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Optimizing Size of Variable Renewable Energy Sources by Incorporating Energy Storage and Demand Response

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ABSTRACT The electricity sector contributes to most of the global warming emissions generated from fossil fuel resources which are becoming rare and expensive due to geological extinction and climate change. It urges the need for less carbon-intensive, inexhaustible Renewable Energy Sources (RES) that are economically sound, easy to access and improve public health. The carbon-free salient feature is the driving motive that propels widespread utilization of wind and solar RES in comparisons to rest of RES. However, stochastic nature makes these sources, variable renewable energy sources (VRES) because it brings uncertainty and variability that disrupt power system stability. This problem is mitigated by adding energy storage (ES) or introducing the demand response (DR) in the system. In this paper, an electricity generation network of China by the year 2017 is modeled using EnergyPLAN software to determine annual costs, primary energy supply (PES) and CO_2 emissions. The VRES size is optimized by adding ES and DR (daily, weekly, or monthly) while maintaining critical excess electricity production (CEEP) to zero. The results substantiate that ES and DR increase wind and solar share up to 1000 and 874 GW. In addition, it also reduces annual costs and emissions up to 4.36 % and 45.17 %.

INDEX TERMS Critical excess electricity production, demand response, EnergyPLAN, energy storage, variable renewable energy sources.

I. INTRODUCTION

In this urbanized and industrialized era of technology, the rapid growth of electricity is satiated by expensive fossil fuels which are depleting quickly and polluting the atmosphere. This leads to switch to clean, cheap and carbon-free Renewable Energy Sources (RES) [1] that has been further divided into controlled RES (hydropower, geothermal, biomass) and Variable Renewable Energy Sources (VRES) (wind and solar). VRES showing continuous growth in electricity production over the last decade, especially in Europe, China and USA. China has recently become the world leader in RES generation by surpassing the USA and Europe and aims for 35% electricity consumption by RES till 2030 [2]. Howbeit, these resources have quasi variability because of relying upon climate, season and location. It brings the uncertainty that causes the system to become unstable and may lead to cascaded failure [3]–[5]. This challenge can be overcome by adding Energy Storage (ES), Demand Response (DR) or both [6]–[8]. Electrical energy is stored in some form and converted to electric power when VRES is insufficient to fulfil the demand. It diminishes uncertainty as well as increases the reliability of the power system network [9], [10]. Nonetheless, its implementation cost is quite high as only 75-80% of stored energy are redeemable. In essence, DR becomes an expedient alternative in easing the integration

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of VRES without having high implementation cost. DR is defined as a change in the user's energy pattern due to the introduction of some incentive package or price signal generated by the electric market. DR programs are classified in many types that have been illustrated in [11] and [12]. Therefore, energy saving and cost-effective alternatives can be found by electricity network integration with other parts of energy (like wind and solar), storage or DR and that creates a smart energy network. Few of the sector- integrated solutions are mentioned below:

The impact of Demand Side Management (DSM) strategies in the penetration of RES are elaborated in [13]. These strategies delay the installation of new generating stations and improve the operation of existing plants by increasing the capacity factor. However, CO_2 emission costs and energy efficiency measures are not considered in this work. Energy storage role to integrate large-scale VRES in the smart energy system is elaborated in [14]. Chauhan and Saini [15] find the optimal size of a stand-alone renewable energy system with the help of a DR strategy which relies on appliances energy consumption schedules. Though this DR strategy reduces the peak hour consumption of the study area, but it is not included in the optimal design of RES. Renewable energy integration is carried out in [16] by energy trading method. Furthermore, geometric programming based optimization is employed for balancing load and reducing energy consumption from the grid. Nevertheless, RES price and aggregator value are not taken into account. Incorporating demand response in home energy management system is proposed by Zunnurain *et al.* [17] that provides daily energy saving of 3%. Modelling of converting the present electrical system to 100% RES is elaborated in [18]. Energy storage addition to address fluctuating nature of RES is demonstrated in [19] and the optimal size of RES, DSM and ES have been discussed in [20]. DR impacts in future electricity systems and integrating high share or VRES are analyzed in [21]. Liu *et al.* [22] proposed load frequency control in small scale power system to compensate renewable energy fluctuation by using demand response and storage battery. Fan *et al.* [23] proposed novel DR scheme to integrate high share of RES.

Modelling power system in software with the addition of storages or DR may increase the electricity production more than the transmission line capacity which is represented by Critical Excess Electricity Production (CEEP). In the real world, CEEP must be zero otherwise breakdown voltage will cause the power outage. Nevertheless, most of the research while modelling and adding ES or DR ignore the inclusion of CEEP while some Lund and Münster [24], Lund [25] include CEEP but not limited it to zero. Therefore, this work makes sure that it does not contradict the real world scenario and that's why CEEP is always limited to zero. European Roadmap 2030 and 2050 has been exploring different options to achieve sustainable and decarbonized renewable energy [26] but such alternatives have been mostly overlooked in Asia. China, the world's biggest CO2 emitter [27], [28] has signed the Paris agreement to reduce CO2 emissions by 60-65% till 2030 [29]. Therefore, it is imperative for China to integrate more renewable energy in the system to develop green society. This study explores different cases (DR and ES) to integrate renewable energy in the system without risking the power system stability. This work aims to be a first study to integrate daily, weekly and monthly DR along with ES on such a large system of China to integrate maximum renewable energy.

The major contributions of this work are:

i) The Electrical network system is modelled by collecting dataset of different production units of China for the year 2017. Further, this model is holistically invested by EnergyPLAN software to determine annual costs, total fuel balance or Primary Energy Supply (PES) and CO2 emissions.

ii) Technical optimizationis carried out by EnergyPLAN to find the optimal case which has least CO2 emission, PES and annual costs while integrating VRES in the system.

iii) ES addition and the effect of daily, weekly and monthly DR in the system significantly reduces above prominent factors (CO2 emission, PES and annual costs) while restraining CEEP to zero. Ultimately, the impact of different scenarios with and without ES and DR are evaluated.

