Scenario-based Stochastic Optimal Operation of wind/ PV/FC/CHP/Boiler/Tidal/ Energy Storage System considering DR Programs and Uncertainties

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Abstract: The main aims of this paper are to 1) predict the uncertainties using the hybrid method of WT-ANN-ICA and 2) determine the optimal generation strategy of a micro-grid (MG) containing wind farms (WFs), photovoltaic (PV), fuel cell (FC), combined heat and power(CHP) units, tidal steam turbine (TST), and also boiler and energy storage devices (ESDs).
The scenario-based stochastic optimization problem is presented to determine the optimal points for the energy resources generation and to maximize the expected profit considering demand response (DR) programs and uncertainties. The uncertainties include wind speed, tidal steam speed, photovoltaic power generation (PVPG), market price, power and thermal load demand. For modeling uncertainties, an effort has been made to predict uncertainties using the hybrid method of wavelet transform (WT) in order to reduce fluctuations in the input historical data. An improved artificial neural network (ANN) based on the nonlinear structure is also used for better training and learning. Furthermore, the imperialist competitive algorithm (ICA) is adopted to find the best weights and biases for minimizing the mean square error of predictions. In the present study, three cases are investigated to confirm the performance of the proposed method. The first case study is programing MG isolated from grid, the second and the third case studies respectively are pertaining to comparison of the prediction of uncertainties using WT-ANN-ICA and WT-ANN methods, and effect of DR programs on the expected profit of energy resources in grid-connected mode.

Keywords: micro-grid, wind farm, photovoltaic, combined heat and power, tidal steam turbine, expected profit.

Nomenclature

i **:** Index of each energy resources, W, CHP, PV, FC, TST, K, B : Index of wind farm, combined heat and power, photovoltaic, fuel cell, tidal steam turbine, electrical energy storage device and boiler, A_W, A_{TST}, A_{PV}, $A_{CHP}-F_{CHP}$, A_{FC}, B_{FC} : Cost coefficients of wind farm, tidal steam turbine, photovoltaic, combined heat and power, and fuel cell, T/t: Total number / index of time intervals, s_p, s_{TSS}, s_W, s_{PV}, s_{PL}, s_{HL}: Index of scenarios for market price, tidal steam speed, wind speed, photo-voltaic power generation, power and thermal load demand respectively, α, β, θ, λ **:**Four marginal points of the electrical-thermal characteristic of combined heat and power, Y : Sufficient large number, $U_{COST}(i,t)$, $D_{COST}(i,t)$: Startup/shutdown cost of $i-th$ generation unit at hour t, $M(i,t)$: Commitment state of $i-th$ generation unit at hour t, ρ_s: Probability of the s_W-th wind speed, $s_{TSS}-th$ tidal steam speed, $s_{PV}-th$ photo-voltaic generation, s_p-th scenario of market price, $s_{PL}-th$ scenario of power load demand, $s_{HL}-th$ scenario of thermal load demand, $C_T(i,t)$**:** Value of total generation cost of $i-th$ generation unit at hour t, $E_P(s_p,t)$: Price of the market (\$/MW) for energy for s_p-th scenario of price at hour t, respectively, $P_{sale}(s,t)$, $P_{buy}(s,t)$: Amount of power sold and bought to/from the market at hour t in MW, $P_G^W(s_W,t)$, $P_G^{TST}(s_{TSS},t)$, $P_{G,CHP}(t)$, $P_G^{FC}(t)$: Power generation of wind farm, tidal steam turbine, heat and power and fuel cell at hour t in MW, respectively, $L_0(s,t)/L(s,t)$: Load before/after applying demand response program, $DR(s,t)$: Percentage of load shifting from hour t, $DR_{\max}$:Maximum load which can be shifted, $L_{shift}(s,t)$: Shifted load from other hours to hour t for $s-th$ scenario, $\varepsilon_{increasrd}(s,t)$: Amount of increased load at hour t, $\varepsilon_{\max}$: Maximum amount of load which can be increased at hour t, $H'(t)$: Total produced heat in combined heat and power and boiler at hour t, $H(t)$: Real heat which the buffer tank could be supplied at hour t, AH(t) : Available heat in the buffer tank, σ :Heat loss rate for heat buffer tank, $SU(i,t)/SD(i,t)$: Startup/Shutdown status of $i-th$ unit at hour t, $Z_{CH}(PV,t)/Z_{DCH}(PV,t)$**:** Charge/Discharge state of energy saving device of photo-voltaic unit at hour t,

$BATT_{COST}$ **:** The cost of buying energy for battery charging, $P_{BATT}^{CH}(K,t)$, $P_{BATT}^{\max CH}(K)$ **:** The amount of charging power of $k-th$ electrical energy storage device at hour t and its maximum limit, $P_{BATT}^{DCH}(K,t)$, $P_{BATT}^{\max DCH}(K)$: The amount of power delivered while discharging electrical energy storage device at hour t and its maximum limit, $\mathrm{ENR}(K,t)$: The amount of saved energy in $k-th$ electrical energy storage device at hour t , δ: Efficiency factor of electrical energy storage device, $t_{on}(FC,t)/t_{off}(FC,t)$: Duration for which fuel cell had been continuously up/down till period t ,$U_{\min}$ /$D_{\min}$: Minimum up/down time of fuel cell, $R^{up}(FC,t)/R^{down}(FC,t)$:Ramp up/down capacity of fuel cell at hour t , $R_{\max}^{up}/R_{\max}^{down}$: Maximum ramp up/down rate of fuel cell, $\hat{y}_{in}/y_{in}$: Predicted/ Real value for $in-th$ input, $WS(s_W,W,t)$: The amounts of wind speed of $W-th$ wind farm for s_W-th wind speed scenario at time t, $P_{WN}(W)$: Rated power of $W-th$ wind farm, $WS_{ci}(W)$: The minimum wind speed required to start power efficiency in wind farm(cut-in speed), $WS_n(W)$: Rated speed, $WS_{co}(W)$: The cut-out wind speed (the wind speed by which turbine puts the blades parallel to wind to prevent damages) , $TSS(s_{TST},TST,t)$: The amounts of steam speed of $TST-th$ tidal steam turbine for $s_{TST}-th$ steam speed scenario at time t , $P_{TST}^{N}(TST)$: Rated power of $TST-th$ tidal steam turbine, $TSS_{ci}(TST)$: The cut-in steam speed, $TSS_n(TST)$: Rated steam speed, $TSS_{co}(TST)$: The cut-out speed of tidal steam turbine, ρ_{water}:The fluid density (kg/m^2), A: The cross-sectional area of the tidal steam turbine (m^2), C_P :The power coefficient.

1. Introduction

In the price based unit commitment (PBUC), the main target of programming would be both profit maximization and generation optimization. The profit is defined as the difference of revenue and cost. Practically, the gross profit depends not only on revenue but also on the total expenditures [1].

