An Optimization Method for Participation of a Wind-solar-hydro Pumped in Daily Ahead Operation

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Abstract
Nowadays, renewable energies to generate electric power have attracted wide speared attention of the market participant. The increase of the wind-solar energy penetration in power system needed to correct existent management methods. The nature of wind and solar generations are random and depend on climate conditions such as wind velocity and solar irradiation (SI). On the other hand, selling energy can boost their profits during high price period that can be done by combination of solar- wind and energy storage, for example, pump hydro storage unit. The main problem in jointing a wind-solar-hydro pumped in the power market is not the same manner as conventional plants and needs day-ahead planning. This paper presents a day-ahead planning of solar-wind-storage so as to satisfy maximum profits for traders and decision making for operators. The method is based on probabilistic forecast by means of ANFIS network and minimization of imbalance of operation penalties.
Key words:
Wind power, solar irradiance, hydro pumped storage, day-ahead planning

1. Introduction

The fossil energy disadvantages fostered development of renewable distributed generation (DG) resources. The generation of wind and solar powers has attracted attentions in many countries. This resource offers significant public health, economic benefits, Reduction of CO2 emission and global warming, local accessibility and so on [1]. The wind farm (WF) output is however variable and conditioned by uncertain characteristics of the wind resource. Also photovoltaic (PV) plants output depends on solar radiation. Therefore growth of power generation from these resources needed to find new ways on power system operation [2]. The electricity must be generated and transmitted as it is consumed and this limitation is incompatible with uncertain output of wind-solar plants. Therefore the wind energy participation in power market is a decision-making problem. A hydro pumped storage (PS) plant is used for generation balancing in the conventional operation plans so as to buy electricity energy and store in the form of gravitational potential energy of water at low price periods. Then sell stored energy through hydro-turbines at high price period. The PS as provides the largest-capacity form of energy storage, is used to back up operating renewable energy like wind-solar resources.

A number of studies have looked the ways of operating wind and solar combined fossil generation. The [3] considered five day-ahead dispatch modes to coordinate wind generation and coal-fired generation. In the paper, unit commitment studied considering wind power variability by means of low computation tools and discussed the impact of wind power on unit commitment with more clarity. In the [4] a probabilistic model of security-constrained unit commitment based on additional reserve capacity requirements proposed in which deterministic approaches is used to minimize the cost of energy, spinning reserve and possible loss of load that is not effective for stochastic behavior of wind generation. In [5] a risk evaluation perspective is used, generating probabilistic forecasting tools to estimate conventional generation outage, load forecasting uncertainty, and wind power forecast uncertainty, and the reserve margin to help making operational decisions are still needed. The [6] discuses cost analysis to determine the most economical reserve margin and present a solution method in this category. The studies in [7] work on planning of a WF based on annual cost for determining the optimal wind turbine (WT) generator installation that its nonlinear and non-differentiable objective functions solved by Genetic Algorithm. In [8] a forecasting method for day-ahead operation of PV power plants based on least-squares optimization presented that reduced the error forecasts. A lot of studies have studied the day-ahead forecasting of PV power output. The [9] presented an artificial weather-based method by means of fuzzy method with reduced forecasting error. In [10] effective parameters on short-term SI forecasting identified and then a neural network trained. According to the study, these parameters include: averaged ambient temperature, date sequence number in one year, average surface irradiance, normalized discrete difference of SI, third-order derivative of the shape difference between surface irradiance and extraterrestrial irradiance.

In the next section WF modeling include wind speed and WT presented. In the third section SI equation and effective parameters to predict PV power investigated. In the next section Adaptive Neuro-Fuzzy Inference System (ANFIS) network based on time series descripted. Finally presented method to day-ahead optimization for wind-solar-storage considered.

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2. WF Modeling

The WT designed in various capacities to connect distribution or transmission network. A group of WTs installed in the same location to provide high electricity power capacity, namely WF. The WF model depends on wind speed model WT model [11].

2.1 Wind Speed Model

The wind power output of WF depends on wind speed that is randomly. Therefore it is necessary to select a suitable wind speed model for WF studied in a case study area. The researchers suggested various wind speed model that mostly based on using time series [12]. In this paper, the hourly wind speed data of Manjil (in Iran) area is shown in Fig. 1 [13].