The rest of the paper is organized as follows: Section 2 elaborates the reference case and computation of the parameters necessary for modelling. Section 3 explains case studies and section 4 depicts results simulation. Finally, section 5 concludes the study and recommends future work.

II. SYSTEM MODEL

EnergyPLAN, Version 13 that released in September 2017 is used for electrical network modelling to perform technical optimization [30], [31]. It is done by adjusting the production components optimally to reduce fossil fuel consumption by lessening the PES. Additionally, it also minimizes annual costs, CO_2 emission and CEEP. EnergyPLAN has been extensively applied to a variety of energy planning and modelling such as integrating 100% RES in some European countries [32]–[35], RES and combined heat and power management [36], [37], transport and renewable energy integration [38]–[40].

System model requires following inputs which serve the role of decision variables.

i. Electricity demand.
ii. Electrical power production units.
iii. Simulation (defining technical limitations and constraints of the components if any)
iv. Costs (Determining investment costs per unit, lifetime and percentage of investment of production units).

Technical optimization reduces the below mentioned performance indicators:

a) PES
b) CO_2 emission
c) Annual costs

Power system stability can be disrupted by under-generation or over-generation that have a dramatic effect on the system which may lead to cascaded failure [41].

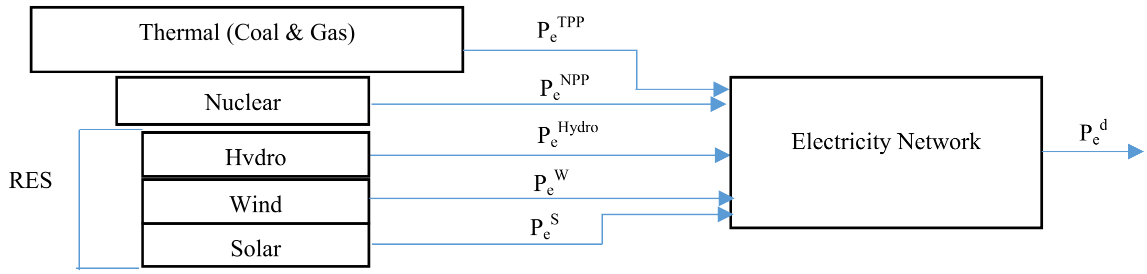

FIGURE 1. China electrical network 2017.

Hence, PP/Import problem, critical excess and grid stabilization problem warnings in EnergyPLAN always assure power system stability during simulating proposed energy model. It should also be noted that the constraints of the components, as well as CEEP, are within limits.

A. SYSTEM INPUTS

Following inputs are used to evaluate the system are given in EnergyPLAN.

1) ANNUAL ELECTRICITY DEMAND

Annual electricity demand of the reference model for the year 2017 is given in Equation 1.

$$P_e^{d(out)} = \sum_{t=1}^{8784} P_{e,t}^{d} \tag{1}$$

where t, $P_e^{d(out)}$ represents the time in hours and annual electricity consumption respectively.

2) PRODUCTION UNITS' ELECTRICAL POWER

Total power demand ($P_e^{d(out)}$) is fulfilled by Thermal Power Plants (TPP), Nuclear Power Plants (NPP), constant RES (hydropower) and VRES (wind and solar). It is represented in Equation 2.

$$P_e^d = P_e^{TPP} + P_e^{NPP} + P_e^{Hydro} + P_e^{W} + P_e^{S} \tag{2}$$

Central power plants tab in EnergyPLAN includes condensing power plant, nuclear and hydropower plants. Total capacity and efficiency are assigned in the input tab for TPP, NPP and hydropower plants but an additional input of water supply is required for the hydropower plant. In addition, the storage option in hydro plants provides ancillary services to the grid.

Wind and Photo Voltaic (PV) supply in intermittent renewable electricity tab entails capacity, stabilization share and correction factor. Stabilization share is the amount of VRES that provide ancillary services for grid stability. Correction factor modifies the hourly distribution profile of VRES that regulates supply between zero and full load but power remains same at zero and full load. In this work, both factors are inputted zero as indicated in Figure 1.

3) INVESTMENT COSTS

Investment costs (C_x^{Inv}) can be determined by multiplying the number of units (P_x) with cost unit (C_{unit-x}) as represented in Equation 3 [42].

$$C_x^{Inv} = P_x \times C_{unit-x} \tag{3}$$

where x is the electricity production unit which can be wind, solar, hydro and so on.

Costs units are defined in GCNY which is abbreviated as Billions in Chinese Yuan Renminb. Hence, annual investment costs are determined as:

$$C_x^{Ann} = C_x^{Inv} \times \frac{i}{[1-(1+i)^{-n}]} \tag{4}$$

where i is the interest rate and n is the life period of the production unit.

III. CASE STUDIES

EnergyPLAN developed by Henrik Lund in 1999 uses Delphi Pascal (DP) programming which is a combination of object oriented programming and integrated development environment [43]. Technical optimization using this freeware software choose the suitable size of variable renewable energy while maintaining CEEP to zero. Optimal wind and solar sizes are determined for calculating CEEP against multiple values of VRES to compute annual costs, fuel consumption and CO2 emissions. VRES multiples values are assigned in the output tab section of EnergyPLAN while in parallel different CEEP regulation strategies can be activated. There are nine different possibilities that can be activated according to an order of priority to hold CEEP to zero. In this work, CEEP regulation 71 is used to minimize critical excess which means first VRES is reduced then VRES together with power plants are decreased to limit CEEP to zero.

