A stochastic framework to evaluate the impact of agricultural load flexibility on the sizing of renewable energy systems

Ayse Selin Kocaman [a, *], Emin Ozyoruk [a], Shantanu Taneja [b], Vijay Modi [c]

[a] *Department of Industrial Engineering, Bilkent University, Ankara, Turkey*
[b] *Mewbourne School of Petroleum and Geological Engineering, The University of Oklahoma, Norman, OK, USA*
[c] *Department of Mechanical Engineering and Earth Institute, Columbia University, New York, NY, USA*

ABSTRACT

Pumping of water for agriculture can be a flexible component of electric demand. In this study, a framework that involves scenario based stochastic programming models is developed to examine the effect of load shifting on the renewable energy system sizing for agricultural load. With the help of this framework, alternative load shifting policies are evaluated to observe how the intrinsic flexibility of agricultural load reduces the amount of investments while designing a renewable system. Using real data from India's Gujarat region, solar and wind cases are evaluated separately to understand the coherency between these sources and the agricultural demand. The value of using a dispatchable source to help with the intermittency of the renewable sources in the systems is discussed. It is also shown that energy storage can be a convenient control mechanism for the integration of renewables; however, is an expensive substitute for demand response programs for agricultural load. Benchmarks for the incentive amounts that can be provided for alternative load shifting policies are presented.

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1. Introduction

Increasing the penetration of renewable energy sources is a promising option for reducing carbon emissions and dependence on fossil fuels. However, the intermittent generation of these sources reduces the system reliability and limits their penetration levels in the absence of any integration measures. Several methods are proposed in the literature to improve the reliability of systems with large amount of renewable energy generation including grid interconnection [1], storage [2], forecasting [3] and demand response [4]. Unlike the methods that aim to smooth out the supply curve, demand response activities encourage energy aware consumption patterns to align demand with variable supply through incentives provided to end use customers [5]. Although there are challenges to demand response deployment [6], the topic has drawn significant attention in the literature due to its acknowledged benefits and future opportunities [7].

Previous work on demand response programs for renewable energy systems has largely focused on the operational effects of such programs mostly for microgrids [8,9]. Stadler et al. [10] review

the effect of demand response on microgrid operations. In another review paper, Wang et al. [11] discuss the value of demand response on multi-energy systems. The number of studies considering demand response in the infrastructure sizing and planning phase, on the other hand, is limited. Among these studies, Erdinc et al. [12] present sizing decisions for a photovoltaic and energy storage system for a smart household with seasonal, week-day, and weekend load variability. Wang et al. [13] simulate a hybrid renewable energy system consisting of solar, wind, and diesel generation and battery storage that must meet residential demand in the Sacramento Valley of California. Viana et al. [14] consider demand response and photovoltaic distributed generation to meet the demand of responsive residential consumers and evaluate the substation peak demand and energy consumption. Nyholm et al. [15] examine the impact of electricity pricing schemes on household solar panel size. Moving beyond residential loads, other papers have examined the effects of demand response programs on systems with aggregated demand. Bitaraf and Rahman [16] use different demand response and energy storage scenarios to reduce curtailment for fixed wind capacities. Behboodi et al. [17] optimize resource portfolio with five components of base, intermediate, peak, intermittent, and reserve generation to meet shifted demand. Pedro and Almeida [18] use hydro, wind and solar energy to

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Nomenclature

Indices and Sets

t, k	Indices for time stages
ω	Index for scenarios
T	Set of time stages
Ω	Set of scenarios