Owners of renewable resources need to predict the uncertainties for optimal planning such as photovoltaic voltage/power generation [2], market price [3], and load forecasting [4], wind farm power generation/wind speed (WS) [5-9]. In [7], firstly, historical data of WF is decomposed using WT and then WF power generation is predicted by ANN. This method is tested in two regions of china. Afterwards, comparing WT-ANN, ANN, and ARMA methods revealed that WT-ANN can significantly reduce the error in spite of ANN and ARMA methods. In [8], the optimal weights and biases of ANN are determined by genetic algorithm (GA), ICA, and ICA-GA methods; then they are tested on six specified data-bases. In the end, the obtained results confirmed that ICA has higher capabilities. Similarly, ANN is employed to predict WF power generation and then ICA, GA, and PSO are chosen to determine the optimal weights and biases [9]. The prediction results were more satisfactory when ICA algorithm was utilized.

The second solution for uncertainty reduction in renewable units including renewable resources is to coordinate other energy resources which are quite expensive, but available and more reliable, such as pump-storage unit, hydro unit, gas turbines, combined cycle power plants, and energy storage batteries [10 - 21]. However, the share of these energy sources should diminish for many reasons [10]. In [11] the coordinated planning of WF, pump-storage unit, and thermal units is presented by the multi-stage stochastic planning and solved by scenario decreasing algorithm of PSO. In [12], the required reserve level is estimated in presence of high-level WF penetration. In [13], the optimal strategy of WF is determined in the real-time market. The wind speed and market price are predicted by ARMA. Moreover, the expected profit is limited by FR and the required reserve is determined due to the error prediction in WF power generation. In [14], the coordinated planning problem of WF and thermal power plants are solved by artificial immune optimization method. This optimization method is implemented on a system including ten thermal power plants and two WFs. A mixed integer programing algorithm is adopted for period planning of operation startup/shutdown and generating/pumping mode of pump-storage unit to maximize the profit in coordinated operation of WF and pump-storage unit [15]. A scenario-based and chance constrained optimization method is hired to consider the WF power generation prediction error. A rolling optimization method for WF coordination with the energy-storage systems in the day-ahead market is presented to increase the profit of these power plants.

The optimal scenario-based operation management of MG including WF, photovoltaic, micro-turbine/fuel cell, and energy storage devices are studied in [16]. In this paper, the considered uncertainties are load, WF power generation, photovoltaic power generation, and market price. In [17], the optimal biding strategy model in an electricity distributed company is considered in order to make the maximum profit in the day-ahead market. In

[18], the modified particles swarm optimization algorithm is used to optimize energy in MG. Moreover, in this study, uncertainty of data is checked using Hong method. In [19] like [18], Hong method is applied for covering uncertainties; however, the modified firefly algorithm is utilized for optimization. In [20], studies on utilization of micro network are made in the presence of generating resources of thermal and electrical energy and also Proton Exchange Membrane Fuel cell power plant along with the hydrogen storage. The modified algorithm of self-adaptive charge search algorithm is applied for optimization. In [21], the objective function is considered to maximize the profit of wind farm, fuel cell, boiler, CHP units, electrical power generation unit and ESDs connecting to a MG regarding uncertainties. The uncertainties are predicted by time series methods.

In this paper, the presented issue can be shortly explained as follows:

1- Prediction of uncertainties via hybrid method (HM) of WT-ANN-ICA. According to the studies in [7-9], prediction of uncertainties using the proposed method can lessen errors of prediction in comparison to ARMA, ANN, WT-ANN, WT-ANN-PSO, and WT-ANN-GA methods. Therefore, this approach may generate scenarios closer to reality and lead to the optimal programming.

2- Generating the scenarios of WS, tidal steam speed(TSS), PVPG, market price, power/thermal load demand and decreasing the scenarios with the scenario-reduction backward method, and modeling them through the tree scenario method.

3- The programming of MG including WFs, PV, TST, FC, CHP units, boiler and electrical and thermal ESDs, considering constraints and the uncertainties of WS, TSS, PVG, market price and power/thermal load demand.

4- Studying the expected profit of energy resources with and without DR program.

2. The Proposed Method

An algorithm is proposed for programming generation and unit commitment of an MG including three WFs, PV, TST, FC, two CHP units, boiler and ESDs with and without considering DR program shown in Fig. (1).

2.1. Scenario-based stochastic modeling

As a result of extending renewable resources and uncertainty in the nature of such resources, the modern complicated power systems should be analyzed in uncertain forms so that operating point and reliability of energy supply occur approximately to the optimal point in reality. Therefore, having access to powerful tools is necessary for transition from uncertain environments with random variables, including their probability contributions, to the certain problems with certain variables. In the modern deregulated markets, the most important random variables are load demands, wind speed, PVPG, and market price. The origin of the above mentioned uncertainties can be found in issues such as weather conditions, temperature variations as well as government and sport planning.

The proposed method for prediction of uncertainties is depicted in Fig. (1). First, it is assumed that the prediction for d-th day can be done and historical data are available for every single hour of 24 hours since 100 days ago.

Stage 1: data homogenization: the historical data are recalled and normalized to improve data homogenization.

Stage 2: Data Processing Using Wavelet Theory: the components and features of data can be extracted via mathematical equations. More specifically, the components and features of time and frequency domain of data signal can be extracted using wavelet technique. The basic equations of WT are as Eq. (1), (2).

$$WT(a,b)=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} f(t)\psi(\frac{t-b}{a})dt \quad a=2^{-j}, b=k2^{-j}\in R, a\neq 0 \tag{1}$$

$$f(t)=\frac{1}{C_{\Psi}^{2}}\iint_{a,b}\Psi_{\psi}\frac{1}{a^{2}}\psi(\frac{t-b}{a})dadb \tag{2}$$

Where, ψ (a, b) is wavelet function and f (t) is input signal on which wavelet function is done until resulting the WT (a, b) signal. Furthermore, a and b are the parameters related to the WT which depend on the type of wavelet function. The approximated values are again decomposed after some iterations; therefore, the signal is decomposed into smaller parts [7, 22]. WT is useful here to suppress the disturbances in historical data and to alleviate the fluctuation of input data. The input data is decomposed into three approximated components (Dh1, Dh2, and Dh3) with lower accuracy along with a more precise component (Ah) which plays the most important role in the prediction process [22]. Stage 3: Artificial Neural Network (ANN): McCulloch and Pitts tried to simulate the ANN by a logical model for the first time but today it is widely used in many fields. In this paper, the chosen ANN comprises three perception layers; the output layer with one neuron, the input layer with five neurons, and the hidden layer with three neurons. This ANN can predict the information of hours d (t+1,……t + 24) for the output signals of WT as the initial data.