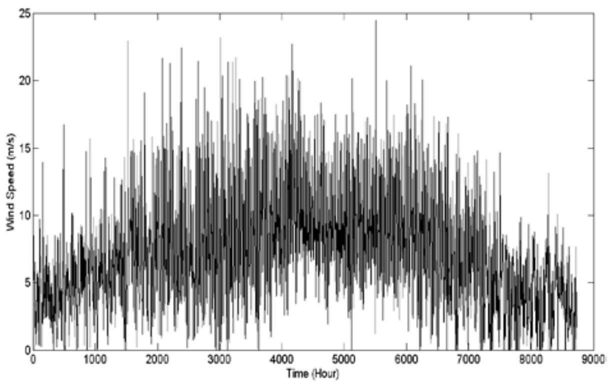

Fig. 1 Hourly Manjil wind speed.

2.2. WT model

The output active power of WF can be calculated by wind speed turbine nonlinearly by means of characteristic power performance curve depending on turbine operating parameters. The curve show active power output at different wind speeds include the cut-in speed, the rated speed and the cut-out speed as show Fig.2 [14].

According to Fig. 1, the WT starts to generate power in the cut-in speed (Vcin). Increasing wind speed (the rated speed Vr), the WT reaches rated turbine power (Pr) and it shuts down to keep loads and generator power from reaching damaging levels in the cut-out speed (Vco).

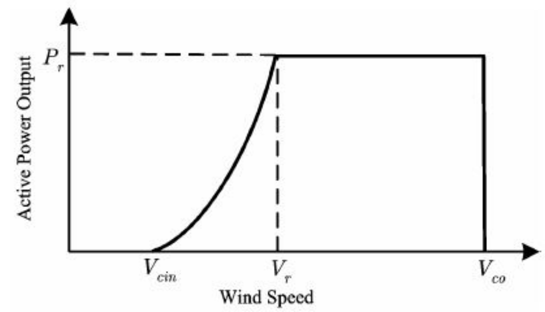

Fig. 2 The WT power performance curve [15].

There are the characteristic values include V_{cin}, V_r, P_r, V_{co} in the WT manufacture catalogue. The following mathematic equation describe characteristic power performance curve:

$$P_{WT} = \begin{cases} 0 & x < V_{cin} \\ P_r.(A + Bx + Cx^2) & V_{cin} < x < V_r \\ P_r & V_r < x < V_{co} \\ 0 & x > V_{co} \end{cases} \quad (1)$$

Where A, B and C depend on technical specifications and can be calculated by mathematic equation as mentioned in [14].

2.3 Determining WF Output Power

After suitable model of WT and wind speed provided, the WF output can be determined. The WF output power is equal total power of each WT, if all of them to be online [15]. It is important to mentioned, the total WT always is not connected because it may be damaged. Therefore the WF output power depends on number of connected WT of WF as following:

$$P_{WF}^{out} = (\frac{N_T - N_f}{N_T}).P_{WF}^{out} \quad (2)$$

Where, P_{WF}^{out} is corrected WF output power, N_f is number of active WT and N_T is number of total WT of WF.

3. PV Plant Model

In this section PV plant modeling described in detailed.

3.1. SI Equations

The SI is the amount of electromagnetic energy incident on a surface from the sun per unit time and per unit area in the wavelength range of the measuring instrument [10].

The energy decreased by planets, other celestial objects, or interstellar gas and dust. Upon [8] about 40% (general level) of the solar energy intercepted at the top of Earth's atmosphere passes through cloud cover (CC) to the surface. The proportion is different under different weather conditions. The solar surface irradiance can be evaluated as following [10]:

$$G_0 = G_s\left(1+0.33\cos\frac{360n}{365}\right)(\cos\delta\cos\varphi\cos\omega+\sin\delta\sin\varphi). \quad (3)$$

where Gs is solar constant suggested a value of 1367 W/m2 [16], n is the date sequence number in one year, n $\in$ [1,365], δ is solar declination, ϕ is latitude, ω is solar hour angle as following [17]:

$$\delta = 23.45\sin(360\frac{284+n}{365}) \quad (4)$$

$$\omega_s = \cos^{-1}(-\tan\varphi\tan\delta) \quad (5)$$

During a day the G_0 can be calculated by semi-sinusoidal model in the clear sky as following [18]:

$$G_0(t) = G_0\sin\left(180\frac{t-t_{sunrise}}{\overline{N}}\right) \quad (6)$$

where $\overline{N}$ is long of day that can be calculated:

$$\overline{N} = \frac{2}{15}\omega_s \quad (7)$$

$$t_{sunrise} = 12-\frac{\overline{N}}{2} \quad (8)$$

The G_0 (from 2016.01.01 to 2016.01.06, Manjil, Iran), is shown in Fig. 3 by semi-sinusoidal model:

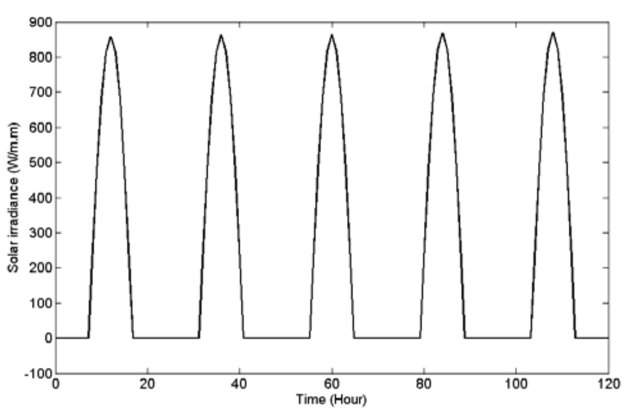

Fig. 3 Semi-sinusoidal model of SI in the Manjil area with latitude 36.46.

The G_0 of CC can derive from [8]:

$$G_{cc} = G_0[0.35+0.65(1-CC)] \quad (9)$$

Where G_{cc} is SI of CC and CC is (0 = clear, 1 = overcast).

3.2. Effective parameters on SI

Based on performed simulation in the [10], the SI depends on:

I. The average surface irradiance (G_{savg}) defined the difference between G_0 extraterrestrial irradiance and surface irradiance G_{cc} ($G_{savg}= G_0 - G_{cc}$).

II. Third-order derivative of SI difference to describe the variation and fluctuation of weather conditions *TOD* ($TOD=d^3G_{savg}/dt^3$). However the maximum value (TOD_{max}) gets more significant for different weather conditions of one day.

III. The normalized discrete difference (*NDD*) of SI is defined:

$$NDD = \sqrt{\frac{1}{k}\sum_{i=1}^{k}(G_{0N,i}-G_{ccN,i})^2} \quad (10)$$

where,

$$G_{0N,i} = \frac{G_{0,i}}{\max_{i=1,2,\dots,k}\{G_{0,i}\}}\times 100 \quad (11)$$

$$G_{ccN,i} = \frac{G_{cc,i}}{\max_{i=1,2,\dots,k}\{G_{cc,i}\}}\times 100 \quad (12)$$

IV. The average ambient temperature of one day T_{avg}.

V. The date sequence number n in one year, $n \in$ [1,365].

VI. The hour number h in one day, $n \in$ (sunrise, sunset).

Therefore the components of SI forecasting model input vector (forecasting factor) are:

$$f_f = [G_{savg}, TOD_{\max}, NDD, T_{avg}, n, h] \quad (13)$$

The SI can forecast by a meta-model based on f_f data of an area.

3.3. PV Generation Model

The active power output of the PV system mostly depends on SI and the PV power generated per unit area can be approximately given by the following expression [19]:

$$P = \eta.S.G_{cc}[1-0.005\times(T-25)] \quad (14)$$

Where, P denotes the PV active power output, η is the conversion efficiency of PV panels, S is the PV array area, and T is the ambient temperature around the PV panels. This paper considers Manjil PV plant that, S is 10000 m^2, η is 0.94 and T is 4$^{\circ c}$.

4. ANFIS Meta Model

Some of the literatures used Artificial Networks for data prediction by means of time series models [20]. In essence, time series predicts the power *p(t)* as [21]:

$$p(t) = a(n) \cdot p(t-n) + (1 - a(n)) \cdot \mu \tag{15}$$

Where, *p(t-n)* is power in time-steps back (*n-1*), *a(n)* is the autocorrelation of the time series n steps back and μ is the mean of the time series. Of course *p(t)* disregarding μ and having n=1, this would be the persistence model itself. In this paper an Artificial Network has been built that can predict *p(t+6)* from the past values of this time series.

