Wind Energy Penetration with Load Shifting from the System Well-being Viewpoint

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Abstract- Due to the pollution of the traditional power generation resources and environmental problems, development of power generation resources has become a major problem in today's world. Because of this reason and economic reasons for fossil fuels, the electricity industry designers and policy-makers are to provide solutions to improve the current situation and to reduce destructive environmental effects. In the meantime, the use of renewable resources such as wind and solar power plants has been a priority of many governments and companies. Because of the uncertainty of the renewable energy resources and their dependence on weather conditions, their influence is along with some problems including the loss of system reliability and reduced power quality. In this regard, demand management and reduced usage in the peak hours and shifting some consumption to low load hours can play a crucial role with respect to the renewable energy influence in the system. The potential demand and load management can play a role in either sides of consumption or generation of the electrical systems in order to reduce costs for consumers and manufacturers. With regard to different behaviors of loads in different sectors over their consumption time, seven different sectors of loads including domestic, industrial, large, commercial, administrative, governmental and agricultural loads are investigated in this paper as load shift and its impact on Well Being and on increasing the system reliability under different scenarios through wind energy. Well Being with sequential Monte Carlo method with/without the fuzzy logic is used for comparison. IEEE-RTS test system is selected to be examined in this study.

Keywords- Demand side management, Load shifting, wind energy sources, well-being analysis.

1. Introduction

Demand side management is a practical solution to encourage customers' cooperation in using the potential of the demand side to make optimal use of electrical energy. Using demand side management is followed by improvement of reliability, prevention of transmission congestion, reduction of environmental effects, improvement of system security, reduction of loss, and increase in new energies penetration [1-4]. In the issue of activation of the demand side response, there are different methods one of which is used based on the possibilities and conditions. The types of these methods are in short as follows: 1- the load response plan based on encouragement, 2- the load response plan based on price. In price based plans, dynamic pricing is used. This is in turn categorized into time of use pricing, critical peak pricing, and real time pricing. There has been considerable research on demand response. References [5] to [8] have dealt with application of these methods and modeling of load under the above conditions. Reference [5] has dealt with the load response model in intelligent systems based on maximization of customers' profits or minimization of costumer's expenses with real time pricing. In reference [6], an examination of customers' behavior and response to real time price through optimal prediction of customers' welfare function and its maximization in a probabilistic fashion has been considered. Reference [7] examines and models load response with emergency and time of use response plans. In this research, the authors have maximized customers' profit and self as well as cross elasticity and the amount of encouragement, and shown their effects on the load profile. In reference [8], optimization of demand response using the time of use pricing method has been examined, and the response model has been provided based on the mean expense values and use and also price difference values at intervals. Different studies have been performed with respect to effects of application of demand side management on the generation and demand sides. These studies cover a wide range of uses of application of the demand side management system. References [9] and [10] have dealt with economic issues in planning in the presence of the DSM plan, and have examined the effects of this plan in planning power systems. References [11] and [12] have considered effects of application of demand side management in transmission and distribution systems. In reference [13], effects of demand side management on reliability of power systems considering load uncertainty have been dealt with. In this study, demand side management has been performed in the load shifting fashion. In reference [14], demand side management has been performed on different load sectors including the seven load sectors available in the system in the load shifting method, and effects of load shifting in different load sectors on reliability of the generation system at HLI level have been discussed. In references [15] and [16], advantages of demand response and demand side management have been examined in agricultural and industrial sectors. Results of these studies demonstrate that usefulness of the demand side management system is different in different sectors, which is reflects behavior and nature of loads in different sectors. As can be observed, many studies have been performed on the issue of demand side management.

Wind energy will pervade power systems more in future due to environmental issues and high technological progress. Due to uncertainty of production, however, wind energy may affect system reliability negatively, which increases as wind energy penetration does [17]. Different ways have been presented in different references for confrontation of risk increase. In references [18]-[20], demand-side potential has been used for confrontation of the effect of the uncertainty of renewable energies like the wind, and it has been demonstrated that the value of risk increase resulting from penetration of renewable energies like the wind can be reduced, and the penetration of this type of energy can be increased using load response in different forms. In reference [21], energy savers like batteries have been used to neutralize wind energy fluctuation in the system. It has been demonstrated in this research that marginal profit decreases as battery size increases. In reference [22], a combination of new energies like solar energy and wind energy has been used, and it has been demonstrated that simultaneous use of renewable energies can have a better effect on the output power of this type of energies and reduce the percentage of risk value increase.

One of the most important items affected by load shifting and wind penetration is the issue of reliability in power systems. The PJM and well-being model methods are proper methods for calculation of reliability criteria. The most important advantage of the well-being model over the PJM method is that this method involves deterministic criteria in calculations of probabilistic indexes to display the operational achievements of power systems. In this method, probabilistic methods are applied and then compared to a constant deterministic criterion. This constant deterministic criterion usually equals the largest unit at each hour. In this method, calculation of well-being indexes at each hour in the comfort zone belongs to either the health or the marginal state. Many studies have been performed in the area of well-being method criteria calculations [23-24]. One of these solutions is the probabilistic method and use of the sequential and non-sequential Monte Carlo technique. The method used in this study involves calculation of well-being method criteria using the sequential Monte Carlo method using the fuzzy method in the presence of demand side management. In this study, the emphasis is on examination of effects of load shifting under different scenarios including load shifting in different load sectors with wind penetration on the criteria of well-being system using the sequential Monte Carlo method and fuzzy logic. The IEEE-RTS reliability test system has been selected for testing and examination.