Hourly simulation at the national level for the specified year, 2017 is performed by EnergyPLAN. Hourly steps demonstrate a greater degree of accuracy in intermittent renewable energy sources. Electrical infrastructure comprehensive modelling in this energy balancing tool requires input data set that contains energy demands, RES sources, conversion units' parameters detail, storage units' limitations and cost data set (annual costs of each production unit, life time and percentage of investment). Input data set including production capacities units and RES hourly distribution profile are collected from China energy balance data

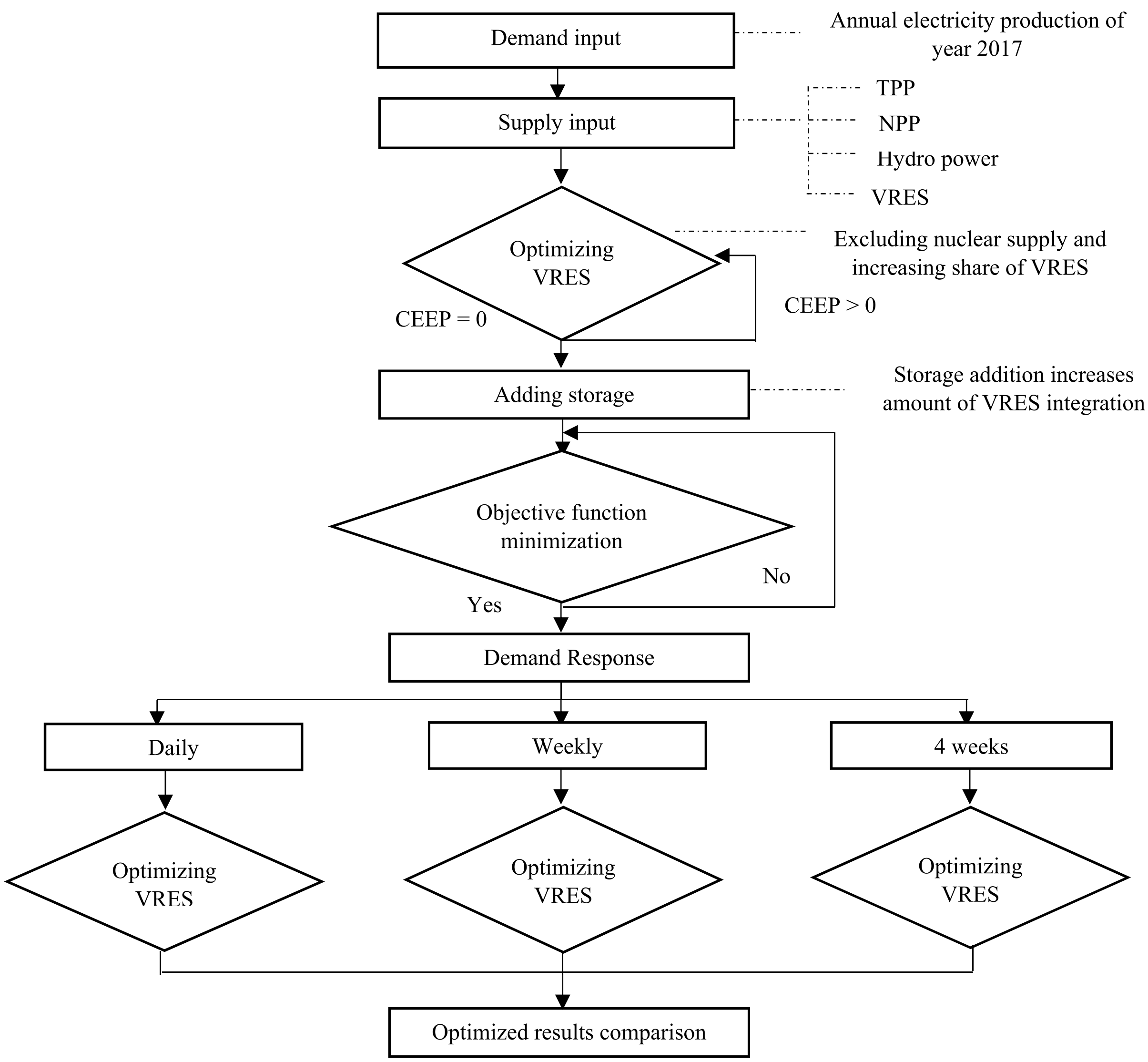

FIGURE 2. Flowchart of optimization of electrical network by using EnergyPLAN.

TABLE 1. Classification of case studies.

Case studies	TPP	NPP	Hydro	Wind	Solar	Storage	DR
Case 1 (Reference case)	√	√	√	√	√	×	×
Case 2 (Excluding NPP)	√	×	√	√	√	×	×
Case 3 (Adding ES)	√	×	√	√	√	√	×
Case 4 (Adding DR)	√	×	√	√	√	×	√
Case 5 (Adding ES and DR)	√	×	√	√	√	√	√

from International Energy Agency (IEA) [44], China energy yearbook 2017 [45], China power industry statistics [46], State grid corporation of China and various state-owned energy corporations websites [47], [48]. Figure 1 depicts the reference model of this research that meets China annual electric demand by various sources technologies. The flowchart of research work and case divisions are illustrated in Figure 2 and Table 1.

TABLE 2. Capacity and share of electrical production components of reference model.

Source technology	Capacity (GW)	Contribution (%)
TPP	1106	69.7
NPP	36.2	3.9
Hydro	341	18
Wind	164	15
Solar	130	2

A. CASE 1 (REFERENCE CASE)

Energy demand forecasting is always hard to predict due to tremendously increasing population, economy and many other factors [49]. Many researchers and organizations predicted future energy demands by considering a lot of assumptions based on different scenario investigation [50]. As far as, China future electricity demand is considered, it can be estimated by considering 1.5% annually increased rate and from 2014-2030 International Energy Agency (IEA) also proposed this national energy demand rate for China [51]. However, this work uses 2017-year data for the reference model which is elaborated in Fig. 1 and is considered as case 1. Production components share of producing electricity are depicted in Table 2.