Parameters

c^I	Annualized investment cost of renewable sources
c^D	Diesel cost
c^S	Storage cost
$g_{t\omega}$	Normalized generation amount of 1 MWp solar or wind system at time t, in scenario ω
$d_{t\omega}$	Demand at time t, in scenario ω
α^{unmet}	Maximum percentage of unmet demand
π_ω	Probability of scenario ω
t^s	Maximum allowed time for demand shift
LT_g	Lifetime of wind turbines or solar panels

i	Interest rate
γ	Storage efficiency
L^{diesel}	Diesel limit in the system

Variables

Cap	Installed MWp capacity of solar or wind
$D_{tk\omega}^{shift}$	Amount of demand shifted from time t to time k, in scenario ω
$D_{t\omega}^{net}$	Net demand shift at time t, in scenario ω
$D_{t\omega}^{unmet}$	Unmet demand at time t, in scenario ω
$p_{t\omega}^{diesel}$	Diesel generation at time t, in scenario ω
$P_{t\omega}^{spill}$	Renewable energy spilled at time t, in scenario ω
$P_{t\omega}^{str}$	Renewable energy sent to storage at time t, in scenario ω
$P_{t\omega}^{rls}$	Renewable energy released from storage at time t, in scenario ω
$P_{t\omega}^{s}$	Renewable energy stored at time t, in scenario ω
$P_{t\omega}^{used}$	Renewable energy directly used at time t, in scenario ω
S	Storage capacity

optimize renewable energy mix in Portuguese. Konstantelos et al. [19] and Chen et al. [20] consider the demand response for the investment planning in the distribution system level. Furthermore [21,22], explore the benefits of demand response to distribution networks planning.

While existing research has primarily explored the effects of demand response programs on infrastructure sizing problems for residential and industrial load types, there are other types of demand, which could provide system benefits when paired with load shifting capabilities. Agricultural loads, the main focus in this paper, are promising alternatives because of the inherent flexible nature of the demand [23]. Despite such loads having some degree of inflexibility (there are certain intervals in which energy is needed to protect crop health and yields [24]), most of the time, farmers can tolerate shifting their productive electricity loads in case of limited resources [25,26]. Compared to other demand response programs that are designed to control, for example, air conditioning demand of residential consumers for a minute or even less amount of time, the farmers' flexibility in the daily levels can provide a huge benefit to the power systems. Several agricultural demand response programs in California have already shown the benefits of such flexibility to utilities [27,28]. Even so, the potential benefits of pairing demand response with agricultural demand have yet to be analyzed with a detailed mathematical modelling.

Motivated by the recent efforts on renewable investments for agricultural feeders [29], in this study, we propose mathematical models to examine the effect of demand response on the renewable energy system sizing for agricultural load. In this problem, the amount of energy used for irrigation as well as the renewable sources can be uncertain. Stochastic optimization models that take this uncertainty into the account in the planning phase of the systems can lead significant investment savings. Previous work that utilizes stochastic optimization techniques on demand response programs for renewable energy systems has largely focused on the operational effects of such programs. Wang et al. [30] and Zhao et al. [31] consider stochastic unit commitment problems with uncertain demand response. Hu et al. [32] analyze the effect of demand response in an energy market with demand uncertainty using a multi-stage stochastic optimization model with multiple objectives. Falsafi et al. [33]. present a stochastic programming model for wind-thermal generation scheduling. Chen et al. [34]

focus on the real-time and price-based demand response management for residential appliances using stochastic and robust optimization frameworks. Jiang et al. [35] study a stochastic day-ahead economic dispatch model considering demand response and wind power. The literature on the optimal sizing of renewable energy systems in general is very rich; however, most of the studies approach the problem in a deterministic way [2]. There is only a limited number of studies that takes the uncertainty into account [2,36,37]; however, these studies neither consider demand response programs nor focus on the agricultural demand.

This paper fills the gap in existing research by providing the following contributions: i) A two-stage stochastic programming framework to evaluate the impact of load shifting as a demand response program on the optimal sizing of renewable energy systems for agricultural load is developed, ii) This framework is then applied using real solar and wind generation and demand data from the Gujarat region in India, iii) Additional models are developed to discuss the value of using a dispatchable source in the system and using energy storage as a substitute for demand response, iv) Benchmarks for the incentive amounts that can be provided for alternative load shifting policies are presented. v) It is shown that the effect of the load shifting programs on the renewable investments is not intuitive and requires a stochastic optimization process.

