6. The daily load curve of this system is as figure 7.

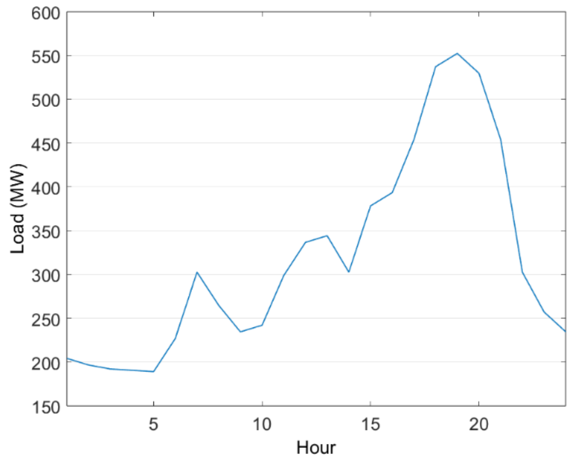


Fig. 7. Daily load curve of the IEEE 30 buses test system.

Table 3- The specifications of wind farms.

Parameter	Wind farm 1	Wind farm 2	Wind farm 3
Cut in speed v_i (m/s)	3.5	3.5	3.5
Rated speed v_r (m/s)	14	14	14
Cut out speed v_o (m/s)	25	25	25
Rated capacity ω_r (MW)	18	70	100
Wind mean speed (m/s)	12.49	8.52	8.52
Wind std[1] speed (m/s)	8.43	5.45	5.45

[1] standard deviation

To study the impact of correlation among wind farms on ED quantities, three wind farms with capacities of 180 MW, 70 MW and 100 MW are in respect installed at buses 19, 21 and 30 of this system. The specifications of these wind farms are listed in table 3.

The simulations are done in five phases:

Phase 1 – simulation of wind speed correlation at wind farms using the LSTM network.

Phase 2 – performing the daily ED of equations (5)-(20) without considering the wind speed correlation at wind farms.

Phase 3 – performing the daily ED of equations (5)-(20) with considering the wind speed correlation at wind farms.

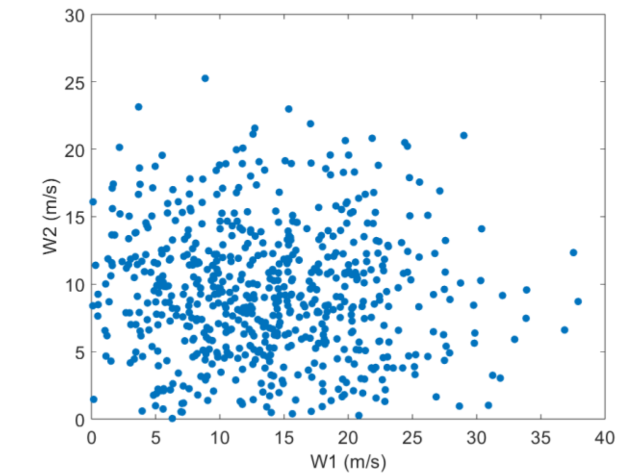
Phase 4 – comparison of the proposed GA-RDPSO algorithm with the GA [17, 18], PSO [19, 20], RDPSO [21] algorithms in solving the daily ED of equations (5)-(20).

Phase 5 – sensitivity analysis on the load levels and the numbers, capacities and correlation intensities of the wind farms.

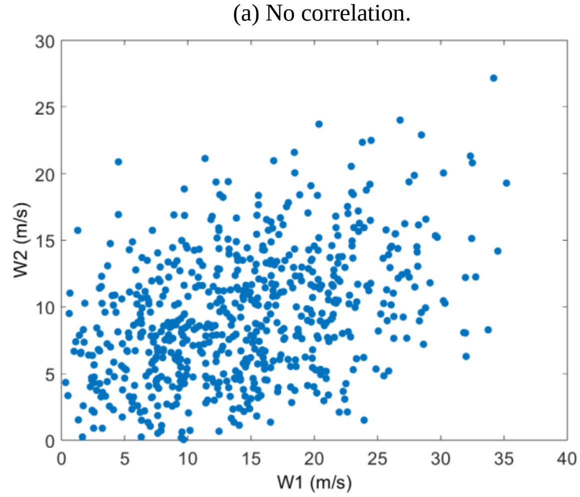
In the phases 1 to 4 of simulations, just wind farms 1 and 2 are assumed to be installed in the system. In the final phase 5, all wind farms are used with different load levels of the power system. This phase of simulation is for sensitivity analysis on the power system load levels and the numbers, capacities and correlation intensities of the wind farms.