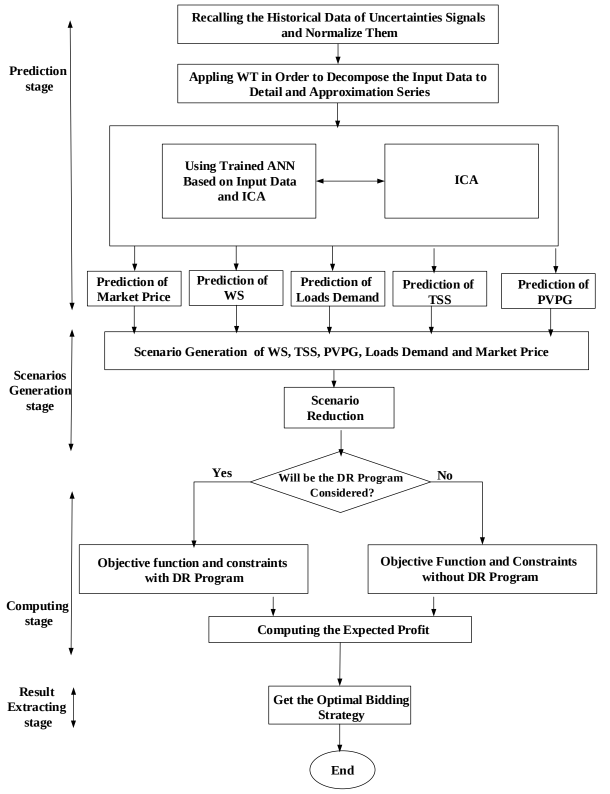


Fig. (1): The flowchart of the proposed method

Stage 4: Imperialist Competitive Algorithm (ICA): ICA is a new optimization strategy based on political and social evolution of human. Basically, to determine the best solution, GA and PSO are inspired with biological evolutions, chromosomes and particles. However, the source of inspiration in ICA is the social-political evolution, and it uses colonies (countries) as the variable for finding the optimal solution [8, 9]. The steps of ICA can be summarized as follow:

1-Creating the initial colonies: according to the neural network input signals (Ah,Dh1,Dh2, and Dh3), and the five neurons in the input layer (IL), three neurons in hidden layer (HL), and one neuron in output layer(OL), the matrixes of wrights (W) and biases (B) which are respectively ILW=[5×4], ILB=[5×1], HLW=[5×3], HLB=[3×1] ،OLW=[3×1], and OLB=[1×1]. Hence, each colony constitutes 47 variables. Initial colonies are selected randomly through specific range based on initial training of ANN. Afterwards, regarding the cost function based on decreasing the prediction error, the optimization of weights and biases are performed within the neural network for better training. The cost function here is mean square error which is implied as Eq. (3).

$$\min FunctionCost \qquad MSE = \frac{1}{IN}\sum_{in=1}^{IN}\left|\hat{y}_{in} - y_{in}\right|^{2} \tag{3}$$

2- Selecting the imperialist: in this stage the colonies with minimum cost are selected as the imperialists.

3- Allocating the other countries as the colony to the imperialists: in this step, some colonies are allocated to each of imperialists and empires. This allocation is done according to imperialists fitness (fewer cost) by stochastic universal sampling method. The stages of 1-3 are the initialization stages of ICA.

4- Performing the act of assimilation or absorption policy: in this stage, each of the colonies is moved towards the imperialist in each empire. This stage proceeds to improve the exploitation of algorithm.

5- Performing the act of revolution: In this stage, the random changes are applied on each of the colonies. This action can improve the exploration of algorithm, and prevent from involving the optimization in the local optimal points.

6- Computing the cost of colonies and imperialists.

7- Comparing the cost of colonies with imperialist in each empire: if a colony holds a lower cost than the imperialist, it will take its place.

8- Evaluating the empires: the cost for each empire is computed according to Eq. (4).

$$Cost_{empire} = Cost_{imperialist} + \frac{0.1}{N_{COL}}\sum_{n=1}^{N_{COL}}(Cost_n) \tag{4}$$

where, N_{CLO} is the number of colonies.

9- Decreasing the colonies: in this stage, a colony is omitted from the weakest empire and transmitted to another empire by roulette wheel method. According this method, the empire with the lower cost has more chance to seize the colony.

10- Omitting the empire: if the weakest empire has no colony, the related imperialist will be transmitted to another empire as a colony.

Stage 5: Studying the termination condition: the stop condition is set based on the number of iterations obtained by trial and error method. If the stop condition of program is satisfactory, the results are moved to the scenario generation stage; otherwise, the algorithm returns to (4) to generate new colonies. ICA flowchart is illustrated in Fig. (2). The uncertainty prediction curves are shown in Fig. (3, a-f).

2.1.1. Generating scenarios and backward method scenarios reduction

According to the stated issues, the determination of optimal strategy for resources connected to the MG is analyzed randomly. To reach this goal, at first, a probability density function is defined for each variable. In this study, the applied probability density function is adopted for power/thermal load demand, TSS, PVPG, and market price with normal distributed functions. In the case of WS, the statistical model is not coordinated with normal distribution but more harmonized with Weibull distribution function.

This distribution function is decomposed into N parts with the mean of zero from the center with the width of α. It is allocated to the occurrence probability and specific error percentage for each level as shown in Fig. (4) [16]. The probability of each occurrence is normalized so that their accumulated distribution function is equal to 1. Then, a number is randomly selected for each uncertainty variable and each time interval by roulette wheel method; hence, an intended scenario is generated.

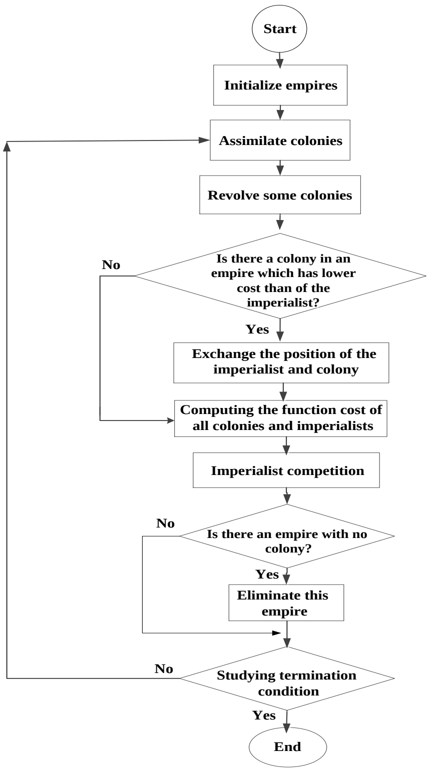
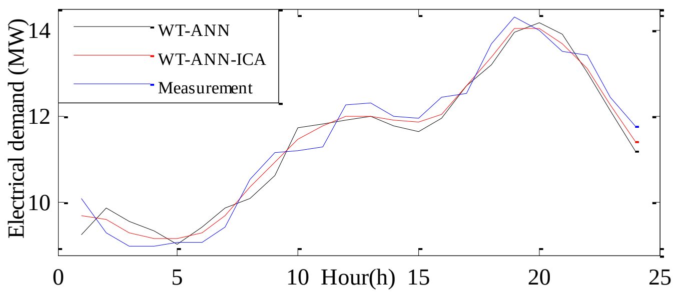
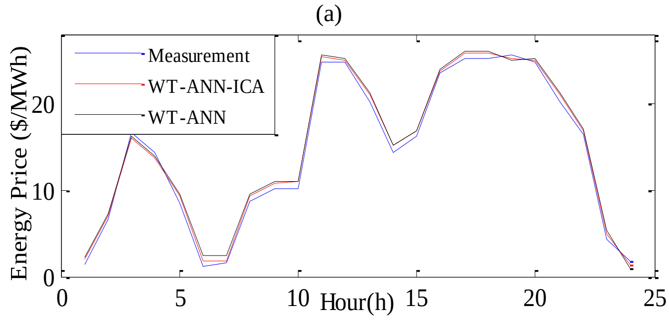