The sections of this paper are presented as follows: Section 2 provides the problem definition and formulation. Section 3 presents the computational analysis. A discussion on alternative systems and models is given in Section 4. Section 5 restates the paper's most salient conclusions.

2. Problem definition and formulation

Pumping of water for irrigation can be a very flexible component of electric demand. In this problem, we develop a conceptual framework that can help us examine the effect of load shifting on the renewable energy system sizing for agricultural load. We focus on an agricultural area where all consumers use electricity for irrigation. Our problem is to design an island type renewable energy system for this group of consumers. We acknowledge that the farmers may have different flexibility limits in terms of irrigation times depending on the crop types. In optimization framework, we

have a parameter that represents the maximum allowed time for demand shift. We evaluate alternative load shifting policies experimenting with this parameter to see how the farmers' flexibility reduces the amount of investments while designing a renewable system. We perform these experiments for solar and wind separately to observe which renewable source is more coherent with the agricultural load and examine the renewable energy curtailment or spillage amounts. As in [38] and [37], in this paper, we refer to energy curtailment or spillage in a period as the use of less wind or solar energy than is potentially available at that time. To help with the intermittency of the renewable sources, we assume that an expensive dispatchable source such as diesel also exists in the system as a back up alternative. In Section 4.1, we also discuss the cases where we remove the dispatchable source from the system and meet the demand partially with different amounts.

We propose a two-stage stochastic programming with recourse model to minimize the investment cost of solar or wind energy sources while penalizing the expected diesel usage. In two-stage stochastic programs, we have a set of decisions to be taken before some random events are realized. These decisions are called first-stage decisions and are usually represented by x. After the realization of event ω, second stage actions y_ω are taken. Therefore, the first-stage decisions x are made before the realization of the random data and hence should be independent of the random data, whereas the second-stage decisions y_ω are functions of the data. A general representation of a two-stage stochastic programming with recourse is provided in (1). We refer the readers to Ref. [39] for more details.

$$\min c^T x + \mathbb{E}[Q(x,\xi)]$$
$$s.t. \quad Ax = b \quad x \geq 0 \tag{1}$$

where $Q(x,\xi)$ is the optimal solution of the second stage problem:

$$\min \quad q^T y$$
$$s.t. \quad Tx + Wy = h \quad y \geq 0 \tag{2}$$

$\xi := (q,h,T,W)$ is the data related to the second stage problem (2) and the expectation operator in problem (1) is taken with respect to the probability distribution of ξ. When ξ has a finite number of realizations (or scenarios) $\xi_\omega = (q_\omega, h_\omega, T_\omega, W_\omega)$ with respective probabilities p_ω, then for a given x, the expectation $\mathbb{E}[Q(x,\xi)]$ is equal to the optimal value of the following linear programming problem (3):

$$\min \quad \sum_\omega p_\omega q_\omega^T y_\omega$$
$$s.t. \quad T_\omega x + W_\omega y_\omega = h_\omega \quad \forall \omega \tag{3}$$
$$y_\omega \geq 0 \quad \forall \omega$$

Then, it is possible to write the two-stage stochastic programming with recourse model as in the following extensive form (4):

$$\min \quad c^T x + \sum_\omega p_\omega q_\omega^T y_\omega$$
$$s.t. \quad Ax = b$$
$$T_\omega x + W_\omega y_\omega = h_\omega \quad \forall \omega \tag{4}$$
$$x \geq 0$$
$$y_\omega \geq 0 \quad \forall \omega$$

In our formulation, the first stage decision variables represent the size of the energy systems. The second stage decision variables are the amount of diesel used, the amount of renewable generation used or spilled and the amount of demand shifted at each time

period for each scenario. We provide the extensive form of our two-stage stochastic programming model below:

$$\min \quad c^I Cap + c^D \sum_{t \in T} \sum_{\omega \in \Omega} \pi_\omega P_{t\omega}^{diesel} \tag{5}$$