3.1. Phase 1 – simulation of wind speed correlation at wind farms using LSTM network

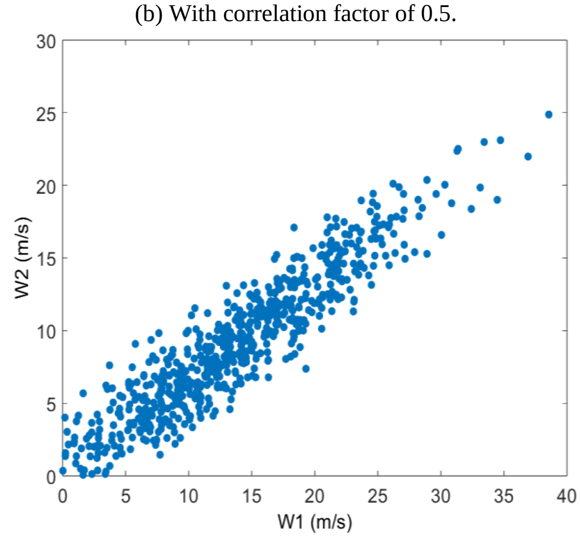
To simulate wind speed correlation at wind farms, three modes are considered: a) no correlation, b) with correlation factor of 0.5 and c) with correlation factor of 0.95. Wind speed correlation is modeled using Copula method. The forecasted speeds using the LSTM network for the next month (720 hours) are shown in figure 8. The horizontal and vertical axes are the forecasted wind speeds at wind farms 1 (w1) and 2 (w2), respectively installed at buses 19 and 21. With these speeds, the generated powers by these wind farms (pw1 and pw2) are shown in figure 9. As expected, in mode (a), wind speeds and wind farms generations stochastically change and are not correlated. However, when the correlation factor increases in modes (b) and (c), wind speeds and wind farms generations will be dependent on each other, and the relationship between them approaches the linear characteristic.



(a) No correlation.

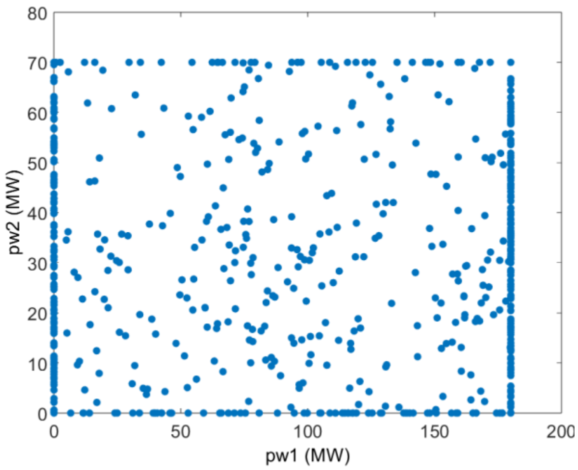


(b) With correlation factor of 0.5.

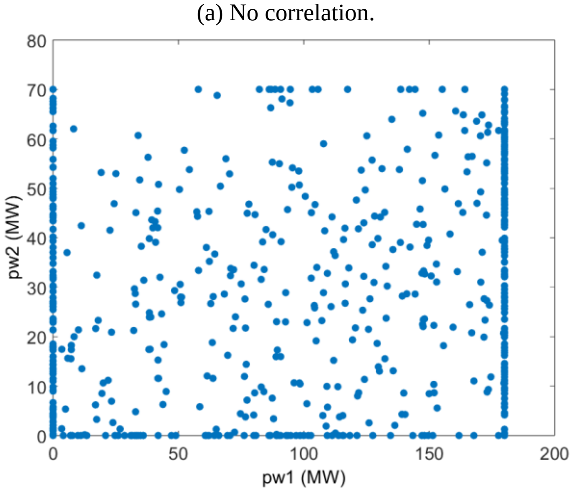


(c) With correlation factor of 0.95.