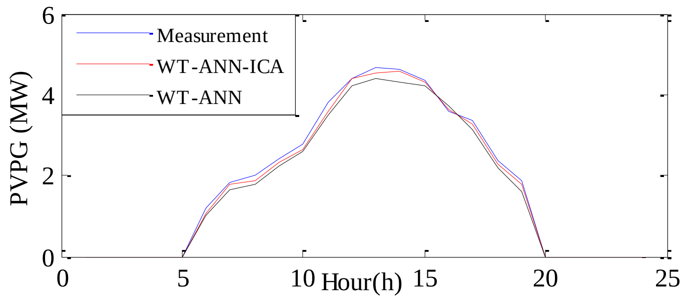
Fig. (2): Flowchart of ICA



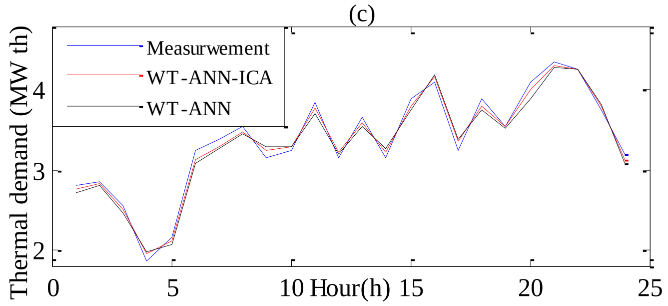
(a)



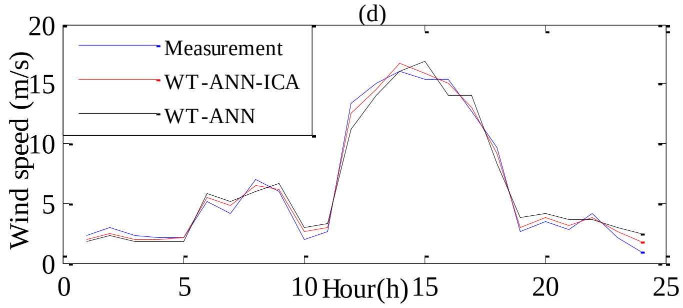
(b)



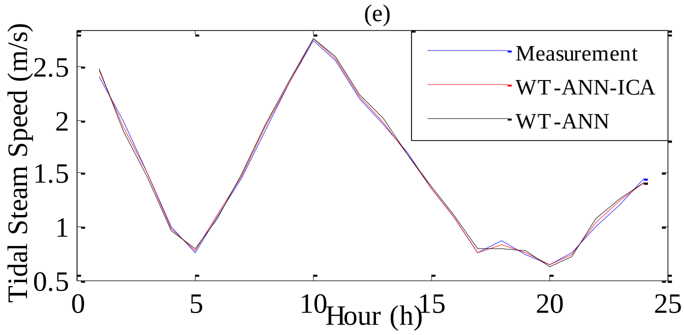
(c)



(d)



(e)



(f)

Fig. (3): The uncertainty prediction curves (a): Electrical demand, (b): Energy price, (c): PV power generation, (d): Thermal demand, (e): Wind speed, (f): Tidal steam speed.

The rate of each scenario is obtained by sum of the error and predicted amount of variable [16]. Eq. (5) shows the amount of scenario for the WS. Consequently, 500 scenarios are generated for each uncertainty.

For modeling all uncertainty parameters including WS, TSS, PVG, market price and power/thermal load demand many scenarios are generated. However, the huge number of scenarios make it burdensome to solve the stochastic problem. In order to solve this problem, the number of scenarios should be declined by the backward method. The basis of this method is to merge the scenarios with close probability into one. This process could continue until reaching the favorable numbers [16, 21]. In this research, the number of scenarios abates down to 10 for each state.

$$P_G^W(w,s,t) = P_{Gforcasted}^W + \Delta P_G^W(w,s,t)$$
$$t = 1,\ldots,24 \qquad s = 1\ldots\ldots s_w \qquad w = 1\ldots\ldots W_N \qquad (5)$$

2.2. Objective function of WFs, PV, TST, FC, CHP units, boiler and ESDs

In this study, the optimal scheduling of MG including WFs, PV, TST, FC, CHP units, boiler and ESDs is examined with the 24– hour time horizon as well as considering uncertainties and DR programs in order to maximize the expected profit. The multi-stage stochastic programing is applied to deal with uncertainties. Since the generation power of units should be determined before applying stochastic processes, they are the first stages or here-and-now decisions and are not dependent to the scenarios. Other variables such as buy or sell power from the market and charge or discharge of storage devices are at the second stage or wait-and-see decisions.

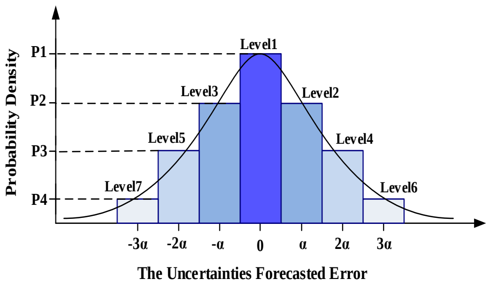


Fig. (4): The probability density function of uncertainties

2.2.1 Problem modeling

In this section, an optimal bidding strategy is modeled and analyzed. The objective function of this optimization problem utilized for the first time is as Eq. (6). The aim is to maximize the expected profit of units considering constraints related to unit usages. The revenue is earned from difference between selling excess energy to the market in grid-connected mode and costs. The costs including buying energy from the market in grid-connected mode, the expenditure of operation, startup and shutdown cost, the cost of charge of electrical ESD and batteries of PV resource are as Eq. (9)-(12). Eq. (15) is the power balancing constraint of MG.

2.2.1.1 Demand response program constrains

The aim of demand response programs is shifting the load of MG from high consumption hours (in which the energy prices are high) to the low consumption hours. It should be noted that planning for load shifting is just able to change a part or percentage of load from an hour to another. [21]

The final load after applying DR program: (Eq. (16))

The maximum amount of movable load: (Eq. (17))

Maximum limit of load in each of the intervals: (Eq. (18))

Load in hour t after applying DR program: (Eq. (19))

Coefficient limit of increasing load: (Eq. (20))

Since in day-ahead markets; generally, clearing is performed for 24 hours ahead, it is assumed that the daily energy expenditure of MG is fixed based on the Eq. (21).

2.2.1.2 CHP units constraints:

As shown in Fig. (5), the electrical power generations of CHP units are not independent from their thermal power and these two powers cannot be controlled separately [26]. In Fig. (5), the electrical-thermal characteristics of CHP units are presented. The operation constraints of CHP units can be extracted from Fig. (5). The area under $\alpha\beta$ curve is formulated by Eq. (22). Eq. (23) and (24) represent models for areas above the curve $\beta\theta$ and $\theta\lambda$ respectively. Both electrical and thermal powers are equal to zero in the case of non-participating CHP units in energy generation according Eq. (25) and (26) respectively.