$s.t.$

$$\sum_{k=t}^{\min(365, t+t^s)} D_{tk\omega}^{shift} - \sum_{k=\max(1, t-t^s)}^{t} D_{kt\omega}^{shift} = D_{t\omega}^{net} \quad \forall t, \omega \tag{6}$$

$$\sum_{t \in T} D_{t\omega}^{net} = 0 \quad \forall \omega \tag{7}$$

$$\sum_{k \in T: k > t} D_{tk\omega}^{shift} \leq d_{t\omega} \quad \forall t, \omega \tag{8}$$

$$g_{t\omega} Cap + P_{t\omega}^{diesel} = d_{t\omega} - D_{t\omega}^{net} + P_{t\omega}^{spill} \quad \forall t, \omega \tag{9}$$

$$P_{t\omega}^{diesel}, P_{t\omega}^{spill}, D_{tk\omega}^{shift}, Cap \geq 0, \quad D_{t\omega}^{net} free \quad \forall t, k, \omega \tag{10}$$

The objective function (5) minimizes the annualized investment cost and expected diesel cost throughout the planning horizon. Constraint (6) is used to define the net demand shift for each time period and scenario. Constraint (7) states that net change in total demand should be zero in each scenario so that total demand amount before and after the adjustments would be the same. Constraint (8) states that total demand shifted from a time period to the future periods cannot exceed the demand in that time period. Constraint (9) is a balance equation that makes sure that the demand is met and excess supply is curtailed. Constraint (10) is the domain constraint.

3. Computational analysis

In this section, we first present our data and perform a preliminary analysis to understand the dynamics of the data sets. We examine the required systems size and energy curtailment amounts if there is no demand response applied and no dispatchable source used when a predetermined percentage rate of the demand is met. Then, we present and discuss the result of our model and present a sensitivity analysis on the cost parameters of the system.

3.1. Data and preliminary analysis

Agriculture is an important economic activity in Gujarat and electricity supply for this sector accounts for about 27% of the total electricity supplied [40]. The Gujarat Government has been proactive on renewable energy front by implementing progressive policies and creating a conducive environment. The efforts are not limited to promoting renewable energy. The government has also made great strides in load management by making investments to agricultural feeders. Pilot programs for the solar-powered water pumps have been some examples of these efforts [40]. We obtained real demand, solar and wind generation data from State Load Dispatch Center for Gujarat, India for four years with daily resolution from April 1st, 2012 to March 31st, 2016. The demand data constitute nearly 6000 agricultural feeders spread across four distribution companies and serving over 1.2 million agricultural customers. Due to the length and resolution of the data obtained, the systems are modelled with a planning horizon of one year and time period of one day. As shown in Table 1, there is an increasing trend in the installed capacities of solar and wind sources in Gujarat.

Table 1
Installed capacity in India's Gujarat region (MW).

	2012–2013	2013–2014	2014–2015	2015–2016
Solar	824	887	1003	1127
Wind	3091	3352	3542	3933

Thus, we divide the real generation data of each year by installed capacity and use normalized generation, i.e. the output of solar and wind energy systems with 1 MWp capacity. We consider each year's data as a different scenario in the stochastic programming models that we propose, therefore capturing the uncertainty of demand and generation. Fig. 1 shows the agricultural load and normalized generation for each year. We observe that the agricultural load is similar for all years, so normalization is not needed. As the load does not deviate throughout the years drastically, making investment decisions based on the previous observations is reasonable for agriculture sector.