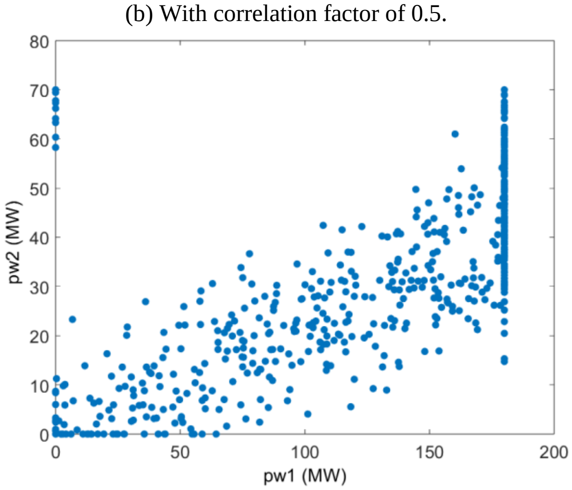
Fig. 8. The forecasted wind speed at wind farms.



(a) No correlation.



(b) With correlation factor of 0.5.



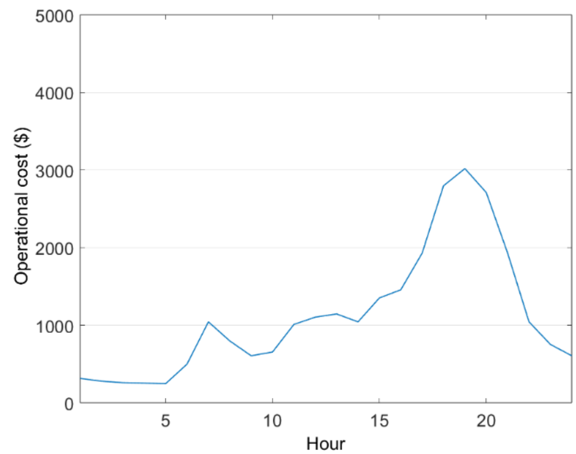
(c) With correlation factor of 0.95.

Fig. 9. Wind farms generations (pw1 and pw2).

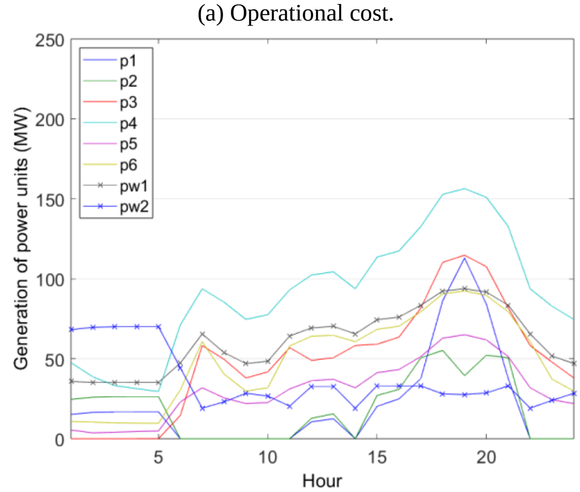
3.2. Phase 2 – performing the daily ED of equations (5)-(20) without considering the wind speed correlation at wind farms using LSTM network

In this phase, the ED problem of equations (5)-(20) is solved for the day ahead without considering the wind speed correlation at wind farms. Initially, this problem is solved using the proposed GA-RDPSO algorithm. The details of the main ED quantities computed by GA-RDPSO are depicted in figure 10. This figure includes (a) the power system operational cost, (b) the generation of power units, (c) the generation reserve of power units, (d) the wind generation curtailment, and (e) power loss.

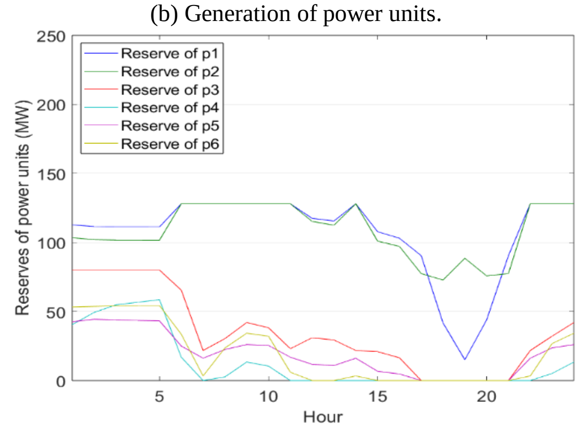
As expected in figure 10(a), the system operational cost follows the system daily load curve presented in figure 7; the minimum and maximum operational costs of the system appear respectively at 5:00 and 19:00 that are the minimum and maximum loading times of the system. As depicted in figure 10(e), similar conclusion can be stated about the system power loss variations. Generations of power units are shown in figure 10(b). The wind farms' generations i.e., pw1 and pw2 change without any correlation to each other. Figure 10(c) shows that, during a day, the generation units p3, p4, p5 and p6 reach to their generation limits and their generation reserves are exhausted in some hours. The wind generation curtailment curve is plotted in figure 10(d). As can be seen, there is no wind generation curtailment at peak loading hours. However, this curtailment is notable in other times.