2. Preliminary Basics

In this section we briefly describe the major theoretical concepts applied in the developed model such as wind energy conversion system , well-being analysis and load shifting .

2.1. Wind Energy Conversion System (WECS)

The wind energy conversion system is basically composed of two major sections: wind speed model and wind generator model. These two items are briefly explained below:

A. *Wind speed modeling:*

The basic prerequisite for investigation of system reliability with the Sequential Monte Carlo method and participation of wind power plants is to simulate wind speed per hour. Different methods have been mentioned in different references for simulation of wind speed. Use of time-series Auto-Regressive Moving Average (ARMA)is an acceptable, popular method for specification of wind speed. The general expression of the ARMA (n,m) model is as follows:

$$y_t = \sum_{i=1}^{n} \Phi_i \times y_{t-i} + \alpha_t - \sum_{j=1}^{m} \Theta_j \times \alpha_{t-j} \qquad (1)$$

Where, y_t is the time series value at time t, $\Phi_i (i = 1, 2, ..., n)$ and $\Theta_j (j = 1, 2, ..., m)$ are respectively auto-regressive and moving average coefficients. α_t is a normal white noise process with zero mean and variance of σ_α^2. In this paper, the simulated wind speed WS_t at time t is obtained from the historical mean speed μ_t, standard deviation σ_t, and the time series y_t as shown in Eq. (2).

$$WS_t = \mu_t + \sigma_t \times y_t \qquad (2)$$

B. *Wind generator model*

The characteristics of the output power of wind turbines are generally different from those of conventional units.

Wind speed has a fundamental effect on the output power of the wind turbine, and there is a nonlinear relationship between output power and wind speed. This function is described by the characteristic parameters of the WTG. In this paper, Eq. (3) is used to obtain the hourly power output of a WTG from the simulated hourly wind speed [12] where P_r, V_{ci}, V_r, and V_{co} are the rated power output, the cut-in wind speed, the rated wind speed, and the cut-out wind speed of the WTG respectively. The coefficients and parameters A, B, C, V_{ci}, V_r, and V_{co} can be found in [12].

$$P(WS_t) = \begin{Bmatrix} 0 & WS_t \le V_{ci} \\ A + B \times WS_t + C \times WS_t^{\,2} & V_{ci} \le WS_t \le V_r \\ 0 & V_{co} \le WS_t \end{Bmatrix} \tag{3}$$

2.2. Well-Being Analysis

In this approach, analytical techniques have been embedded in probabilistic criteria. The well-being system framework has been designed in calculation of health, marginal, and risk criteria. The well-being system model has been displayed in Figure 1.The system is in health state if there is additional reserve to meet analytical criteria like largest unit loss. In reserve state, the system does not face problems, but it lacks sufficient reserve to face analytical criteria. In risk state, the load is higher than the generation capacity. The risk probability is the very LOLP criterion. There are analytical and simulation methods to estimate the well-being system indexes. Due to the advantages of the simulation method, the sequential Monte Carlo method is used for estimating the well-being system indexes.

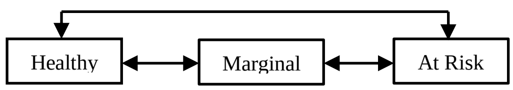

Fig. 1. Well-being model

A. *Well-being system analysis using Monte-Carlo method*

In the Monte Carlo method, the power system state is specified by a number of contingencies, which alter the system state accidently or analytically [26]. If the generating units have the three states available, partially available, and unavailable, the following parameters are defined.

-MTTF: Mean time to Failure-MTTD: Mean time to derated. -MTTR: Mean time to repair

-MTDR: Mean time to derated Repair

$$Up\ time = smaller\ of \begin{pmatrix} -MTTF * \ln X_1 \\ or \\ -MTTD * lnX_2 \end{pmatrix} \tag{4}$$

$$Down\ time = -MTTR * lnX_3 \tag{5}$$

$$Derated\ time = -MTDR * LnX_4 \tag{6}$$

Where x's are random numbers between zero and one. The history of each generating unit states is calculated independently upon time and separately from other units, and the whole generating system's history is obtained by adding them over an annual time period.

Well-Being Indexes Calculation Procedure is as follow:

1. Each unit's capacity diagram is calculated separately, and then, all units are combined together, and the whole available capacity diagram for the whole system will be presented (cap in).

2. In each time period of the diagram, the largest available generating unit will be calculated. Its corresponding capacity will be subtracted from the available capacity diagram obtained in the first step. Therefore, the available capacity is obtained without the largest unit in that time period (cap in-CLUS).