The ANFIS model has an Artificial Network structure to conduct fuzzy system that possesses easy training with a good accuracy [22]. The neural network has benefited conducting fuzzy inference to model non-linear system based on feed-forward calculation of output and back-propagation learning capability. The ANFIS introduced based on Takagi-Sugeno fuzzy inference system that include [23]: input membership functions (MF) (or fuzzification section), IF-THEN rules (or inference section) and output equation (or defuzzification section). In the ANFIS, parameters of fuzzification and inference sections are determined by a five layers Artificial Neural Network (ANN) in training process by input-output data. We used ANFIS GUI (Graphical User Interface) of MATLAB toolbox Usually every data collection to model a system based on input-output data, divide to 3 sets as following: 60% for training, 20% for checking of training process to avoid overtraining and 20% for testing.

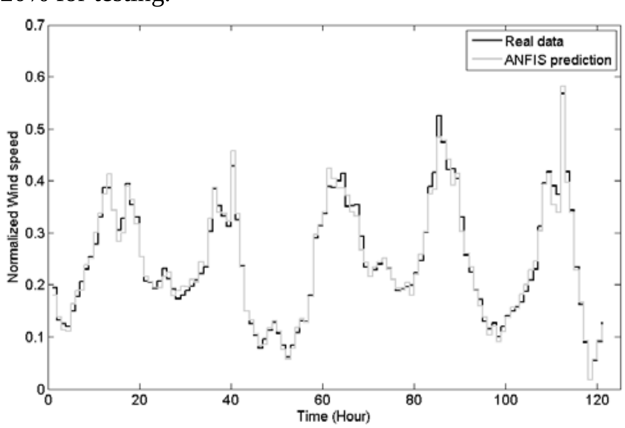

Fig. 4 ANFIS Prediction for wind power generation.

Therefore solar or wind power can predicted by ANFIS based on time series method as following: *p(t+6)* can predicted from the past values of this time series, that is, *p(t-18)*, *p(t-12)*, *p(t-6)*, and *p(t)*. Therefore the training data format is [24]:

$$\begin{bmatrix} p(t-18) & p(t-12) & p(t-6) & p(t) & p(t+6) \end{bmatrix} \tag{16}$$

Where, *p(t)* is hourly wind or solar data.

The Fig. 4 and Fig. 5 show ANFIS prediction for solar and wind power in the Manjil area from 2016.01.01 to 2016.01.06.

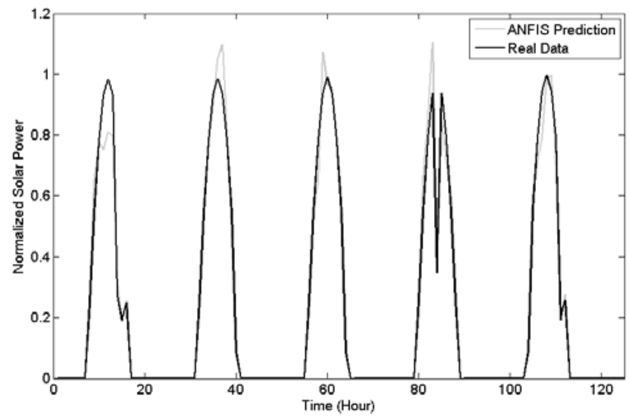

Fig. 5 ANFIS Prediction for PV power generation.

5. Day-Ahead Optimization

Nowadays the electricity markets point on participation of uncertainty renewable resource like wind-solar resource. The participation of wind-solar plant contains bidding strategy and responsibility for any deviation from contract [24]. Therefore hydro-pumped device used to compensate wind power deviations and minimize imbalance costs in the market. In day-ahead market, trader offered operational strategy to sell power based on wind-solar power prediction method. It is clear that higher value of the available wind power, leading to higher economic profit [1]. The strategy determine the power sold directly to the grid as it is produced (P_{DGGi}) and residual power (P_{Hi}) supplied by hydro-storage unit during the operational settlement day that result of forecast error. The stored energy (E_{i-1}) for producing PH_i reserved during previous time period by a fraction of wind-solar production (P_{DGPi}). The objective function gets static data of the hydro power plant, wind-solar power and spot price forecasts for the next day; then is solved by linear programing algorithm and providing the daily operational strategy should amount of P_{DGPi} and P_{Hi} to be followed with the aim of maximize profit of wind-solar-storage plant operation.