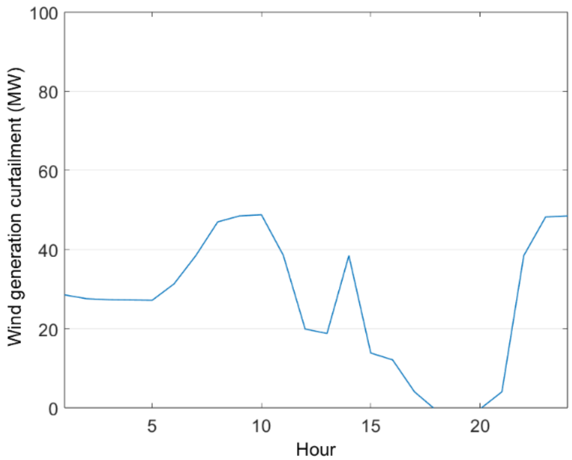
(a) Operational cost.



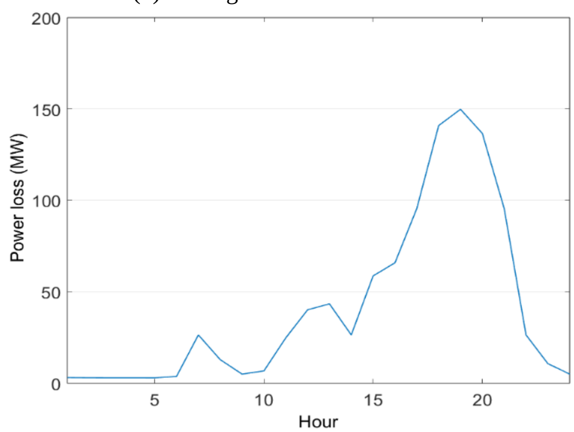
(b) Generation of power units.



(c) Reserve of power units.



(d) Wind generation curtailment.



(e) Power loss.

Fig. 10. ED quantities, no correlation, solved by the proposed GA-RDPSO.

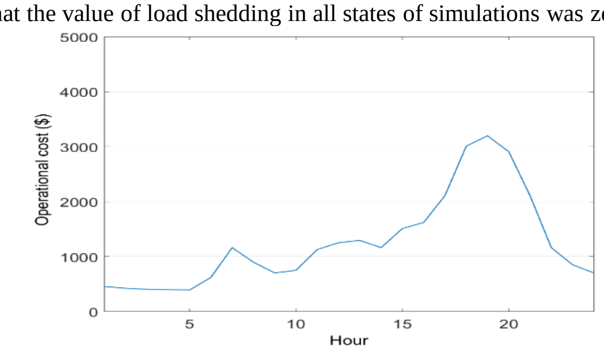
3.3. Phase 3 – performing the daily ED of equations (5)-(20) with considering the wind speed correlation at wind farms

Now, considering the correlation factor 0.95 between wind speeds at wind farms pw1 and pw2, the simulations are re-run. The results are depicted in figure 11. It can be seen that, in comparison with the no correlation mode, the system operational cost has increased. This is due to increase in thermal units' generations, especially generations of units p1, p4, p5 and p6 at peak loading hours, as shown in figure 11(b). Also in figure 11(b), the correlation between the wind generations pw1 and pw2 is clear. For the same reason, in figure 11(c), the generation reserves of thermal units especially the reserves of the mentioned units are more reduced. Compared to the 10(d), more wind generation curtailment is done in figure 11(d) when wind speed correlation is taken into the ED account. In both simulation phases, the system power losses are approximately the same. Of course, correlation led to a slight increment in losses.