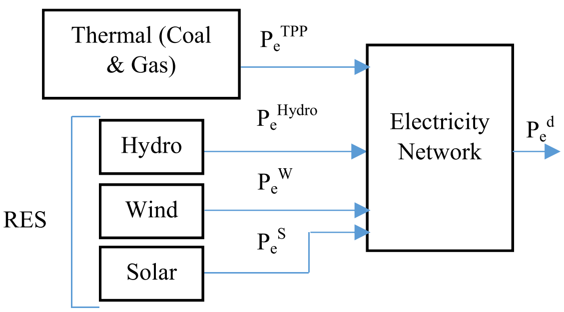

FIGURE 3. Exclusions of nuclear supply from reference model.

TABLE 3. Capacity and share of electrical production components after excluding nuclear supply.

Source technology	Capacity (GW)	Contribution (%)
TPP	1011	60.3
Hydro	341	18
Wind	550	18
Solar	203	3.7

B. CASE 2 (NUCLEAR SUPPLY EXCLUSION)

Compared to the reference model, NPP supply is excluded in this case that results in the reduction of TPP supply and enhances VRES share as demonstrated in Figure 3 and Table 3. Nonetheless, TPP supply can be reduced to a certain limit because of its share in stabilizing units. Additionally, VRES share can also be increased up to a specific amount because of CEEP constraint. Exclusion of most expensive nuclear supply has a considerable effect on cost that is shown in the results section. Note that the hydropower supply remains constant throughout this research.

$$P_e^d = P_e^{TPP} + P_e^{Hydro} + P_e^W + P_e^S \tag{5}$$

TABLE 4. Capacity and share of electrical production components after adding electricity storage.

Source technology	Capacity (GW)	Contribution (%)
TPP	1005	58.5
Hydro	341	18.0
Wind	611	19.8
Solar	203	3.70

C. CASE 3 (ES ADDITION)

This case is the modification of case 2 with an additional feature of electricity storage as shown in Figure 4.

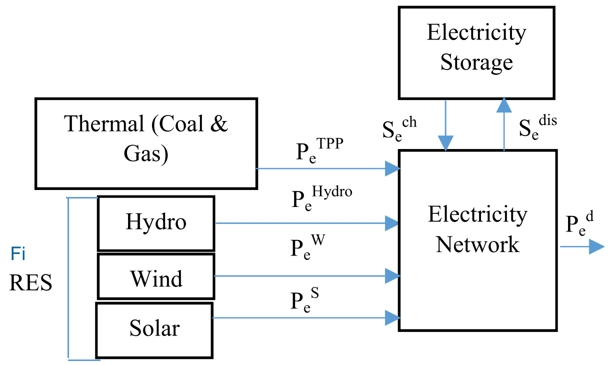

FIGURE 4. Addition of electricity storage.

The well-established and mature ES technology pumped hydro is used to increase the possibility of integrating more VRES in the power system by eliminating the uncertainty issues as this fixed storage capacity can be taken out at any time. This storage capacity helps in reducing power producing components capacity that proves its scintillated performance by diminution PES, cost and emissions. Charging capacity (pump capacity), discharging capacity (turbine capacity) and electric efficiency parameters are required for modelling pumped hydro ES.

$$P_e^d = P_e^{TPP} + P_e^{Hydro} + P_e^W + P_e^S + S_e^{dis} - S_e^{ch} \tag{6}$$

where, S_e^{dis} and S_e^{ch} represents the discharging and charging capacities respectively.

In the case of ES, it should not be recommended that charging and discharging occur simultaneously which may have a negative impact on the system [19] (like increase in size and capital costs). Equations (7) and (8) indicates that charging and discharging cannot exceed their maximum limits and introduction of the binary variable μ_e(0-1) in these equations makes sure that two phenomena cannot occur simultaneously.

$$0 \le S^t_{e,ch} \le \mu_e S^{\max}_{e,ch} \tag{7}$$

$$0 \le S^t_{e,ch} \le (1 - \mu_e) S^{\max}_{e,\mathrm{dis}} \tag{8}$$

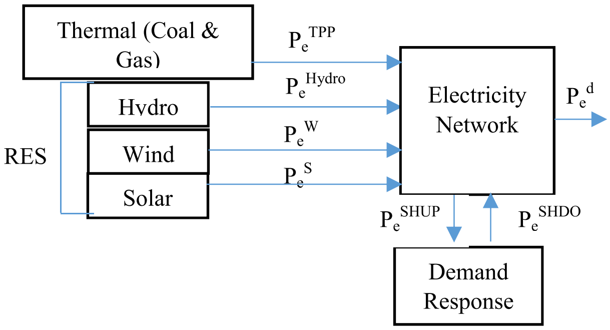

FIGURE 5. Addition of DR and observing its impact on the energy system.

Maximum and minimum energy stored is:

$$En_e^{\min} \leq En_e^t \leq En_e^{\max} \tag{9}$$

After the end of the dispatch period, the final energy stored must be equal to its initial value which is computed as:

$$En_x^{8784} = En_x^0 \tag{10}$$

D. CASE 4 (DR ADDITION)

In this work, DR in the form of load shifting is added to the system as specified in Figure 5. DR is introduced as flexible demand that has the ability to shift from one-time interval to another but it needs the special equipment like smart meter and Advanced Metering Infrastructure (AMI). Other than energy demands and supply, EnergyPLAN also requires cost analysis (that includes investment cost per unit, lifetime and percentage of investment) to perform technical optimization. Cost of all production units except instruments related to DR activities are listed in the general cost section. Therefore, to fully cover the impact of adding DR on the system, the costs of such equipments are inserted in 'additional costs' section of EnergyPLAN. Though total power consumption during this load management remains same but load shifting from peak to valley interval causes a reduction in annual costs. The DR amount is assumed to be 10 percent of total electricity demand and EnergyPLAN gives the option of adding this amount in the input section. EnergyPLAN also facilitates the distribution of DR into daily, weekly and four weeks over the yearly time period. Both, PES and RES electricity production share are increased in comparison to case 3. Further, monthly DR signifies maximum VRES integration than daily and weekly DR as demonstrated in table 5.