5.1. The Objective Function

The aim is to store distributed energy include wind and solar energy, during low price periods to sell at a high price date. Also the hydro-pump unit operates as reserve for compensating its forecasting errors in day-ahead operating plan. This is the objective function which can be calculated by:

$$Max\sum_{i=1}^{h}(p_i \cdot P_{Gi} - c_{pump} \cdot P_{DGPi} - c_{hydro} \cdot P_{Hi}) \quad (17)$$

s.t.

$$P_{Gi} = P_{DGGi} + P_{Hi} \quad (18)$$

$$P_{DGi} = P_{DGGi} + P_{DGPi} \quad (19)$$

$$P_{DGi} = P_{wind_i} + P_{solar_i} \quad (20)$$

where p_i is the day-ahead spot price for time interval i that well-predicted; h is the number of hours of the day; P_{Gi} is the active power delivered to the network by the wind-solar–hydro plant, during interval i; P_{DGi} is the available wind-solar power for a given WF and PV unit during the time interval i; P_{DGPi} is the fraction consumed by the hydro pumping station; P_{DGGi} is the amount of P_{DGi} that is sold directly to the grid as it is produced; c_{pump} is the cost of pumping; c_{hydro} is the cost for producing energy from stored energy; P_{Hi} is the active power produced through conventional hydro production [25].

5.2. The Constraints

$$E_{i+1} = E_i + t.\left[\eta_p \cdot P_{DGPi} - \frac{P_{Hi}}{\eta_H}\right] \quad (21)$$

$$0 \le E_i \le E^M \quad (22)$$

$$E_1 = E_r^{begin} \quad (23)$$

$$E_{24} = E_r^{end} \quad (24)$$

$$0 \le P_{Hi} \le P_H^M \quad (25)$$

$$P_{Hi} \le \eta_H \cdot \left[\frac{E_i}{t} + \eta_p \cdot P_{DGPi}\right] \quad (26)$$

$$P_{Pi} = \sum_{k=1}^{K} P_{DGPi,k} \quad (27)$$

$$0 \le P_{Pi} \le P_P^M \quad (28)$$

Where, E_i is the amount of energy that is stored in the reservoir in period i, η_H, η_P are efficiency of hydro and pump unit respectively.
The next constraint has set to increase the robustness of the approach [25]:

$$P_{DGGi} + P_{DGPi} \le \left[P_{DGi}\right]_{1-\alpha} \quad (29)$$

Where, the $[P_{DGi}]_{1-\alpha}$ is $1-\alpha$ quantile of the distribution of P_{DGi}.
The above function objective function can be solved by means of low computation linear programming by "linprog" function in MATLAB environment.

6. Case Study and Results

The case study consist in a WF with capacity of 252 MW and a hydro station with a generation capacity of 190 MW (92% generation efficiency) and a pumping capacity of 184 MW (84% pumping efficiency) and PV unit as mentioned. The system is located in the Manjil. The 603 MW of storage capacity is available for compensation activities. The cost of pumping and the cost for producing energy from stored energy are 3.5 $/kW and 2.92 $/kW respectively. It supposes that the trader provided price curve for 2016.01.03 as Fig. 6.

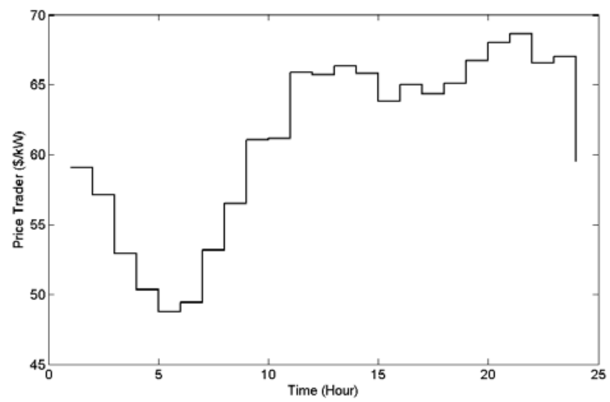

Fig. 6 Predicted spot price of market.

The Fig. 6 show high spot price take place at 19-23 pm. Therefor results of optimization are in Fig. 7.