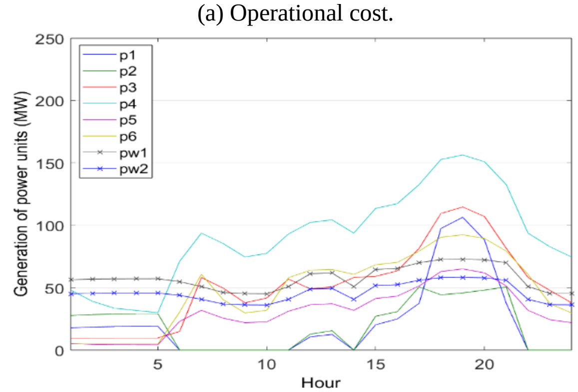
3.4. Phase 4 – comparison of the proposed GA-RDPSO algorithm with the GA [17, 18], PSO [19, 20], RDPSO [21] algorithms in solving the daily ED of equations (5)-(20).

Now, the capabilities of the proposed GA-RDPSO with the capabilities of the well-known GA [17, 18], PSO [19, 20] and RDPSO [21] algorithms in solving the daily ED of equations (5)-(20) is compared. The simulations are done with and without considering wind speed correlation at the wind farms. The total results of the daily ED calculated by them are given in figure 12 and tables 4 and 5. These figures and tables again verify that wind speed correlation can notably manipulate the ED quantities; totally, this correlation has led to more system operational cost, more thermal units' generations, less thermal units' reserves, less wind farms' generations, more wind generations curtailments.

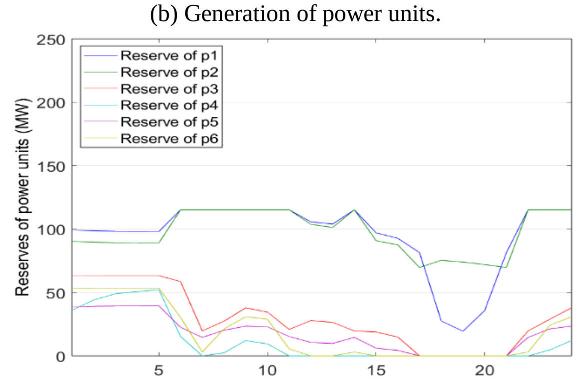
From the system operational cost point of view, with and without wind speed correlation, the proposed GA-RDPSO led to the lowest cost. Without wind speed correlation, GA, PSO, RDPSO and the proposed GA-RDPSO provided 28,992$, 28,723$, 28,186$ and 26,844$ for the operational cost. These costs became in respect 32,940$, 32,638$, 32,033$ and 30,220$ by these algorithms when correlation is taken into the ED account. Also, the GA-RDPSO provided the minimum value for thermal units' generation in both states of with and without wind speed correlation. Moreover, thermal units' reserve became the minimum using the proposed algorithm. And, this algorithm led to the maximum value for wind farms' generation and consequently the minimum value for wind farms' curtailment. This means that the solution obtained for the daily ED by the GA-RDPSO algorithm is the best in contrary to other ones. These simulation results show that, in respect, the proposed GA-RDPSO, RDPSO, PSO and GA provided better solutions for the considered ED with and without wind speed correlation. Of course, the GA-RDPSO algorithm needed the most cpu run time, approximately 11% more than other algorithms' run times. Figure 12 and tables 4 and 5 show that the value of load shedding in all states of simulations was zero.



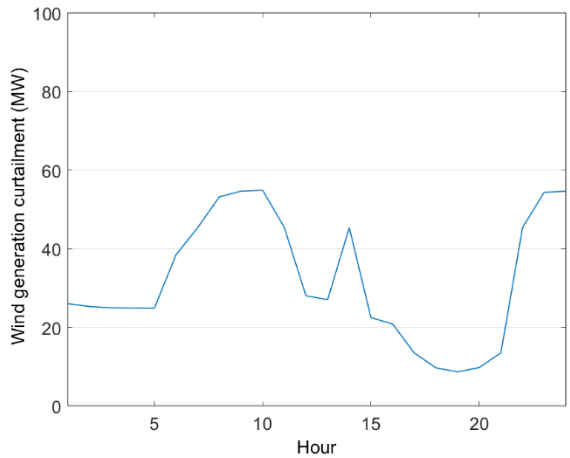
(a) Operational cost.