$$P_e^d = P_e^{TPP} + P_e^{hydro} + P_e^W + P_e^S + P_e^{DR,\,SHDO} - P_e^{DR,\,SHUP} \tag{11}$$

E. CASE 5 (DR AND ES ADDITION)

This case assesses the performance indicators when appending both ES and DR as delineated in Figure 6 and expressed in equation 12.

$$P_e^d = P_e^{TPP} + P_e^{hydro} + P_e^W + P_e^S + \ldots,$$
$$\ldots S_{dis}^e - S_{ch}^e + P_e^{DR,\,SHDO} - P_e^{DR,\,SHUP} \tag{12}$$

TABLE 5. Capacity and share of electrical production components after adding demand response.

Case 4	Different DR scenarios	Capacity (GW) PP	Wind	Solar
1	Daily DR after optimization	902	641	300
2	Weekly DR after optimization	902	871	400
3	4 weeks DR after optimization	902	1234	600

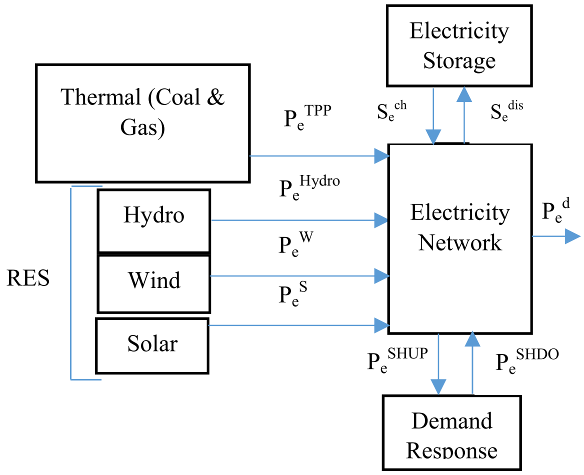

FIGURE 6. Addition of DR and observing its impact on the energy system.

The total amount of power shifted from one time period (shift down, SHDO) period to other (shift up, SHUP) remains same as shown in equation 13. Further, there is a limit up to which DR can be shifted during one-hour interval. The maximum and minimum limit is specified in Equation 15. Usually, EnergyPLAN specified it to be 1000 MW but it is not mandatory that all of this demand be shifted during the specified hour.

$$\sum_{t=1}^{8784} P_{e,t}^{DR,SHDO} = \sum_{t=1}^{8784} P_{e,t}^{DR,SHUP} \tag{13}$$

$$P_e^{DR(\min)} \leq P_e^{DR} \leq P_e^{DR(\max)} \tag{14}$$

Similar to ES, binary variables are also introduced in this case to make sure that two operations do not occur simultaneously. These shifting up (μ_e^{SHUP}) and shifting down (μ_e^{SHDO}) binary variables are shown in Equation 15.

$$0 \leq \mu_e^{SHUP} + \mu_e^{SHDO} \leq 1 \tag{15}$$

The proposed work first observes the impact of these three DRs without optimizing VRES. Just like ES, DR also facilitates the VRES integration, therefore, three DRs addition will further increase the share of VRES that is depicted in Table 6. ES and DR combination makes the system economically viable than rest of the scenarios as it causes substantial reduction in carbon footprints along with annual costs.