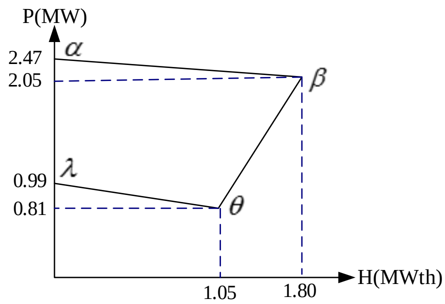


Fig. (5): The electrical-thermal characteristic of CHP units

2.2.1.3 Heat energy storage device constraints

The heat buffer tank is generally added to CHP units and boiler, then acts like a thermal storage. The total amount of generated thermal energy is obtained from Eq. (27). The delivered thermal energy to the buffer tank influenced by losses (η_{loss}) and generated excess heat (η_{gain}) respectively in the shutdown and startup modes of CHP units and boiler at hour t can be resulted from Eq. (28) [21]. Therefore, the thermal power available for buffer tank at hour t is computed from Eq. (29). The Eq. (30) represents heat storage capacity of buffer tank and Eq. (31), and (32) indicate gradient rate of increasing and decreasing thermal energy. The heat capacity limits of boiler can be expressed as Eq. (33).

2.2.1.4. Fuel cell constraints:

The power capacity limits of boiler: (Eq. (34)).

Minimum up time constraint: (Eq. (35)).

Minimum down time constraint: (Eq. (36)).

Generation rate constraints: (Eq. (37)-(38)) [14].

2.2.1.5 WFs constraints:

Characteristics of power generation for wind farms are non-linear according to the wind speed which varies under the influence of type, dimension, and design of turbine. Generally speaking, the generation power of wind unit can be obtained by Eq. (A.39).
Moreover, A, and Bare determined by Eq. (A.40),(A.41) [25].

2.2.1.6. PV constraints:

Limits on the ESD of the PV unit while getting charged and discharged: (Eq. (A.42), Eq. (A.43)).
Charge/discharge switching constraint: (Eq. (A.44)).
Initial / terminal energy of the battery: (Eq. (A.45)).
Amount of saved energy in the battery: (Eq. (A.46)).
The power generation of the PV unit: (Eq. (A.47)).

2.2.1.7. Electrical energy storage device constraints

The constraints of electrical energy storage devices are similar to the Eq. (A.42)-(A.47) which are related to PV constraints. The difference between them is that the charging and discharging of these devices and other constraints are dependent on scenarios pertaining to the WS, PVPG, power/thermal load demand, while the PV constraints are just affected by PVPG.

2.2.1.8. Tidal turbine

In order to extract the tidal energy and generate power electricity, two ways can be used:
1. tidal stream system that uses kinetic energy of the free flowing water and
2. Tidal barrage system that makes use of potential energy of the ocean in height. Usually, this method is not used due to the environmental conditions [27].

The generation power of tidal stream turbine can be obtained by Eq. (A.48).

$$MAX \quad ER_T = \sum_{t=1}^{T} \left[\sum_{s\in S} \rho_s \left(P_{sale}(s,t).E_P(s_p,t) - P_{buy}(s,t).E_P(s_P,t) - C_T(s,W,PV,TST,FC,CHP,K,B,t) \right) \right] \tag{6}$$

$$\rho_s = p_P \times \rho_W \times \rho_{TSS} \times \rho_{PV} \times \rho_{PL} \times \rho_{HL} \tag{7}$$

$$s = s_P, s_W, s_{PV}, s_{PL}, s_{HL}, s_{TSS} \tag{8}$$

$$C_T(s,W,PV,TST,FC,CHP,K,B,t) =$$

$$\left(\begin{array}{l} \sum_{W=1}^{W_N} A_W.M(W,t) + \sum_{CHP=1}^{CHP_N} (C_{CHP}(P,H).M(CHP,t)) + (A_{PV}. + BATT_{COST}(PV,t)).M(PV,t) + \left(A_{FC} + B_{FC}.P_G^{FC}(s,t)\right).M(FC,t) \\ + BATT_{COST}(K,t).M(K,t) + A_B.P_G^B(s,t).M(B,t) + A_{TST}.M(TST,t) + \sum_{i\in CHP,FC,B} \left\{ U_{COST}(i,t).SU(i,t) + D_{COST}(i,t).SD(i,t) \right\} \end{array} \right) \tag{9}$$

$$C_{CHP}(P,H) = A_{CHP} + B_{CHP}.P_{G,CHP}(t) + C_{CHP}.P_{G,CHP}^2(t) + D_{CHP}.H_{G,CHP}^2(t) + E_{CHP}.H_{G,CHP}(t) + F_{CHP}.H(t).P(t) \tag{10}$$

$$BATT_{COST}(K,t) = [a^{CH}(K)Z_{BATT}^{CH}(K,t) + b^{CH}(K)P_{BATT}^{CH}(s,K,t)] + [a^{DCH}(K)Z_{BATT}^{DCH} + b^{DCH}P_{BATT}^{DCH}(s,K,t)] + CC(K) \tag{11}$$

$$BATT_{COST}(PV,t) = [a^{CH}(PV)Z_{BATT}^{CH}(PV,t) + b^{CH}(PV)P_{BATT}^{CH}(s_{PV},PV,t)] + [a^{DCH}(PV)Z_{BATT}^{DCH} + b^{DCH}P_{BATT}^{DCH}(s_{PV},PV,t)] + CC(PV) \tag{12}$$

$$SU(i,t) = M(i,t) \times (1 - M(i,t-1)) \qquad i \in CHP, FC, B \tag{13}$$

$$SD(i,t) = (1 - M(i,t)) \times M(i,t-1) \qquad i \in CHP, FC, B \tag{14}$$

$$P_{buy}(s,t) + \sum_{CHP=1}^{CHP_N} P_{G,CHP}(t) + P_G^{FC}(t) + \sum_{W=1}^{W_N} P_G^W(s_W,W,t) + P_{BATT}^{DCH}(s_{PV},PV,t) + P_G^{TST}(s_{TSS},TST,t) + P_{BATT}^{DCH}(s,K,t) = \tag{15}$$

$$P_{sale}(s,t) + P_{BATT}^{CH}(s_{PV},PV,t) + P_{BATT}^{CH}(s,K,t) + \left\{ (1 - DR(s,t).L_0(s,t) + L_{shift}(s,t) \right\}$$

$$L(s,t) = (1 - DR(s,t)) \times L_0(s,t) + L_{shift}(s,t) \tag{16}$$

$$DR(s,t) \le DR_{\max} \tag{17}$$

$$0 \le L_{increased}(s,t) \le \varepsilon_{increased}(s,t) \times L_0(s,t) \tag{18}$$

$$L_{increased}(s,t) = L_{shift}(s,t) - (DR(s,t) \times L_0(s,t)) \tag{19}$$

$$\varepsilon_{increased}(s,t) \le \varepsilon_{\max} \tag{20}$$

$$\sum_{t=1}^{T} L_{increased}(s,t) = \sum_{t=1}^{T} \left(DR(s,t) \times L_0(s,t) \right) \tag{21}$$