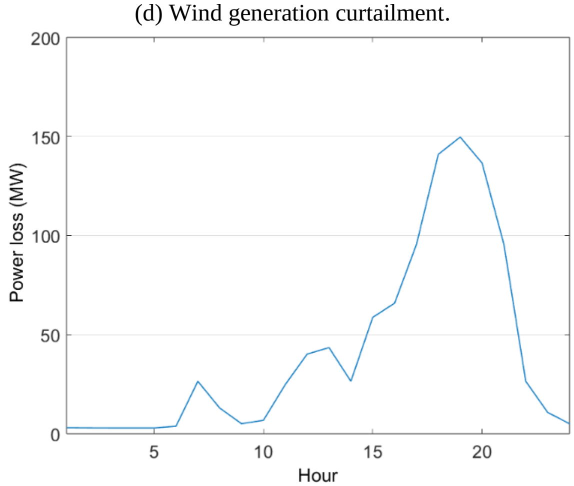
(b) Generation of power units.



(c) Reserve of power units.



(d) Wind generation curtailment.



(e) Power loss.

Fig. 11. ED quantities, with correlation factor of 0.95, solved by the proposed GA-RDPSO.

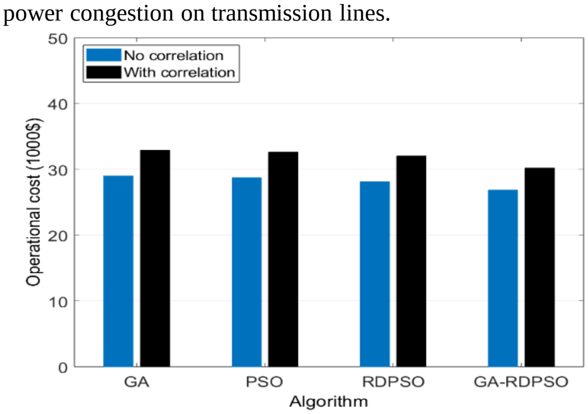
3.5. Phase 5 –sensitivity analysis on the load levels and the numbers, capacities and correlation intensities of the wind farms.

To deep validate the capabilities of the presented approach and the proposed GA-RDPSO, a comprehensive sensitivity analysis on the load levels and the numbers, capacities and correlation intensities of the wind farms is done in this subsection; The approach is tested for the cases of the base load and the load increment of 20% of the power system. At each load level, the correlation factors of 0.5 and 0.95 among the wind farms generations are considered. Also, these simulations are done with two wind farms (installed at buses 19 and 21) and three wind farms (installed at buses 19, 21 and 30), with the specifications presented in the table 3. The obtained simulation results are summarized in table 6. Wherein, the results of table 6(a) and table 6(b) are in respect for the correlation factors of 0.5 and 0.95.

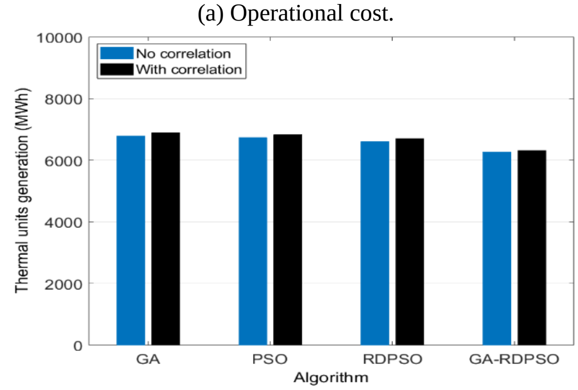
Table 6(a) shows, the lower correlation intensity among wind farms increases the wind generation absorption by the power system and decreases its curtailment. In consequence, due to more wind generation absorption, the generations of thermal units reduce and their reserves increase. This led to lower operational cost of the power system. For instance, in the case of the base load with three wind farms, the daily wind generation absorption increases from 3,280 MWh to 3,375 MWh when the correlation factor decreases from 0.95 and 0.5. The daily wind generation curtailment decreases from 1,075 MWh to 980 MWh. Also, the daily generations of thermal units reduce from 5,379 MWh to 5,359 MWh, and their total reserves increase from 7,426 MWh to 7,446 MWh. In consequence, the daily operational cost of the power system decreases from 25,761$ to 25,666$, due to the reduction of correlation factor among wind farms.