3. In the next step, the load diagram is combined sequentially with the two diagrams above, and the system indexes are calculated as follows:

2.3. DSM Measures

In load shifting, in load peak hours, the amount of load decreases, and the same amount of decreased load will be served during low-load hours. Therefore, in this method, load will be shifted from load peak to low-load hours. This method is applied as follows[14]:

$$\overline{L(t)} = \begin{cases} P & t \in \Omega \\ L(t) + A & t \in \Psi \end{cases} \tag{7}$$

$$A = a\left[\frac{\sum_{t\in\Omega}(L(t) - P)}{N}\right] \tag{8}$$

P:Pre-Specified peak

L(t): basic load

:Modified load model $\overline{L(t)}$

: set of off-peak hours during which the energy is recovered;

Ω : set of off-peak hours during which the energy is recovered:

A : MW load added to each off-peak hour

N : Number of off-peak hours

a: percentage of the energy reduced during on-peak hours that is recovered during off-peak hours. a is set to be 100% in this paper.

The percentage of the decreased energy provided during low load is assumed to be 100% in this investigation. That is, it has been assumed that the total unserved energy in load peak is served during low-load hours.Load shifting (LS) has been performed in different load sectors, and based on the specified load peak, the amount of energy has been shifted from load peak to low load, and it has been assumed that the shifted load has been served immediately in low load. The load peak in different load sectors and power factors are shown in Table 1.As shown in this Table , the total peak of the system is 2754.75 MW, while in the original plan, the load peak has been 2850 MW, and this is because the load peak does not occur at the same time in all sectors.

Table 1. Different load sectors Peak load and load factor

sector	Peak(MW)	Load Factor (%)
Agricultures	113.1	38.38
Large User	855.01	63.44
Residential	968.99	57.48
Government	145.35	56.26
Industrial	399.01	83.42
Commercial	284.99	54.41
Office	57.02	61.73
System	2754.75	63.80

3. Developed Methodology

This section intends to describe the approach used to include demand response and wind penetration in generation system well-being assessment. Block diagram of method can be seen in Figure 2. The step-by-step description of the proposed approach is as follows:

1. System identification and data preparation including wind data, load data in seven load different load sectors, conventional generating units data and wind turbine generators data.
2. Create a capacity model for the conventional generating units using chronological simulation.
3. Construct a capacity model for wind turbine generators (WTG) using time-series ARMA model and WTG power output according section II. Wind energy penetration is considered 100, 200, 300 and400 MW separately.As discussed heretofore, the stochastic nature of wind speed is modeled via time-series ARMA model. In this paper, the following ARMA model borrowed from [11] is taken into use as follows

$$y_t = 1.772\times y_{t-1} + 0.1001\times y_{t-1} - 0.3572\times y_{t-3} + 0.0379\times y_{t-4} + \alpha_t - 0.5030\times\alpha_{t-1} - 0.2924\times\alpha_{t-2} + 0.1317\times\alpha_{t-3} \quad \alpha_t \in \mathrm{NID}(0, 0.524760^2) \quad (9)$$

It should be mentioned that mean (μ) and standard deviation (σ) of wind speed are respectively 19.46 km/h and 9.7 km/h. The WTG units used in this paper are assumed to have rated power of 2 MW, cut-in, rated, and cut-out wind speeds of 14.4, 36 and 80 km/h, respectively.

4. Obtain the total generating capacity model by combining the capacity models obtained in Steps 2 and 3.
5. Determination of hourly load in a chronological order for different load sectors during the year.
6. Apply Load Shifting of load sectors with different levels and update load profile.
7. Well-Being based calculations with a certain criteria in determination of health and marginal states, like the largest production unit, is associated with essential defects. In such situation, even minor fluctuation of the load may trigger big changes in the health state probability. This state is more obvious especially when the largest collaborative unit is substantially bigger than other units. This problem can be solved by means of fuzzy logic approach. Therefore, in this article, Well-Being model is used with Sequential Monte Carlo and fuzzy logic approaches according the load obtained from load response in step seven.