Nathan and Modi in [41] show that it is possible to generate between 2.7% and 14.6% of the electricity demand in 32 regions of the United States by using solar panels without storage so that 95% of the solar generation is utilized and baseload generation is preserved. Similarly, we first perform preliminary calculations on meeting agricultural load with solar or wind energy without any non-renewable energy source and demand response in order to gain a rough understanding of the baseline system performance. We quantify the amount of curtailed energy by multiplying the normalized generation output with a capacity value that would be needed to meet the desired percentage of the demand and taking the difference between this value and the demand. Fig. 2 shows that curtailment in the wind case is quite significant. More specifically, in order to meet 90% of the agricultural load without any demand response, approximately 15% of the solar generation needs to be curtailed. With wind generation, curtailment increases to 60% in order to meet the same demand. The system achieved lower curtailment with solar generation since both agricultural load for irrigation and solar generation decrease on rainy days and increase on sunny days. As shown in Fig. 1, wind energy sources generate more electricity in a year but with wider fluctuations. Average yearly normalized generation is 1643 MWh and 1465 MWh for
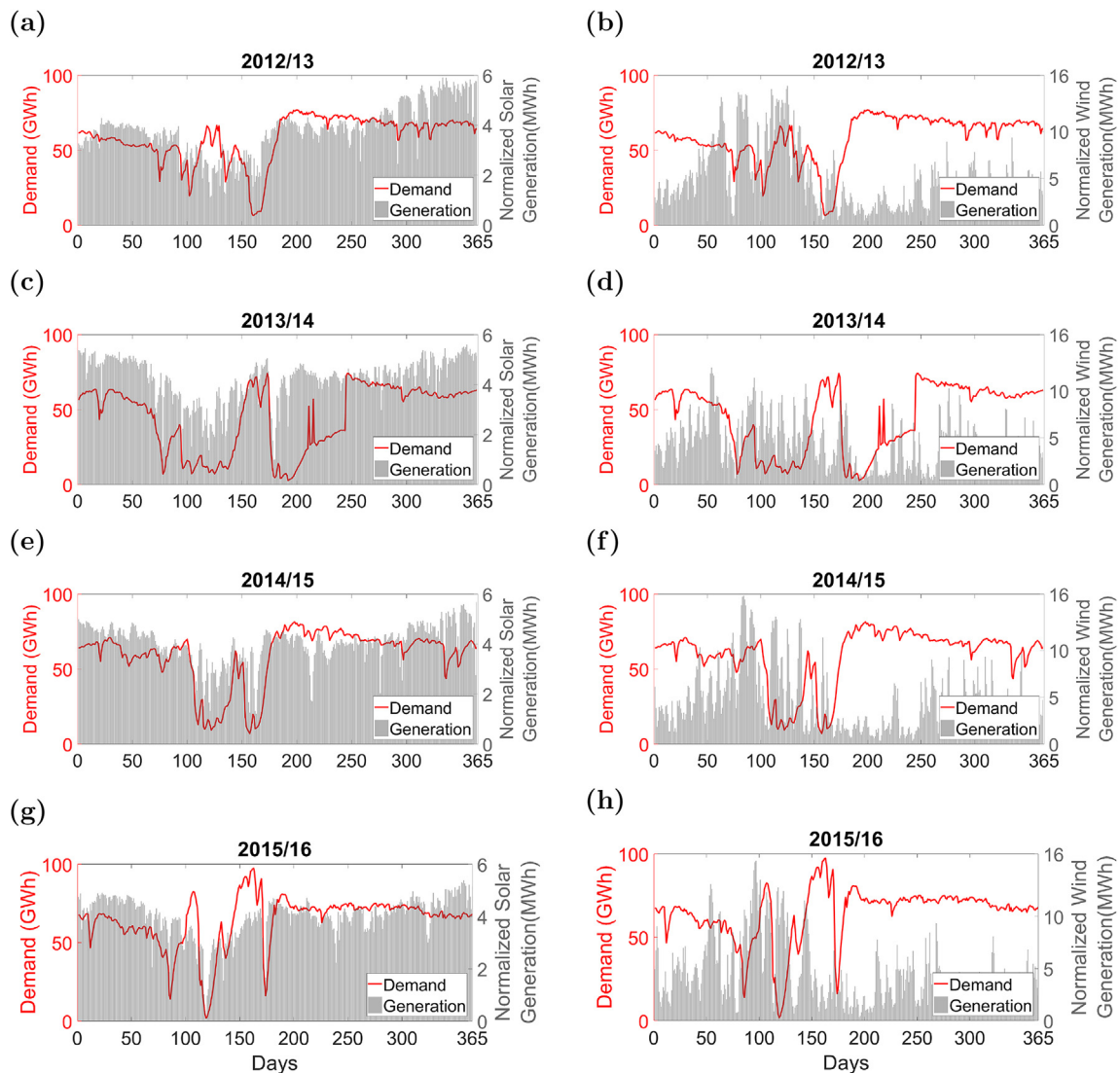