As expected, when the numbers and capacities of wind farms increase, the power system absorbs more wind power generation. Then, the generations of thermal units and in consequence the daily operational cost of the power system reduce. In the case of the base load, when the numbers of wind farms change from two to three, the daily wind farms generations increase from 2,349 MWh to 3,280 MWh. Then, the generations of thermal units reduce from 6,287 MWh to 5,359 MWh and the daily operational cost decreases from 30,110$ to 25,666$.

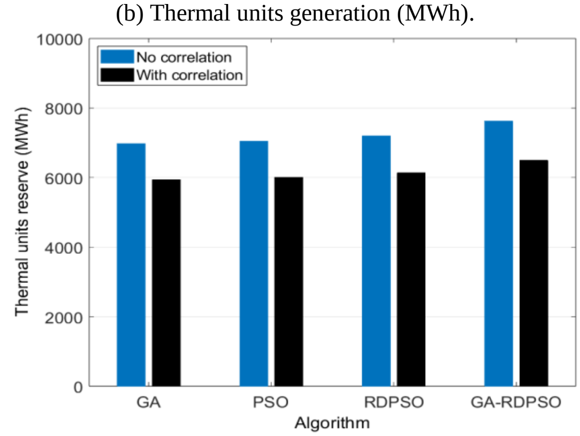
In the right column of table 6, the simulation results are represented for the load increment of 20% in the power system. So, more wind and thermal generations are extracted to meet this load increment. Also, the wind generation curtailments and the thermal units reserves decrease, and the power system operational cost increase. An increase in power losses appears that is expected due to the power congestion on transmission lines.



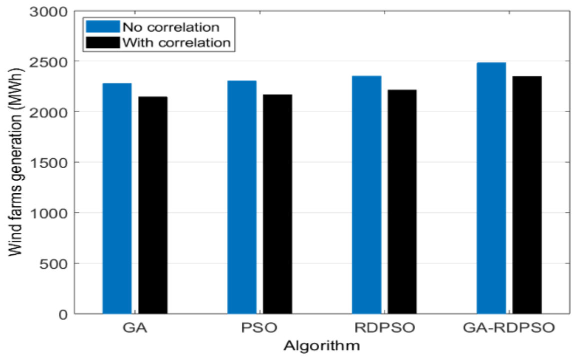
(a) Operational cost.



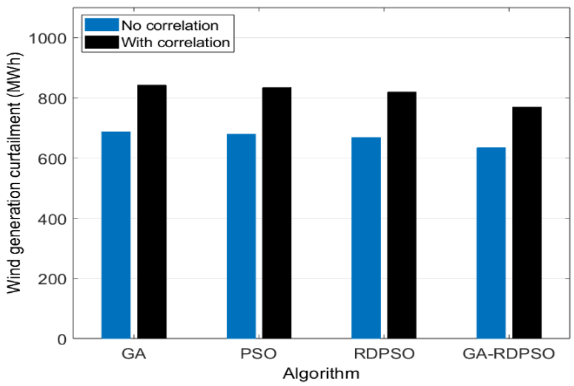
(b) Thermal units generation (MWh).



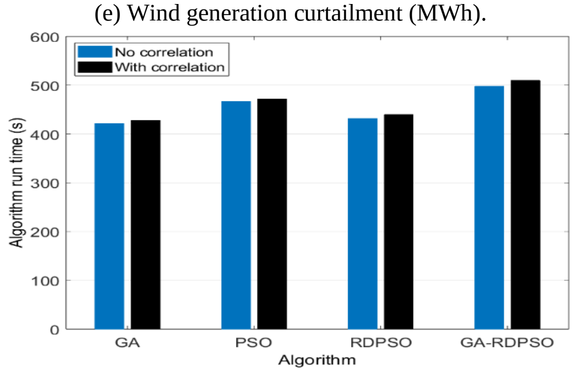
(c) Thermal units reserve (MWh).



(d) Wind farms generation (MWh).



(e) Wind generation curtailment (MWh).



(f) Algorithm run time (s).

Fig. 12. Comparison of GA, PSO, RDPSO and the proposed GA-RDPSO

Table 4 The ED quantities, no correlation, solved by different algorithms.