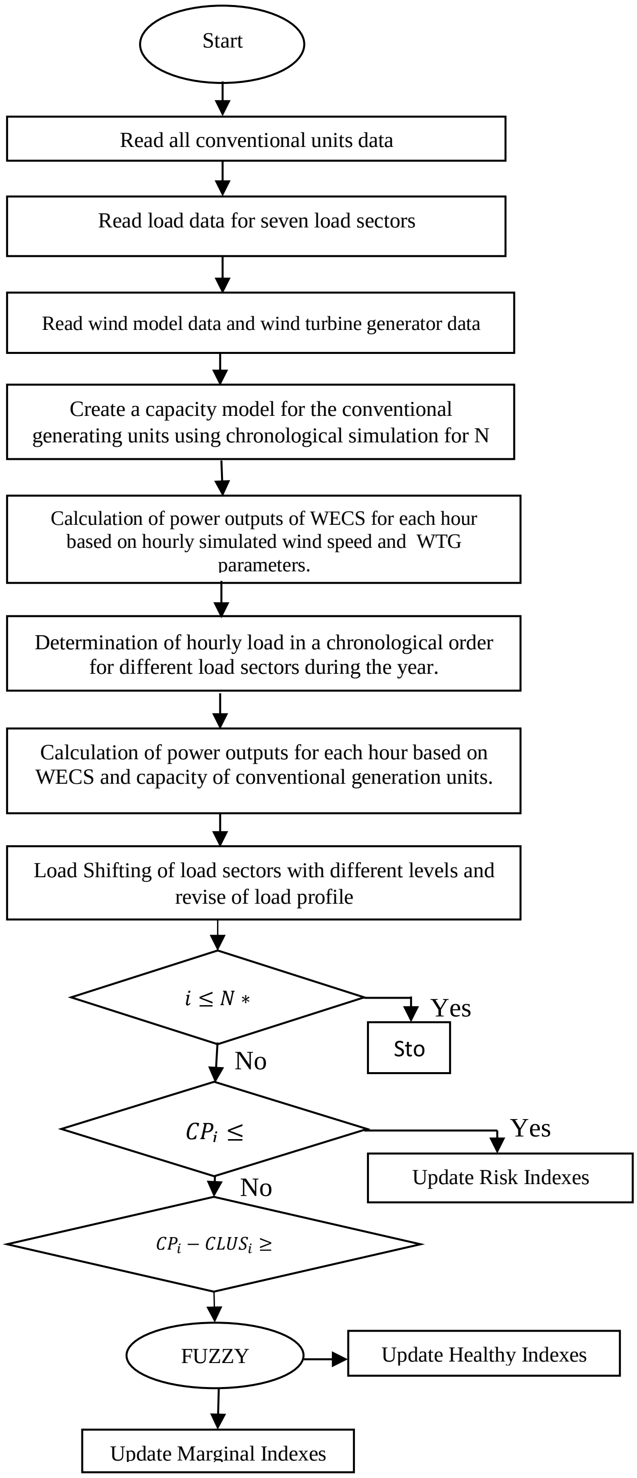

Fig. 2. Block diagram of the developed methodology

In this method, a specific membership function is used to determine to what extent the hour belongs to the health and marginal states, and it is divided between the health and marginal states based on the membership function. For instance, an hour that does not have reserve as much as the largest unit, but where the load is not lost with the loss of other sharing units, also shares in health state calculation. To specify how each hour's probability shares in health probability calculation, the correction coefficient is introduced as follows. To specify the correction coefficient, the following parameters are defined [8]:

1- The proportion of the number of available units the failure of which does not lead to load loss to the total number of the sharing units at that hour.

2- The .proportion of the value of load lost at each hour due to loss of the largest sharing unit at that hour to the size of the largest sharing unit at that hour. The sequential Monte Carlo method is used for determining available capacity. In this method, first, available capacity at each hour is obtained for several years and compared to sequential load. Therefore, at each hour, we know the available capacity, number of sharing units at that hour, largest available unit at that hour, etc. Let available capacity value at each hour i be cp_i Assuming mc_i units out of N to be available and nc_i units to fail, the state at this hour can be represented as follow:

$$up_1 \le up_2 \le \cdots\cdots \le up_{mci} \tag{10}$$

$$cp_i = \sum_{j=1}^{mc_i} up_{ij} \tag{11}$$

$$mc_i + n_{ci} = N \tag{12}$$

up_{ij} : Capacity of the jth unit in service in hour C_i

cp_i : Capacity of the ith contingency C_i

If $cp_i < Load,$ ith hour belongs to the risk domain.

If $cp_i \ge Load$, ith hour belongs to the comfort domain;

i,e. healthy or marginal state. Modification factors in ith hour is as follow:

$$w_{1i} = \frac{m_{i1}}{mc_i} \tag{13}$$

$$w_{2i} = 1 - \left[\frac{Load - (cp_i - CLUS_i)}{CLUS_i} \right] \tag{14}$$

Healthy and marginal state probabilities are calculated as follow:

$$P(H) = \sum_{j=1}^{N\times 8736} \left(j | cp_i \ge Load \right) \tag{15}$$

$$P(R) = \sum_{j=1}^{N\times 8736} \left(j | w_{1i} = 0, w_{2i} = 0 \right) \tag{16}$$

$$P(M) = 1 - P(H) - P(R) \tag{17}$$

w_{1i} : First modifications factors associated with ith hour

w_{2i} : Second modifications factors associated with ith hour

$CLUS_i$: Capacity of largest units in ith hour

Load : System load at the given hour.

m_{ci} : Set of in service units in ith hour which their single outage will not result in load interruptions

8. Form the required reliability indices by observing the system capacity model over a long time period. The simulation can be terminated when a specified degree of confidence has been achieved.

4. Numerical Results

For investigation of the effects of the responses of different load sectors, load shifting has been performed in three 5, 10, and 15percent in the different load sectors, and based on the specified load peak, the amount of energy has been shifted from load peak to low load, and it has been assumed that the shifted load has been served immediately in low load. The load peak in the different load sectors has been limited to 85, 90, and 95 percent of load peak in that sector. Table 2 displays the effects of application of load shifting in the different sectors and its effects on the entire system's load peak. From this table, it is evident that official and agricultural loads do not affect the system's load peak, considering their low peak values and the period of use which is not simultaneous with the system peak. The greatest effects are from gross loads and then residential loads. In the 15% shifting, namely LS85, the value of the system's load peak reduction resulting from gross loads is about 4.6 percent, and in residential loads, it is 3.5 percent, which amounts to a reduction of 11.4 percent when applied in all the sectors, where the effects of gross and residential loads are 40.3 percent and 30.7 percent, respectively. The amount of cooperation and effectiveness of large users and commercial loads on load profile compared to the normal system load for 48 typical hours is demonstrated in Figure 3. Load shifting and wind penetration under five different scenarios has been investigated as follows:

Table 2. Effect of load sectors load shifting on system peak load

DSM	LS80	LS85	LS90	LS95
Agr.	2754.75	2754.75	2754.75	2754.75
Off.	2745.36	2748.21	2751.06	2754.1
Gov.	2728.61	2735.87	2743.14	2750.60
Com.	2697.77	2712.02	2726.27	2740.7
Ind.	2674.97	2694.92	2714.87	2735.00
Res.	2609.42	2657.87	2706.32	2754.75
La.	2583.77	2626.77	2669.27	2712.05
All Sec.	2303.40	2438.90	2542.35	2672.70
Org	2754.75			

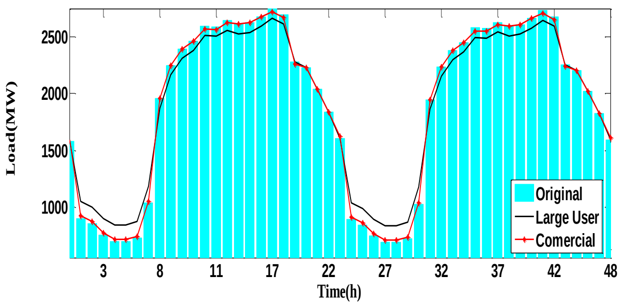

Fig. 3. System load profiles with load shifting for large users and commercial user sector

Scenario 1: In this scenario, the system has been analyzed in the presence of the entire system load without load response for comparison between the applied fuzzy method and the ordinary one, and the well-being system criteria have been calculated in each case along with the unserved energy. The results appear in Table 3. As seen in the table, the probability value of the well-being state has increased from 0.951884 to 0.979286, and marginal state probability has decreased from 0.0436313 to 0.016302. The values of unserved energy and risk state probability have not changed, and are 4949.32 megawatt hours and 0.004412, respectively.

Table 3. System criteria with and without fuzzy methods in scenario 1.

	P(H)	P(M)	LOLP	EENS
Without fuzzy	0.951884	0.0436313	0.004412	4949.32
With Fuzzy	0.979286	0.0163020	0.004412	4949.32

Scenario 2: In this scenario, load shifting has been applied to the entire system load, and the calculations of the well-being system criteria have been done with fuzzy method. The results appear in Table 4. As observed in the table, the reliability criteria improve considerably as the entire system load is shifted, and the higher the load response, the greater the effect on the improvement of the criteria. For instance, with a load shifting of 5 percent, the risk probability value, or LOLP, improves by 41.5 percent, and with a load peak of 90 percent, it improves by 70 percent. Load profile in these three states is displayed in Figure 4.for comparison to the normal system load.

Table 4. System criteria with and without fuzzy methods in scenario 2.

	P(Health)	P(Margin)	LOLP
LS95	0.987022	0.010396	0.002582
LS90	0.992384	0.006298	0.001318
LS85	0.995787	0.000602	0.000611

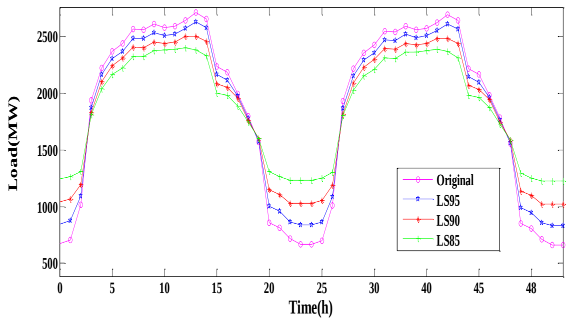

Fig.4. Load Profile with system load shifting in scenario 2.

Scenario 3: In this scenario, load response has been applied alone in different load sectors, and the effects of its application on the system's well-being criteria have been investigated. The system criteria along with the unserved energy value in the different states and load response in the different sectors are displayed in Table 5. As seen in the table, the values of load shifting effectiveness are different from one another in the different load sectors. For instance, in the 10-percent demand shifting in the different load sectors, the most effective are large users with a well-being state probability value of 0.987185, increased by 0.0079 compared to the system's normal state with a value of 0.979286, and the risk probability has decreased by 0.001987, that is, by 45 percent. After large users, the most effective respectively include industrial loads with a well-being state probability increase of 0.004343 and a risk probability decrease of 0.001087, and residential loads with a well-being probability increase of 0.0011 and a risk probability decrease of 0.000338, and the least effective are agricultural loads with a well-being state probability increase of 0.00002 and a risk state probability decrease of 0.000067, which are almost ineffective. Even though they have the highest load peak, residential loads are less effective than gross, industrial, and commercial loads, and this depends on composition, hour diagram, and load peak continuity time in the different sectors. Gross, industrial, and commercial loads have peaks with more continuity, and their load curves are flatter. However, in residential loads, the load peak has a shorter continuity period and is less flat. As compared to the second scenario, for 90-percent load peak, gross loads alone can compensate for 67 percent of the overall improvement in well-being state probability in the second scenario as compared to the first. Moreover, in view of the improvement in risk state probability by 0.001987 and in view of the improvement in risk state probability by 0.003094 as compared to the second scenario, it has been estimated that large users alone can make up for 64 percent of the improvement. This means that in light of the nature of the load in the different sectors and their different profiles in giving load responses, the necessary caution should be taken so that investment is made in loads with higher response.