Fig. 1. Daily demand and normalized generation data in Gujarat, India for four years. Curves show the demand and bars show the normalized generation. Demand-normalized solar generation and demand-normalized wind generation data is presented in the left and right columns, respectively. We observe that wind generation is more in quantity and has higher fluctuation than solar generation.
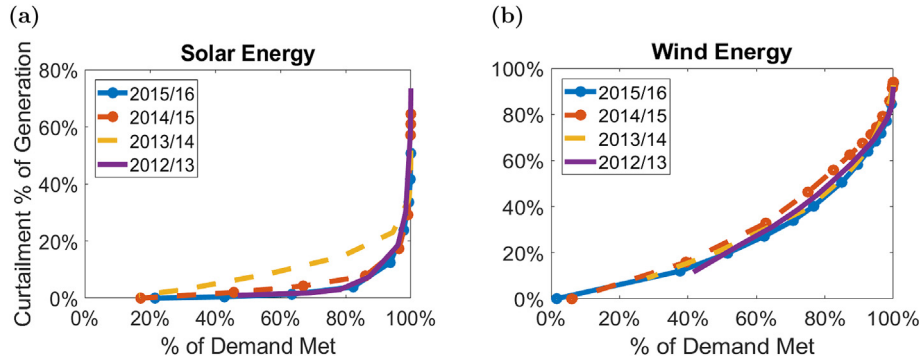
Fig. 2. Curtailed generation when different percentages of demand are met using (a) solar and (b) wind energy. In order to meet 90% of the agricultural load without any demand response, approximately 15% of the solar generation needs to be curtailed, whereas curtailment amount is about 60% in the wind case.

Table 2
Parameters for renewable energy systems [2].

System Component	Lifetime (LT_g)	Investment Cost
Solar Panel	30 years	$1.6/Wp
Wind Turbine	20 years	$2/Wp

wind and solar energy, respectively. Therefore if demand response programs can better utilize curtailed energy, we expect significant benefits when these programs are paired with wind generation.

3.2. Numerical results

We integrate diesel generation into the system as a proxy for fast-ramping, dispatchable energy generation, which costs $250/MWh [37] and examine the role of demand response on the system sizing. Table 2 shows the lifetime and the cost parameters used throughout the paper for solar and wind energy systems. In our objective function, we minimize the costs of both first stage and time indexed second stage decision variables for our one year planning horizon. Therefore, we annualize the investment cost of the sources by an annualization factor, which is defined as $(i/(1 - (1 + i)^{-LT_g})$, where i is the 5% interest rate and LT_g is the lifetime of the renewable energy system g. All of our mathematical models are solved optimally using IBM ILOG CPLEX Studio IDE 12.8.0, therefore we present the optimal value for each system described.

Although it may not be practical, we analyze different load shifting policies up to 24 days as demand shift periods in order to fully capture changes in the optimal solar and wind generation capacity. In Fig. 3 (a,b), we show that more solar than wind generation capacity is installed in their respective optimal solutions. Fig. 3 (c,d) indicate that solar generation meets the agricultural load more cost effectively than wind and the gap between the annual system cost for solar and wind case remains stable when demand shift period is extended from 0 days to 24 days. For both wind and solar cases, system costs decline down to 88% of the initial cost when demand is allowed to shift over the full 24 days.