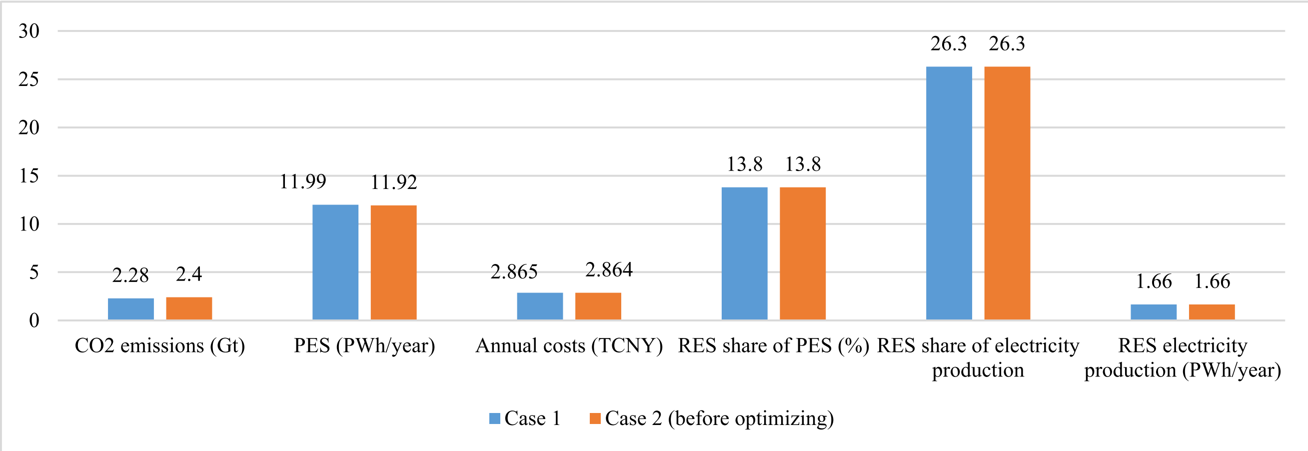

FIGURE 7. **EnergyPLAN results for case 1 and case 2.**

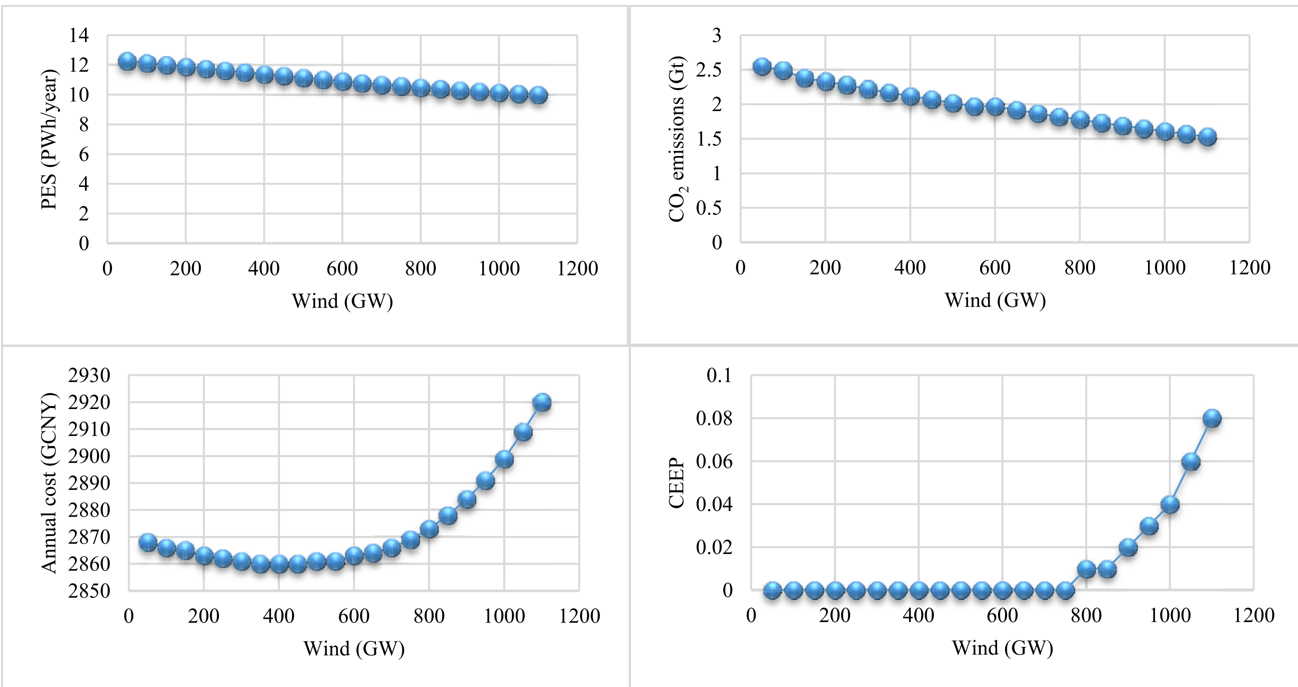

FIGURE 8. **Finding optimum wind size without exceeding CEEP.**

IV. SIMULATION RESULTS AND DISCUSSION

A. CASE 1 AND CASE 2

The data of the most recent year (2017) is set as a reference model due to its availability that determines annual costs, emissions and PES. Then, exclusion of nuclear supply without altering VRES is carried out to discover its effect on the above eminent factors. Hence, this exclusion not only descends the PES but also slightly reduces annual costs because NPP supply is considered to be the most expensive source than all [52]. However, CO_2 emissions are increased due to the increment in the share of TPP electricity production as sketched in Figure 7.

Two of the objective functions are alleviated without optimizing and increasing the share of VRES. Hence, the exclusion of NPP share can be given to VRES to assess if it descends or ascends the annual costs in comparison to case 1. Figures 8 and 9 show the results of case 2 to find the optimal amount of wind and solar when NPP supply is excluded. However, optimal means that these sources do not cross beyond transmission capacity while finding the least cost solution with minimum emission and PES.

Though CO_2 and PES are diminished to a minimum at the maximum wind power supply (1100 GW) but both the value of CEEP and annual costs increase. Annual costs are