$$P_{G,CHP}(t) - P_{G,CHP}(\alpha) - \frac{P_{G,CHP}(\alpha) - P_{G,CHP}(\beta)}{H_{G,CHP}(\alpha) - H_{G,CHP}(\beta)} (H_{G,CHP}(t) - H_{G,CHP}(\alpha)) \le 0 \tag{22}$$

$$P_{G,CHP}(t) - P_{G,CHP}(\beta) - \frac{P_{G,CHP}(\beta) - P_{G,CHP}(\theta)}{H_{G,CHP}(\beta) - H_{G,CHP}(\theta)} (H_{G,CHP}(t) - H_{G,CHP}(\beta)) \ge -(1 - M(CHP,t)) \times Y \tag{23}$$

$$P_{G,CHP}(t)-P_{G,CHP}(\theta)-\frac{P_{G,CHP}(\theta)-P_{G,CHP}(\lambda)}{H_{G,CHP}(\theta)-H_{G,CHP}(\lambda)}(H_{G,CHP}(t)-H_{G,CHP}(\theta))\geq-(1-M(CHP,t))\times Y \quad (24)$$

$$0\leq H_{G,CHP}(t)\leq H_{G,CHP}(\beta)\times M(CHP,t) \quad (25)$$

$$0\leq P_{G,CHP}(t)\leq P_{G,CHP}(\beta)\times M(CHP,t) \quad (26)$$

$$H'_T(t)=\sum_{CHP=1}^{CHP_N}H_{G,CHP}(t)+H_{G,B}(t) \quad (27)$$

$$H_T(t)=H'_T(t)-\eta_{loss}SU(i,t)+\eta_{gain}SD(i,t) \qquad i\in CHP,B \quad (28)$$

$$AH(t)=(1-\sigma)AH(t-1)+H_T(t)-H_{HL}(t) \quad (29)$$

$$AH_{\min}\leq AH(t)\leq AH_{\max} \quad (30)$$

$$AH(t)-AH(t-1)\leq AH_{charge}^{\max} \quad (31)$$

$$AH(t-1)-AH(t)\leq AH_{dischage}^{\max} \quad (32)$$

$$H_{G\min}^{B}(B).M(B,t)\leq H_G^B(B,t)\leq H_{G\max}^{B}(B).M(B,t) \quad (33)$$

$$P_{G\min}^{FC}(FC).M(FC,t)\leq P_G^{FC}(FC,t)\leq P_{G\max}^{FC}(FC).M(FC,t) \quad (34)$$

$$[t_{on}(FC,(t-1))-U_{\min}(FC)]\times[U(FC,(t-1)-U(FC,t)]\geq 0 \quad (35)$$

$$[t_{OFF}(FC,(t-1))-D_{\min}(FC)]\times[U(FC,t)-U(FC,(t-1))]\geq 0 \quad (36)$$

$$R^{up}(FC,t)=\min\{R_{\max}^{up}(FC,P_{G\max}^{FC}(FC)-P_G^{FC}(FC,t)\} \quad (37)$$

$$R^{down}(FC,t)=\min\{R_{\max}^{down}(FC),P_G^{FC}(FC,t)-P_{G\min}^{FC}(FC)\} \quad (38)$$

$$P_G^W(s_W,W,t)=\begin{cases}0 & 0\leq WS(s_W,W,t)<WS_{ci}(W)\\ P_{WN}(W).(A(w).WS^3(s_W,W,t)-B(W)) & WS_{ci}(W)\leq WS(s_W,W,t)<WS_n(W)\\ P_{WN}(W) & WS_n(W)\leq WS(s_W,W,t)<WS_{co}(W)\\ 0 & WS_{co}(W)\leq WS(s_W,W,t)\end{cases} \quad (39)$$

$$A(W)=\frac{1}{WS_n^3(W)-WS_{ci}^3(W)} \quad (40)$$

$$B(W)=\frac{WS_{ci}^3(W)}{WS_n^3(W)-WS_{ci}^3(W)} \quad (41)$$

$$0\leq P_{BATT}^{CH}(PV,s_{PV},t)\leq P_{BATT}^{\max CH}(PV)Z_{CH}(PV,s_{PV},t) \quad (42)$$

$$0\leq P_{BATT}^{DCH}(PV,s_{PV},t)\leq P_{BATT}^{\max DCH}(PV)Z_{DCH}(PV,s_{PV},t) \quad (43)$$

$$0\leq Z_{CH}(PV,t)+Z_{DCH}(PV,t)\leq 1 \quad (44)$$

$$ENR(PV,t=1)=ENR_{ini}(PV),ENR(PV,t=24)\geq ENR_{end} \quad (45)$$

$$ENR(s_{PV},PV,t)=ENR(s_{PV},PV,t-1)+P_{BATT}^{CH}(s_{PV},PV,t-1)-P_{BATT}^{DCH}(s_{PV},PV,t-1) \quad (46)$$

$$P_{sale}^{PV}(s_{PV},PV,t)=P_G^{PV}(s_{PV},PV,t)-P_{BATT}^{CH}(s_{PV},PV,t)+\delta P_{BATT}^{DCH}(s_{PV},PV,t) \quad (47)$$

$$P_G^{TST}(s_{TSS},TST,t)=\begin{cases}0 & 0\leq TSS(s_{TSS},TST,t)<TSS_{ci}(TST)\\ P_{TST}^{N}(TST).(\frac{TSS(s_{TSS},TST,t)-TSS_{ci}(TST)}{TSS_n(TST)-TSS_{ci}(TST)})^3 & TSS_{ci}(TST)\leq TSS(s_{TSS},TST,t)<TSS_n(TST)\\ P_{TST}^{N}(TST) & TSS_n(TST)\leq TSS(s_{TSS},TST,t)<TSS_{co}(TST)\\ 0 & TSS_{co}(TST)\leq TSS(s_{TSS},TST,t)\end{cases} \quad (48)$$

Where:

$$P_{TST}^{N}(TST)=0.5.\rho_{water}.A.C_P.TSS_n^3(TST)$$

3. Numerical Example

In this part, firstly, the structure of MG and numerical data concerned with energy resources are studied and then simulation results of optimal operation for the stochastic problem are analyzed.

3.1 Configuration of MG

In this paper three case studies will be examined:

1. Planning of isolating MG with predicting uncertainties by hybrid method of WT-ANN-ICA,
2. Planning and determining the optimal strategy of MG energy resources connected to grid and comparing hybrid prediction methods of WT-ANN and WT-ANN-ICA, in order to examine the influence of predicting uncertainties upon the profit amount of MG, and
3. Programming and determining the optimal strategy of MG connected to the grid and applying hybrid prediction method of WT- ANN-ICA for predicting uncertainties and exploring the effect of DR problem on the profit of MG.