We also use other performance metrics such as expected diesel generation amount and curtailed renewable energy amount to compare solar case and wind case further in Fig. 4. We find that the values for all these metrics in the solar case are less than wind case for all demand shift periods. Moreover, Fig. 4 (a,b) show that diesel energy meets between 1% and 5% of the total demand in solar case for all demand shift periods; this quantity is between 20% and 35% in wind case. Lastly, as seen in Fig. 4 (c,d), curtailed energy is between 14.5% and 19% of generation in the solar case, and between

18% and 31% in wind case.

Additionally, we find that the effect of demand response on the sizing of renewable energy systems and diesel usage is highly dependent on the demand shift period. According to Fig. 3 (a,b) and Fig. 4 (a and b), the system generation capacity increases and amount of diesel generation declines when the demand shift period is between 0 and 8 days in the solar case, and between 0 and 4 days in the wind case. In contrast, the system generation capacity decreases and the amount of diesel generation increases for larger demand shift periods, especially for the wind scenario. We can understand these effects by considering the following: initially, excess demand is shifted to days with curtailed renewable energy, and the demand curve more closely aligns with the renewable energy generation profile. At this stage, an additional 1 MWp capacity of solar panels or wind turbines can satisfy more demand with less curtailment and the unit cost of 1 MWp solar or wind capacity per kWh of demand met declines. Consequently, installed capacity increases and the unit cost of renewable energy sources declines until a certain demand shift period. Hereafter, further extensions in demand shift period have a reverse effect, which can be explained by the variability in renewable energy generation throughout the year.

Fig. 5 (a,b) and (c,d) display the changes in the supply and demand curves due to load shifting when the demand shift period is 4 days and 24 days, respectively. In the wind scenario with 4 days shifting, curtailment occurs between 10th and 80th days as a result of the intra-annual variability in wind generation. When the demand shift period is extended to 24 days, demand is smoothed out to utilize the curtailed energy between 10th and 80th days, so smaller system capacity would be enough for 10th and 80th days. However, the renewable energy generation between 250th and 350th days becomes scarcer due to declining installed capacity, resulting in more consumption of diesel energy. As a result of the trade-off between the cost of diesel generation and the investment cost of wind energy system in the objective function, the reduction in the investment cost dominates the increase in the diesel generation cost and thus, the annual system cost descends. At these higher demand shifting periods, an increase in diesel consumption allows for a more substantial decrease in installed renewable generation capacity.