Table 5. System criteria with load shifting without wind penetration in scenario 3

	P(H)	P(M)	LOLP	EENS	EENS	P(H)	P(M)	LOLP	EENS
La85	0.990115	0.008135	0.00175	1774.5	Off90	0.979736	0.015969	0.004295	4800.55
Res85	0.982231	0.0142	0.003569	3878.8	Go90	0.980054	0.015743	0.004203	4679
In85	0.985491	0.011634	0.002875	3073.97	Agr90	0.979263	0.016319	0.004418	4949
Com85	0.981692	0.014553	0.003755	4095.88	La95	0.983478	0.013196	0.003326	3581.4
Off85	0.980035	0.015737	0.004228	4700	Res95	0.978918	0.016606	0.004476	4846.5
Go85	0.980665	0.015291	0.004044	4477	In95	0.98156	0.0146	0.00384	4236.95
Agr85	0.979263	0.016319	0.004418	4949	Com95	0.979682	0.016043	0.004275	4720.82
La90	0.987185	0.01039	0.002425	2532	Off95	0.979432	0.016192	0.004376	4902
Res90	0.980412	0.015514	0.004074	4474.34	Go95	0.979522	0.016124	0.004354	4860.59
In90	0.983629	0.013046	0.003325	3613.44	Agr95	0.979263	0.016319	0.004418	4949
Com90	0.980621	0.01535	0.004029	4414.94					

Therefore, spending time and costs of demand side management application in certain load sectors can be followed by better results, and prevents from spending time and costs in the sectors with low effects. Unserved energy values in different states demonstrate that gross and industrial loads have the highest effects on reduction of the unserved energy value. With a shifting of only 10 percent in these two load sectors, the unserved energy value can be reduced by 48.8 percent for large users and by 27 percent for industrial ones, and for higher effects, simultaneous shifting of these two load types can be used. Although the system's highest load peak is associated with this group, a 10-percent shifting of residential loads shows an only 9.5-percent reduction of unserved energy, and this once again highlights the fact that in demand side management, considering enormous communication systems and data transmission costs, the desired results can be obtained through application only in certain load sectors.

Scenario 4: In this scenario, penetration of wind energy in the system has been investigated. First, wind energy amount has been added to the generation system in the form of 200 MW consisting of 100 units 2 MW capacity, and the well-being system criteria have been calculated. The probability of the well-being and marginal states has been demonstrated in Table 6. Along with LOLP and EENS with load shift in different load sectors. As is clear from the table, the 200 MW energy penetration has reduced EENS from 4949 MW hours to 4193 MW hours, that is, by about 15.53 percent. The reduction value has increased by load shift in different sectors, and with 15 percent load shift in large users, the value has decreased to 1547.61 MWh, that is, by about 68.7 percent, and has experienced the highest effect. Industrial loads follow them with 2610.2 MWh, that is, 47.2-percent reduction, and next, residential and commercial loads have the highest effects, respectively. Agricultural loads have the lowest effect with only 13 MWh of reduction relative to the 200-MW penetration of wind energy. Moreover, the 200 MW penetration of wind energy reduces LOLP from 0.004412 to 0.003714, that is, by 15.6 percent, which has reached 67 percent with the 15-percent shift in large users. The rest of the cases are presented in the above table for comparison. Even though they have the highest share in the overall system load, residential loads have lower performance in load shift than industrial loads, which results from the profile of the load sector.

Sensitivity analysis: For investigation of the effect of wind energy penetration value on this, wind energy in the ranges of 100, 200, 300, and 400 MW has been examined with and without load shift in different load sectors. Table 7.Presents well-being healthy and marginal state probability, unserved energy value, and risk probability value for a load shift of 15 percent in different load sectors. As observed, the criteria have improved as wind energy has penetrated, and as wind energy penetration value increases, so does the amount of improvement. However, load shift is more effective on improvement of the criteria in certain load sectors, such as gross and industrial loads. For example, for 100-MW penetration of wind energy, risk probability value is reduced from 0.004412 to 0.004092, that is, by 7.2 percent, while this amount of risk reduction reaches 63.3 percent only with a load shift of 15 percent in the gross load sector. The reduction is 39.8 and 25.2 for industrial and residential loads, respectively. It is only agricultural loads that almost do not affect criterion improvement, which is due to the load profile. Figures 5. to 7. Present the amount of change in well-being probability, risk probability, and unserved energy value as wind energy penetration and load shift value change in different sectors. As observed, these criteria improve more as load shift value increases. However, improvement increase value is different in different sectors, and the slope values of the curves are different as shift value increases. And this demonstrates that the sensitivity of the criteria is different in different load sectors based on load structure and profile. The highest sensitivity is in the gross, industrial, residential, commercial, public, and official load sectors, respectively, and agricultural loads are almost ineffective.