In cases 2 and 3, the MG is able to exchange energy with network based on electrical load demand and market price. Stochastic programming is applied on a typical MG depicted in Fig. (6). The case studies will be performed on three WFs, two CHP units, a TST, a PV, a boiler, a low temperature fuel cell (PAFC), an electrical energy storage device, a heat buffer tank along with the fixed and responsive electrical and also fixed thermal loads. The startup and shutdown costs of units are presented in table (1). The heat buffer tank data and cost coefficients of CHP units are shown in table (2). Both $DR_{\max}$ and $\varepsilon_{\max}$ are assumed 30%. The electrical-thermal characteristics of CHP units are displayed in Fig. (5). The parameters of WFs include: $WS_{co}(i)=25^{m/s}$, $WS_{n}(i)=11^{m/s}$, $WS_{ci}(i)=2.5^{m/s}$, and the rated output power are equal to $P_{WN1}=1.5^{MW}$, $P_{WN2,3}=2.4^{MW}$. Historical data pertaining to the WS, electrical demand and market price, electrical energy storage devices data and photovoltaic power generation are respectively proposed in [23], [24], [21] and [16]. The PV nominal power generation is $P_{\max}^{MW}=4.68, P_{\min}^{MW}=0$ and $\delta=0.75$. Table (3) lists the parameters used for the tidal steam turbine [27].

Table (1): The startup and shutdown cost of units

Unit	UCOST	DCOST
CHP units	20	20
Fuel Cell	0.0207	0.0207
Boiler	9	9

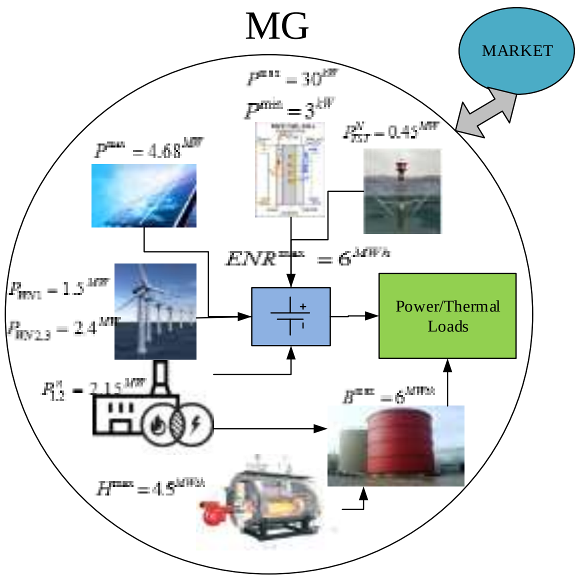


Fig. (6): Typical MG under study

4. Simulation results

1. Case study 1: planning of MG in the grid- isolated mode: In this case, $P_{buy}=P_{sale}=0$ and the objective function is just concluded in cost terms of energy resources. The uncertainties are predicted by hybrid method of WT-ANN-ICA. The simulation results obtained from the first case study are listed in table (4). According to table (4), the generation cost is equal to the amount of objective function and $2032.76. In this state, the WF, TST and PV are not working with their maximum capacity, while the cost of generating them is zero and this occurs due to the thermal load of MG. The CHP units produce heat to provide thermal load. The electrical-thermal characteristics of CHP units are the generation factor for both heat and electrical power.

2. Case study 2: in the second case, the effect of exchanging electrical energy with grid in connected mode and also the effect of more accurate prediction of random parameters on MG planning are studied by comparing hybrid methods of WT-ANN-ICA and WT-ANN. The MG planning in the presence of all economic and technical constraints and also the problem of DR will be solved. The results regarding to the second case study are presented in table (4). According to table (4), using WT-ANN-ICA prediction method, the generation cost increased by 13.77% in the case study 2 as compared to the first case. The profit of MG resulted from taking part in the market is $792.64 and $909.93for WT-ANN and WT-ANN-ICA respectively. This profit is due to the sale of power to the main grid.

Table (2): The heat buffer tank data and cost coefficients of CHP units

CHP units	A_{CHP}=0.0435	B_{CHP}=36	C_{CHP}=12.5	D_{CHP}=0.027	E_{CHP}=0.6	F_{CHP}=0.011
Heat Buffer Tank	$\eta_{loss}=0.6$	$\eta_{gain}=0.3$	$\sigma=1\%$	$AH_{discharde}^{\max}=$ $AH_{charge}^{\max}=2$	$AH_{\max}=7$	$AH_{\min}=0$

Table (3): The tidal steam turbine data

Rated Speed	2.4(m/s)
Cut-in Speed	0.7(m/s)
Cut-out Speed	4.2(m/s)
Power Coefficient	0.47
Cross-sectional Area	3.006(m^2)

Table (4): Case studies results

State	Prediction method	Cost of buying energy($)	Revenue from the sale of energy($)	Generation cost($)	Value of OF($)	Expected Profit($)
Case 1	WT-ANN-ICA	-	-	2,032.76	-2,032.76	-
Case 2	WT-ANN	281.6	1,295.78	2,254.30	-1240.12	792.64
	WT-ANN-ICA	266.93	1,456.96	2,312.86	-1122.83	909.93
Case 3	WT-ANN-ICA	387.57	1228.45	2,161.59	-1320.71	712.05

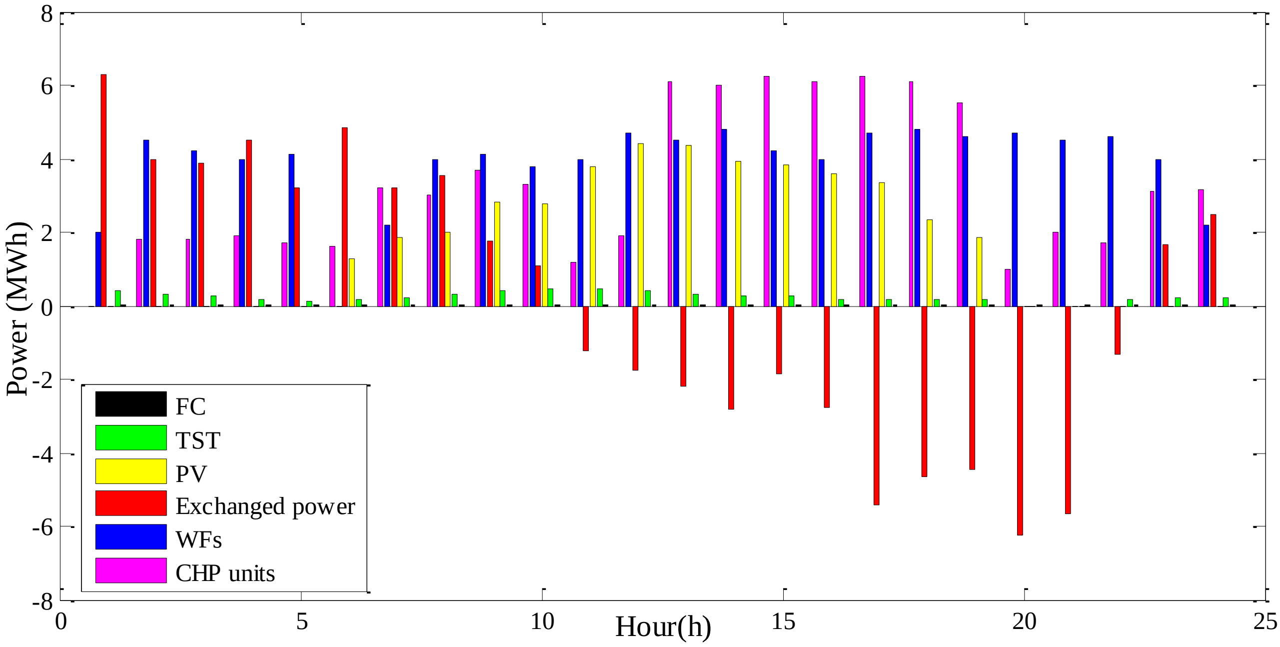


Fig. (7): The generated power of resources in the planning horizon

The generated power of resources in the planning horizon is shown in Fig. (7). The expected amount of buying and selling powers, WFs, TST and PV power generation are illustrated in Fig. (7). According Fig. (7), WFs, TST and PV power generations are readjusted at their maximum capacity.