Quantity (for 24 hours)	GA [17, 18]	PSO [19, 20]	RDPSO [21]	Proposed GA-RDPSO
Operational cost ($)	28,992	28,723	28,186	26,844
Thermal units generation (MWh)	6,795	6,732	6,607	6,263
Thermal units reserve (MWh)	6,974	7,050	7,202	7,622
Wind farms generation (MWh)	2,281	2,306	2,355	2,485
Wind generation curtailment (MWh)	687	680	668	634
Load shedding (MWh)	0	0	0	0
Power losses (MWh)	996	995	994	990
Algorithm run time (s)	422	467	432	498

Table 5 The ED quantities, with correlation factor of 0.95, solved by different algorithms.

Quantity (for 24 hours)	GA [17, 18]	PSO [19, 20]	RDPSO [21]	Proposed GA-RDPSO
Operational cost ($)	32,940	32,638	32,033	30,220
Thermal units generation (MWh)	6,896	6,833	6,707	6,310
Thermal units reserve (MWh)	5,942	6,007	6,137	6,495
Wind farms generation (MWh)	2,147	2,170	2,217	2,349
Wind generation curtailment (MWh)	842	834	819	770
Load shedding (MWh)	0	0	0	0
Power losses (MWh)	1004	1003	1001	996
Algorithm run time (s)	428	472	440	510

Table 6 The ED quantities with different load levels and different numbers, capacities and correlation intensities of the wind farms.

(a) With correlation factor of 0.5.

Quantity (for 24 hours)	The base load		Load increment of 20%	
	Two wind farms	Three wind farms	Two wind farms	Three wind farms
Operational cost ($)	30,110	25,666	34,023	28,999
Thermal units generation (MWh)	6,287	5,359	7,104	6,055
Thermal units reserve (MWh)	6,518	7,446	5,701	6,750
Wind farms generation (MWh)	2,417	3,375	2,586	3,611
Wind generation curtailment (MWh)	702	980	533	744
Load shedding (MWh)	0	0	0	0
Power losses (MWh)	994	948	1,179	1,128
Algorithm run time (s)	510	518	510	518

(b) With correlation factor of 0.95.

Quantity (for 24 hours)	The base load		Load increment of 20%	
	Two wind farms	Three wind farms	Two wind farms	Three wind farms
Operational cost ($)	30,220	25,666	34,149	29,110
Thermal units generation (MWh)	6,310	5,359	7,130	6,078
Thermal units reserve (MWh)	6,495	7,446	5,675	6,727
Wind farms generation (MWh)	2,349	3,375	2,513	3,509
Wind generation curtailment (MWh)	770	980	606	844
Load shedding (MWh)	0	0	0	0
Power losses (MWh)	996	948	1,182	1,123
Algorithm run time (s)	510	518	510	518

4. Future Studies and Limitations

Although this article made a significant effort towards analyzing the effect of wind speed correlation at wind farms on the ED in power systems; the Copula method was able to model the wind speed correlation efficiently. And, the proposed GA-RDPSO successfully computed the ED with worthy results. However, notable studies have been conducted in the field of applications of artificial intelligence (neural networks, etc.) in improving the performance and operation of energy systems [28-30]. As a key research avenue for the interested researchers, the proposed methodology in this paper can be enhanced and re-implemented using the artificial intelligence tools.

5. Conclusions

The effect of wind speed correlation at wind farms on ED using the Copula Method was analyzed in this paper. Wind speed was modeled and forecasted using the LSTM network for the next month. So, correlation among wind speeds and consequently among wind power generations was modeled and simulated using Copula method. Finally, the effects of wind power generations and correlation among them on ED quantities were investigated. The GA-RDPSO was proposed to solve the related optimization problem of the ED. According to the obtained simulation result, the LSTM network acceptably forecasted the wind speed. The wind speed was successfully modeled and simulated using the Copula method. Also, the GA-RDPSO had better performance in finding the optimal solution for the ED problem, in comparison with the well-known algorithms such as GA, PSO and RDPSO. The simulation results illustrated that, correlation among wind speeds at wind farms notably affects the ED quantities; it leads to increase in the power system operational cost, increase in conventional units' generation, and decrease in wind generation absorption. Consequently, more wind generations will be curtailed due to correlation among them. The proposed methodology can easily be implemented on any real case study.

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