Table 6. System criteria with 200 MW wind penetration in Scenario 4.

Wind200	EENS	P(H)	P(M)	LOLP	Wind200	EENS	P(H)	P(M)	LOLP
La85	1547.61	0.9916103	0.0069337	0.001456	Com95	4001.80	0.9827388	0.013677	0.003584
La90	2175.45	0.9891105	0.008904	0.001985	Off85	3964.99	0.983028	0.013435	0.003537
La95	3044.34	0.9859614	0.011285	0.002753	Off90	4048.71	0.9827711	0.013622	0.003606
Res85	3316.16	0.9848552	0.012165	0.00298	Off95	4134.10	0.982511	0.01381	0.003679
Res90	3796.78	0.9833549	0.013243	0.003402	Go85	3777.68	0.9835623	0.01305	0.003388
Res95	4248.76	0.9820086	0.014208	0.003784	Go90	3947.19	0.9830402	0.013435	0.003525
In85	2610.20	0.9876591	0.0099738	0.002367	Go95	4100.49	0.9825898	0.013757	0.003653
In90	3056.40	0.9860812	0.011169	0.00275	Ag85	4179.97	0.9823671	0.013912	0.003721
In95	3576.61	0.9843226	0.01247	0.003207	Ag90	4179.97	0.9823671	0.013912	0.003721
Com85	3475.84	0.9844511	0.012421	0.003128	Ag95	4179.97	0.9823671	0.013912	0.003721
Com90	3743.78	0.9835443	0.013084	0.003372	LS100	0.9823875	0.0138985	0.003714	4193

Table 7. System criteria with 100-400MWwind penetration in Scenario 4.

	P(H)	P(M)	LOLP	EENS
100MW Wind				
LS100	0.9808416	0.0150664	0.004092	4686
La85	0.990803	0.0075805	0.001616	1734.03
Res85	0.98352	0.013183	0.003297	3703.23
In85	0.986537	0.010811	0.002652	2917.89
Com85	0.98306	0.013453	0.003487	3881.86
Off85	0.98153	0.01454	0.003929	4426.36
Go85	0.982105	0.014131	0.003764	4219.45
Agr85	0.9808416	0.0150664	0.004092	4686
200MW wind				
LS100	0.9823875	0.0138985	0.003714	4193
La85	0.9916107	0.0007155	0.0014560	1555.03
Res85	0.9848549	0.0059428	0.0029803	3332.00
In85	0.9876584	0.0037555	0.0023671	2622.69
Com85	0.9844515	0.0062016	0.0031280	3492.48
Off85	0.9830274	0.0072164	0.0035373	3983.97
Go85	0.9835621	0.0068312	0.0033879	3795.77
Agr85	0.9823875	0.0138985	0.003714	4193
300MW Wind				
LS100	0.9837032	0.0129228	0.003374	3805
La85	0.9922934	0.0001550	0.0013327	1402.24
Res85	0.9859918	0.0050772	0.0027120	3020.42
In85	0.9886075	0.0030231	0.0021505	2379.48
Com85	0.9856251	0.0053128	0.0028432	3168.70
Off85	0.9842994	0.0062668	0.0032149	3614.88
Go85	0.9848013	0.0059090	0.0030708	3443.47
Agr85	0.9837032	0.0129228	0.003374	3805
400MW wind				
LS100	0.9848389	0.0120661	0.003095	3487
La85	0.9928784	0.0058981	0.0012235	1277.74
Res85	0.9869780	0.0105384	0.0024836	2764.08
In85	0.9894260	0.0085939	0.0019801	2177.63
Com85	0.9866414	0.0107468	0.0026118	2901.98
Off85	0.9853981	0.0116556	0.0029463	3312.77
Go85	0.9858675	0.0113183	0.0028142	3155.48
Agr85	0.9848389	0.0120661	0.003095	3487

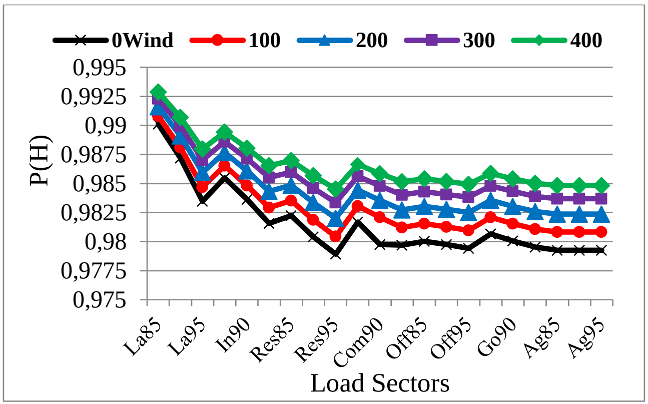

Fig. 5. Healthy probability with different wind penetration in scenario 4

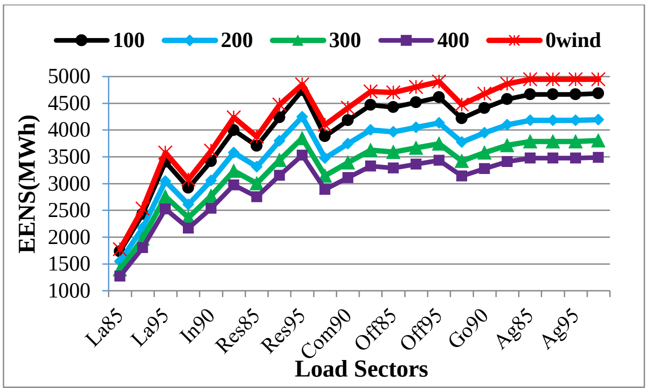

Fig. 6. EENS with different wind penetration in scenario 4.