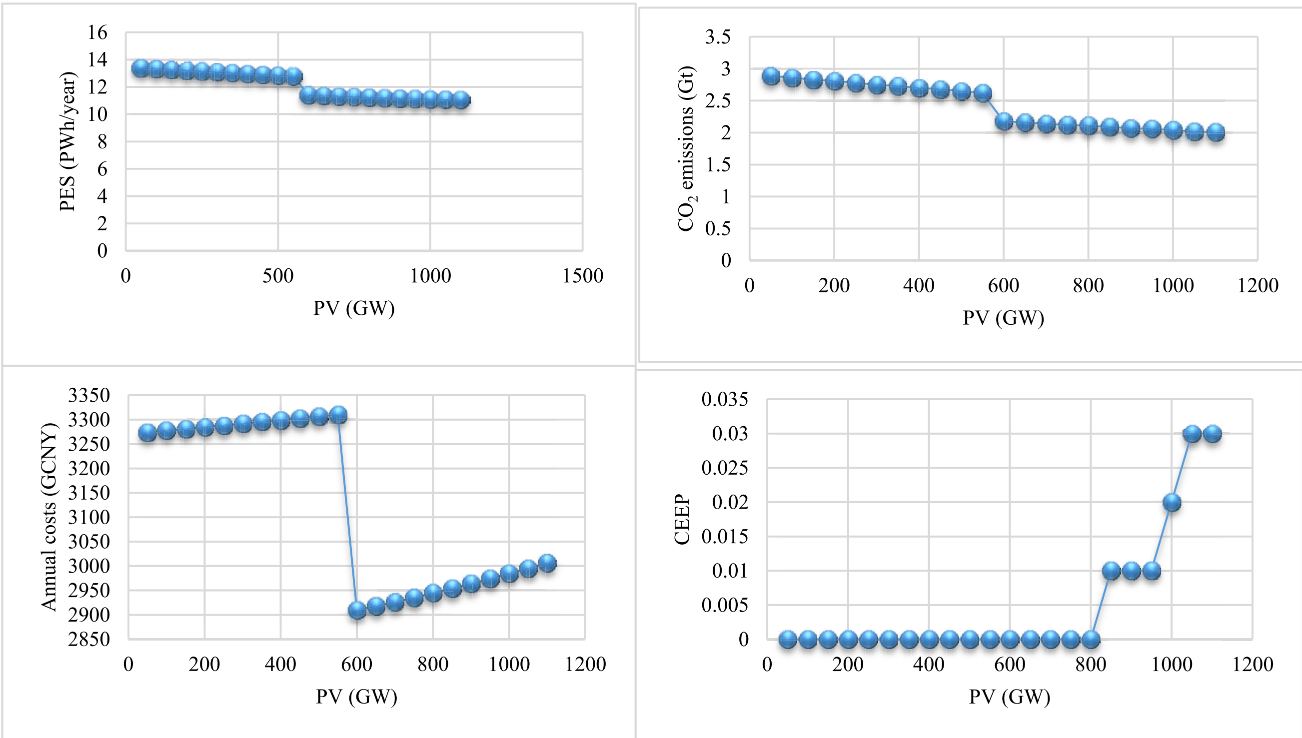

FIGURE 9. Finding optimum PV size without exceeding CEEP.

TABLE 6. Effect of DR and ES on production supply, before and after optimizing VRES.

Subcases of case 5	Different DR scenarios	Capacity (GW)		
		PP	Wind	Solar
1	Daily, weekly & 4 weeks DR without optimization	1005	611	203
2	Daily DR after optimization	893	705	300
3	Weekly DR after optimization	874	864	500
4	4 weeks DR after optimization	902	1000	874

minimum at 450 GW supply of wind, but CO_2 emissions and PES are not minimized. Similarly, CO_2 and PES are also reduced to the minimum at maximum PV supply (1100 GW) but annual cost is minimized at 550 GW supply and increases beyond this value. The steep decline in annual costs of PV at 580 GW is justified by learning curve theory of PV. This theory discussed by Connolly *et al.* [30] which states that up to a certain limit increase in PV capacity results to decrease in costs.

Therefore, a compromise has to be made for either one of the factors between emissions, PES and annual costs to get the best-optimized results. Considering all the aforementioned factors, final optimized values chosen for wind and PV are 550 GW and 203 GW respectively.

As discussed above that CO_2 emissions increases in case 2 (without optimization scenario) but after optimizing VRES, this tradeoff is eliminated as now CO_2 is reduced from 2.40 (Gt) to 1.99 (Gt), PES 11.92 (PWh/year) to 10.96 (PWh/year) and annual costs from 2864 (GCNY) to 2815 (GCNY). Additionally, RES electricity production is increased to 2.50 PWh/year and RES share of PES and RES share of electricity is ascended to 22.8% and 39.7% respectively.

B. CASE 3

Energy storage addition has become very popular choice to address stochastic nature of renewable energy sources, especially in Europe such as Madeira Island in Portugal [10], Germany [53] and so on. The addition of ES dispenses more opportunities for integrating VRES as it can store surplus energy and detaches that energy when VRES supply is insufficient. Consequently, a tremendous reduction in all three parameters is noted which is recorded in Table 7.

C. CASE 4

Besides energy storage, demand response is also viable alternative to add renewable energy in the system without jeopardizing system stability [2], [54], [55]. In this work, DR is divided into daily, weekly and monthly DR that distribute flexible demand (0.63 PWh) into 365 days, 52 weeks and 12 months respectively. It checks to see if it can move the demand over a specified period in order to improve the VRES

TABLE 7. Summary performance and comparison results of three case studies.

Different scenarios	CO_2 emissions (Gt)	PES (PWh/year)	Annual costs (GCNY)	RES share of PES (%)	RES share of electricity production (%)	RES electricity production (PWh/year)
Case 1 (reference case)	2.28	11.99	2865	13.8	26.3	1.66
Case 2 (before optimization)	2.40	11.92	2864	13.8	26.3	1.66
Case 2 (after optimization)	1.99	10.96	2815	22.8	39.7	2.50
Case 3 (including storage)	1.93	10.82	2813	24.2	41.5	2.62

TABLE 8. Summary performance of case 4 (after optimization).

Different DR scenarios	CO_2 emissions (Gt)	PES (PWh/year)	Annual costs (GCNY)	RES share of PES (%)	RES share of electricity production (%)	RES electricity production (PWh/year)
Daily	1.85	10.62	2761	26.2	44.1	2.8
Weekly	1.56	9.95	2769	33.5	52.9	3.3
4 weeks	1.12	8.94	2817	46.7	66.2	4.2

TABLE 9. Summary performance of case 5 (before and after optimization).

	Different scenarios	CO_2 emissions (Gt)	PES (PWh/year)	Annual costs (GCNY)	RES share of PES (%)	RES share of electricity production (%)	RES electricity production (PWh/year)
Case 5 before optimization	Daily	1.92	10.80	2751	24.2	41.5	2.62
	Weekly	1.91	10.78	2745	24.2	41.5	2.62
	4 weeks	1.91	10.77	2740	24.2	41.5	2.62
Case 5 after optimization	Daily	1.78	10.47	2758	27.7	46.0	2.9
	Weekly	1.52	9.86	2766	34.6	54.0	3.4
	4 weeks	1.25	9.23	2857	42.6	62.4	3.9

integration. Case 4 (especially weekly DR) proves to be the best case in terms of integrating VRES and decarbonizing atmosphere as shown in table 8 but it does not turn out to be economically viable due to increment in annual costs.

D. CASE 5

The last case includes both ES and DR but this case has been further divided into six subcases. First, the impact of daily, weekly and 4 weeks DR are highlighted separately without increasing VRES share. Then, three DR scenarios are evaluated again while integrating more VRES and observing its effect on costs and other factors which are summarized in Table 9.