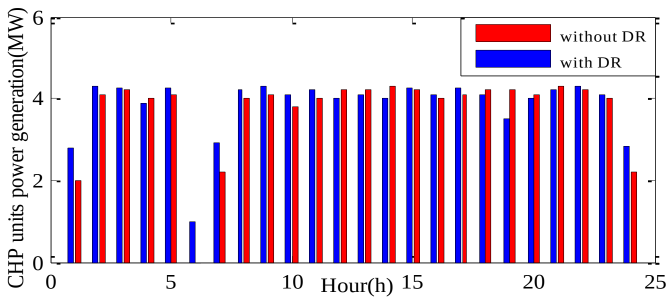
Therefore, the excess WFs, TST and PV power generations can be saved in devices of electrical energy storage and shifted to the hours with more demand (higher price) or can be on offer to the market. In Fig. (8-c) and (8-d), the generated thermal power of CHP units and boiler are shown respectively. According to Fig. (8-c) and (8-d), considering costly expenses of generation, the boiler is less involved in supplying thermal demand, as compared to CHP units.

Due to the stochastic nature of WFs, TST and PV power generations, market price and power/thermal load demand, more accurate prediction of these random parameters led to generating scenarios proximate to reality and with greater possibility. Consequently, a more detailed planning can be achievable. In table (4), the obtained results of MG planning are compared by prediction hybrid method of WT-ANN and WT-ANN-ICA. The results indicate 14.79% increased profits of MG in WT-ANN-ICA method in comparison with WT-ANN Method.

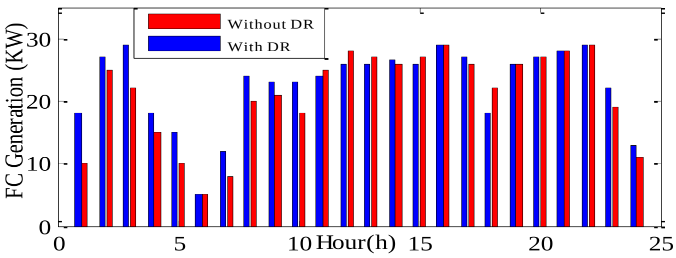
3. Case study 3: to explore the effect of DR program on determination of generation strategy of MG. In the third case, the MG planning is studied without DR program in order to investigate its effects on the expected profit of MG by hybrid prediction method of WT-ANN-ICA. Table (4) shows the results of case study 3 versus 2. The expected profit decreased while the cost of generation dropped slightly. According to table (4) the expected profit of MG in the third case study is $712.05 which approximately decreased 27.7% as compared to the second case study (applied DR program). This reduction in profit of MG indicates the efficacy of DR program on the optimal planning of these units.

Regarding table (4), the objective function values of both cases 2 and 3 are negative. That is because of high energy demand inside the MG and lack of possibility to offer excess power to the main grid.

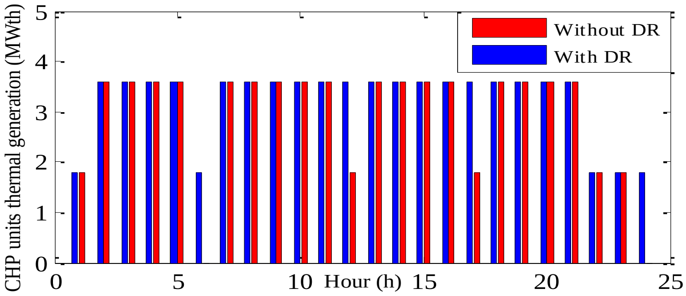
The difference between energy generation of resources with and without DR is illustrated in Fig (8). The received and delivered power to grid with and without DR are depicted in Fig (8-a). Regarding this figure, the movable loads can be shifted from peak time to other hours when the energy price is lower and make profit.



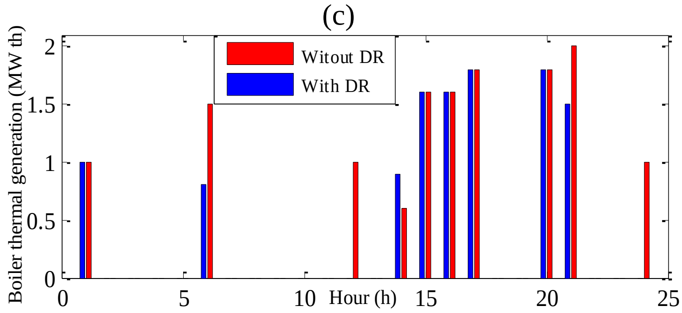
(a)



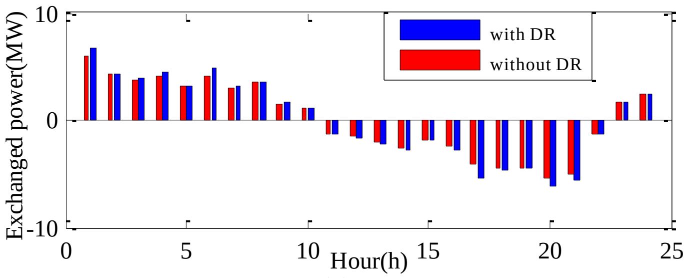
(b)



(c)



(d)



(e)

Fig (8): Energy generation of resources with and without DR

5. Conclusion

In this paper, an algorithm was suggested to ascertain optimal strategy of a MG including WFs, PV, TST, fuel cell, CHP units, boiler and ESDs, by considering economic and technical constraints and DR program. This research aimed to present an optimization program to maximize the profit of MG in grid – connected mode, and to minimize the cost of energy resources in grid- isolated mode. The uncertainties are WS, TSS, PVPG market price and power/ thermal load demand which are predicted by hybrid prediction methods of WT-ANN and WT- ANN-ICA, and related scenarios are generated by probability density functions appropriate to each uncertainty and scenario reduction method. The simulation results represent that applying more accurate prediction method, some scenarios proximate to reality and with greater possibility are generated. Hence, a more detailed and precise planning is achieved and the expected profit of MG might be increased. If the method of WT-ANN-ICA is used rather than WT-ANN, the expected profit of MG will be increased by 14.79%. Furthermore, the expected profit can be risen by applying DR program.

According to the studied cases, although the DR program increases the generation cost by 7%, the expected profit rises more than 27.7% and it goes to $909.93, while without considering DR program, this profit would be $712.05.

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