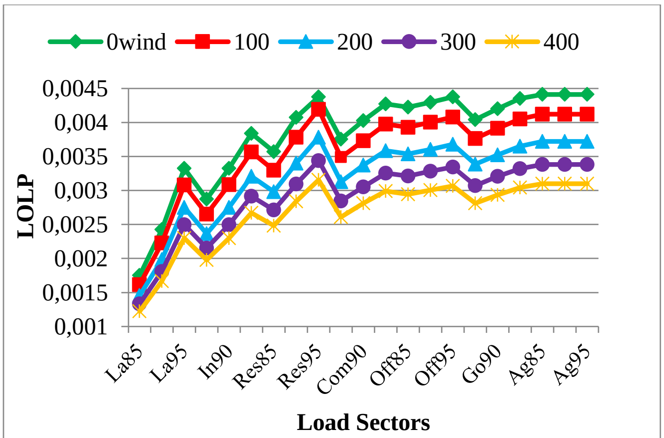

Fig. 7. EENS with different wind penetration in scenario 4.

Scenario 5: In this scenario, the system criteria have been investigated with 200-MW penetration of wind energy and 100-MW increase in overall system load divided proportionally between different load sectors with a 15-percent load shift in different load sectors as well as with the overall load shift. The results appear in Table 8. Without load response and with 200-MW wind energy and 100 MWs of load more than the normal system load, unserved energy value has increased from 4949 MW to 8365 MW. Risk value has increased from 0.004412 to 0.007004, and well-being state probability has changed from 0.979286 to 0.970491. The criteria have improved with a 15-percent load shift in different load sectors, except in agricultural loads. It is only in the gross load sector that the criteria have improved even compared to the system state with normal load. Unserved load value has decreased from 8365 MWh to 3117 MWh. Risk value has also decreased to 0.002833, and the criteria have also relatively improved in the other sectors. In the next section, load shift has been applied to the overall system load with 100 MW of extra load compared to the normal load of the system in the presence of 200 MW of wind energy. As observed in Table 9. the 15-percent load shift of the overall system load allows more wind penetration or increase in overall system load in the presence of wind energy. Only 5-percent load shift makes 100-MW system load increase possible with only 200 MW of extra wind energy with no change in the system criteria.

Table 8. System criteria with 200MWwind penetration and 100MW extra load in Scenario 5.

	Eloss	**P(H)**	**P(M)**	**P®**
La85	3117.59	0.9856703	0.01149594	0.00283379
In85	5246.02	0.9792179	0.01617859	0.00460347
Res85	6690.02	0.9743706	0.01972686	0.00590249
Com85	5631.09	0.9776927	0.0173462	0.00496114
Off85	7881.71	0.9717386	0.02162197	0.00663941
Go85	7529.06	0.9725857	0.02102385	0.00639048
Ag85	8330.55	0.9705828	0.0224385	0.00697865
LS85	1073.86	0.993698	0.00526263	0.00103957
LS90	2267.24	0.988751	0.00918273	0.00206634
LS95	4613.84	0.981011	0.0149066	0.00408221
LS100	8365.67	0.970491	0.022505	0.00700421

Table 9. System criteria with 200MWwind penetration and 100MWextra load in Scenario 5.

	EENS	P(H)	P(M)	LOLP
LS85	1073.86	0.993698	0.00526263	0.00103957
LS90	2267.24	0.988751	0.00918273	0.00206634
LS95	4613.84	0.981011	0.0149066	0.00408221
LS100	8365.67	0.970491	0.022505	0.00700421

4. Conclusion

The overall system load consists of different sectors, each of which has a totally different load peak, profile, and load factor. A change in the load curve of any of these sectors as a result of load shift and application of demand-side management can affect the public well-being system criteria differently. Load shift has the highest effects on improvement of the reliability criteria and decrease in the costs concerning unserved energy (ECOST) in large, industrial, residential, and commercial loads, respectively. Even though residential loads were expected to be more effective on improvement of the reliability criteria of the system with higher load peaks, gross and industrial loads are more effective, and this results from the nature and temporal consumption curves of the loads. Agricultural, official, and public loads are almost ineffective, and it is not suggested that demand-side management be applied in these groups in light of the cost values. In light of its uncertainty and alternation, wind energy penetration can lead to increase in the risk and unserved energy value of the system. Moreover, in light of the high costs of wind power plants, it can be a good option for increasing the penetration of wind energy in the system to use the demand-side potential. Furthermore, in view of the different behaviors of the different load sectors and different effects of management of these sectors on improvement of the system criteria, it can be a good option for application of demand-side management and enforcement of increase in penetration of new energies to use gross and industrial loads.

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