As stated above, PES and CO_2 are minimized more in case 4 in comparison to case 5 but ascending annual costs does not make this case ideal. Therefore, the combination of ES and DR are needed to make the system economically viable while keeping the emissions minimum. In case 5, best results before optimizing are achieved in 4 weeks DR scenario where three objective functions have plummeted in comparison to all aforementioned cases. Further, in the after optimizing scenario, PES and CO_2 are reduced to the minimum in 4-week scenario but annual cost increases than weekly and daily scenario. Therefore, in this case, there is a tradeoff between CO_2, PES and annual costs. The overall comparison of all seven cases have been summarized in Figure 10 and it makes sure that CEEP for all the cases are zero. Moreover, it demonstrates that reduction in cost and PES in case 2 (before optimizing VRES size) in comparison to case 1 is justified because now less energy is required to fulfill electric demand and the most expensive supply has been excluded. However, CO2 emissions are increased due to the increment in the share of TPP electricity production. This tradeoff is eliminated when the NPP supply share is given to VRES that reduces all three factors. Likewise, alleviation of objective functions in case 3 and 4 is more as compared to the first two cases because ES and DR act as additional storage which integrates more VRES. These two cases not only reduce dependency on

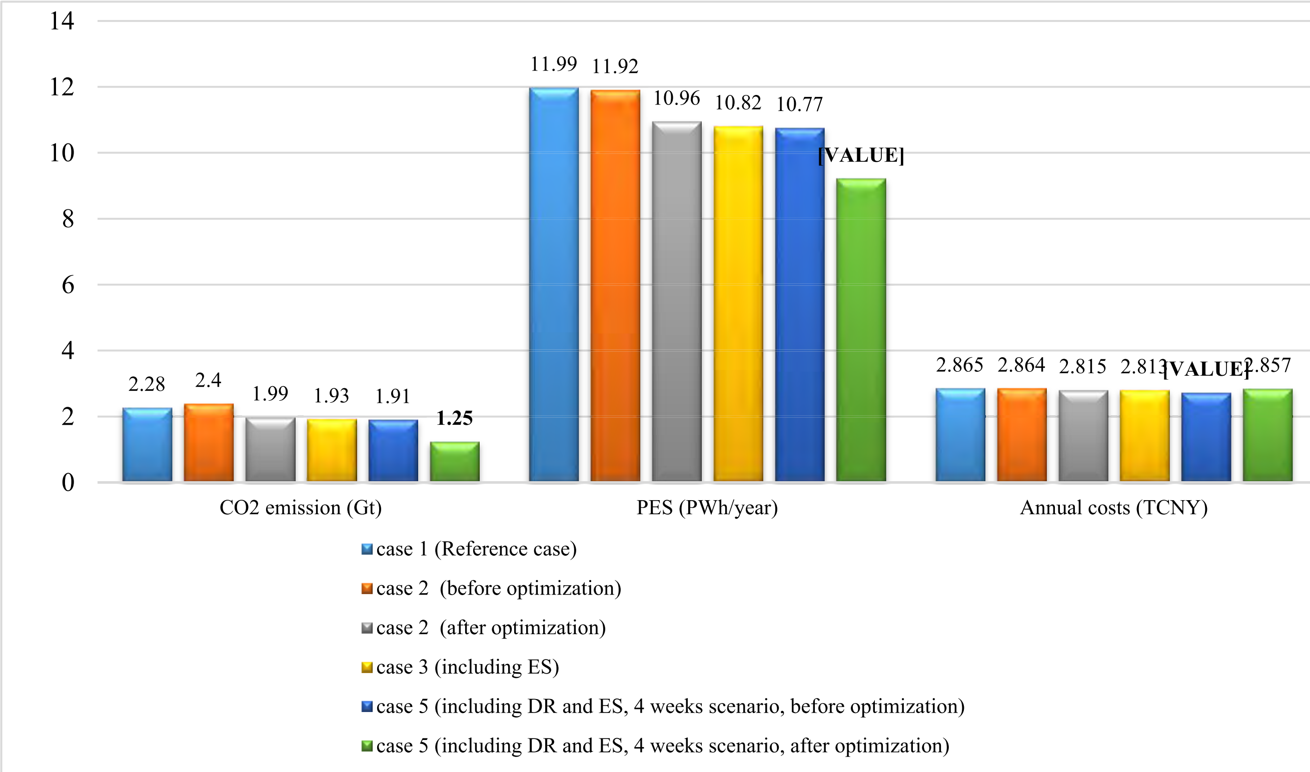

FIGURE 10. Comparison of optimum results for PES, CO2 emissions & annual costs against 6 different cases.

fossil fuel sources but also minimize the annual costs more than aforementioned scenarios. Finally, the combination of ES and DR scenario proves to be the most economical option to integrate VRES.

V. CONCLUSIONS AND FUTURE WORK

User-friendly, deterministic input/output EnergyPLAN tool is used to model the electrical network of China as it takes only a few seconds for the computation of the whole year (2017). The research is divided into five case studies that illustrate the optimal combination of VRES, ES and DR that not only help to decarbonize the atmosphere by reducing fuel consumption but also reduce the annual costs as well. However, the integration of excess VRES increases production more than the transmission capacity, which is represented in the form of CEEP. Consequently, the addition of storage and DR (daily, weekly and monthly) in this research not only enhanced the VRES integration without exceeding CEEP but also achieved significant improvement in minimizing the objective functions. The proposed work acquired successive decrement in CO_2 emissions (2.28 Gt to 1.12 Gt), PES (11.99 PWh/year to 8.94 PWh/year) and annual costs (2865 GCNY to 2740 GCNY) from case 1 to case 5. It is concluded that case 4 (DR 4-week, after optimization scenario) is best suited when the focus is to reduce greenhouse gases. On the contrary, case 5 (ES and DR 4- week, before optimization scenario) can be chosen when cost is the main consideration.

This research can be further extended to multiple energy carriers like heating, cooling and hydrogen demands in the system by incorporating integrated demand response. It may add complexity to the system but will increase the flexibility and reliability while restraining the operating costs and emissions to the minimum.

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