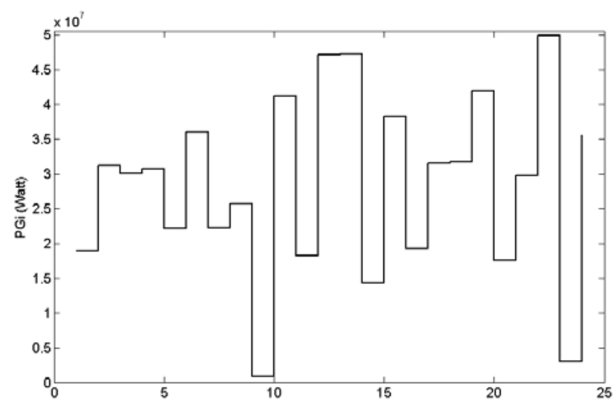

Fig. 7 Total of hourly wind-solar generation in the day-ahead market.

The Fig. 7 consist in hourly solar and wind power by ANFIS predicted data for α=0.85 in the day-ahead market for 2016.01.03. The large value of α may increase risk of market while can increase day-ahead profit. Therefore trader must use trade-off between risk and profit.

The Fig. 8 and Fig. 9 show it is better to generate power in the high price period and consume in the low price period. Upon illustrated result, for example at 22 pm, the Operational Strategy can be determined. The hourly price trader is 66.6 $/kw that is high relatively rather than another periods. Therefore it is affordable to sell power in the high price period, thus the algorithm determine 103,798,847 watt by hydro-storage unit (P_{Hi}), 54,733,021 watt by the power sold directly to the grid (P_{DGGi}) and ANFIS meta-model predict 49,952,095 watt by wind generation (there is not the solar generation in this period). The mentioned values show high price spot value conducts algorithm to discharge available power of storage somewhat the storage afoul of the power with considering next hourly price value.

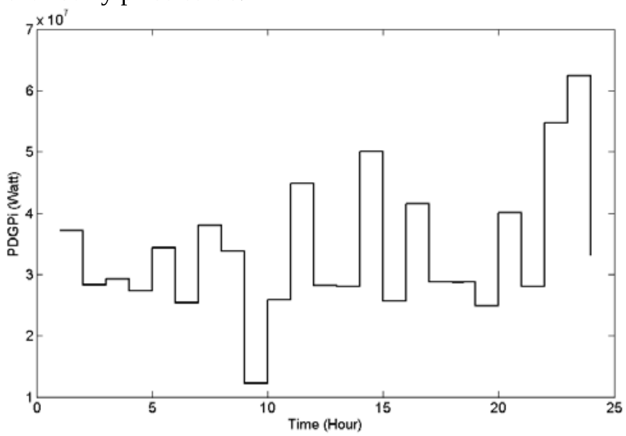

Fig. 8 The consumed power by pumping unit.

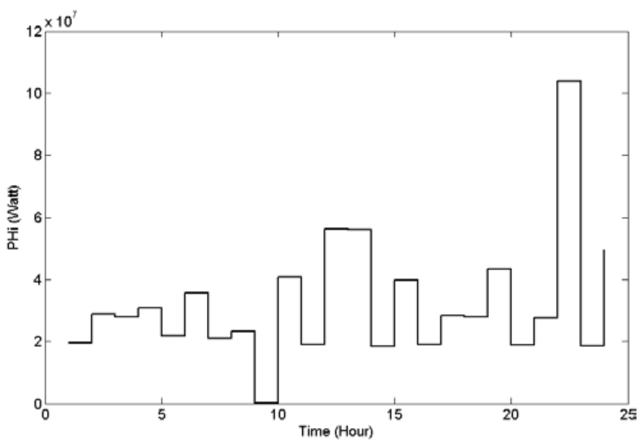

Fig. 9 Hourly power generation of hydro-turbine unit.

The results show combined wind-solar-hydro operation leads to a 10% increase in revenue that is equal 4.9 M$ profits.

7. Conclusion

This paper presented an optimization method to provide day-ahead operation with considering a new way to predict solar and wind production by means of ANFIS network. The ANFIS based on time series technique is a rough straight method between prediction methods. Therefor we identify effective parameters on solar prediction and provide yearly wind speed data to train ANFIS networks. After predicting generated power, low computation optimization technique use to specify delivering and storing power with considering spot price of electricity market. The simulation show the presented method increased revenue in the day-ahead market.

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