Fig. 6 demonstrates that the reduction in annual system cost per shifted load is always less than or equal to the unit cost of diesel generation, which is $250/MWh. Therefore, installing additional 1 MWp of solar or wind capacity becomes reasonable if the marginal cost of renewable energy sources is less than the unit cost of diesel energy in the presence of demand response. This marginal cost value can also be used as a benchmark for the incentives that can be
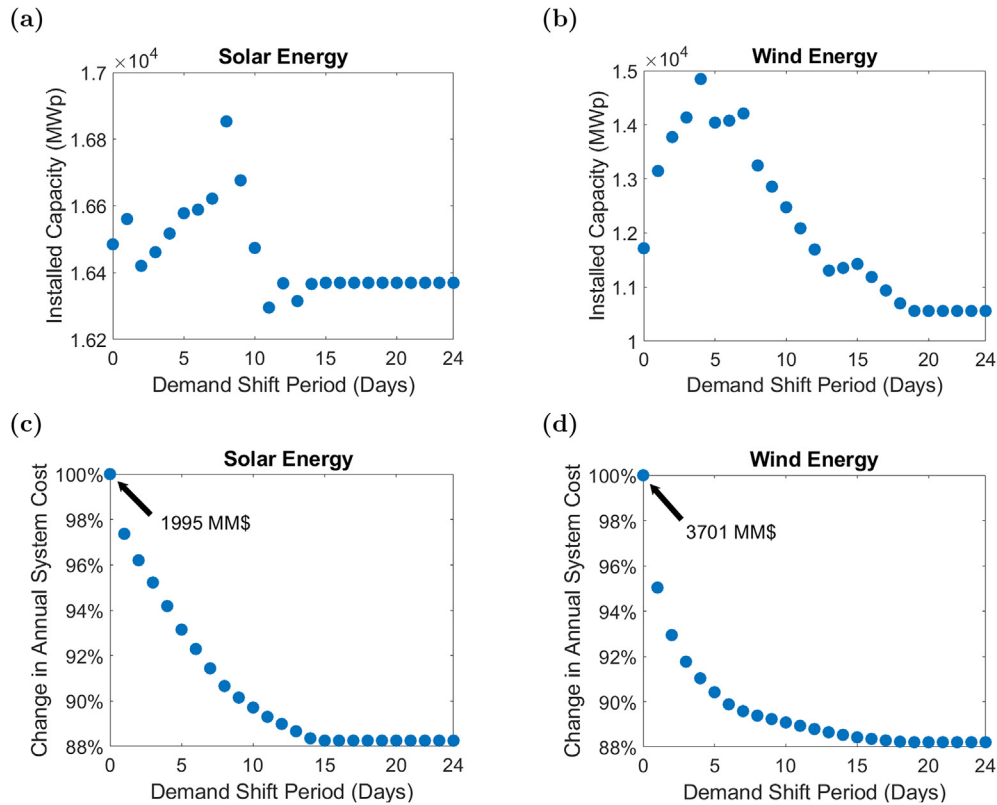
Fig. 3. The effect of demand response on (a,b) installed capacity and (c,d) percentage change in annualized system cost. Required solar installed capacity is more than wind capacity in their respective optimal solutions. Solar generation meets the same amount of load in a more cost effective manner than wind for all demand shift periods.

offered to the farmers.

In this analysis, the data with finer resolution might seem to help obtain more accurate results. However, our initial experiments performed by 3-hourly data (obtained by distributing the daily demand data in alternative ways using different distribution assumptions) showed that the effect of the finer resolution beyond daily data might not provide further improvements on the results. Moreover, to observe the importance of uncertainties considered in the recourse problem, we calculated the Value of Stochastic Solution (VSS) for solar and wind cases. To calculate the VSS, we first replaced the random quantities by their mean values and solved the "mean - value" problem to obtain a first stage solution, *x*. We fix the first stage solution at *x* and solve the problem for all scenarios. The difference between the obtained objective value and the solution of our original problem gives us the VSS [39]. We observe that the VSS is about 2% on average for all demand shift periods and goes up to 3% of the stochastic programming solution for some cases. Lastly, as in [2,37], we assume that the unit cost of diesel generation is constant, although in practice diesel price changes overtime. Our preliminary analysis shows that the daily variation in diesel price does not change the main message that we deliver with our results.

3.3. Sensitivity analysis on the cost of dispatchable generation

To understand the effect of the ratio between the cost of the dispactable source and investment cost of the renewable sources, we perform a sensitivity analysis on the cost of the diesel energy keeping the investment cost of the renewable constant. Tables 3 and 4 show the cost of the systems, installed capacities, expected curtailment amounts as a percentage of generation and expected diesel usage as a percentage of demand when the unit cost of diesel

energy are doubled and halved for solar and wind cases and when demand shift period is equal to 0,1,5 and 10. We observe that in the solar case, diesel contribution in the system decreases about 2% and increases about 8% when the cost of diesel generation is doubled and halved, respectively. However, in the wind case more than 10% decrease is observed in the diesel usage when the diesel cost is doubled, whereas the diesel contribution is increased by more than 30% when the cost is halved. Moreover, curtailment amounts in the wind case are also more sensitive to diesel cost than the solar case. Here we conclude that demand response can offer a reasonable alternative to carbon-intensive generation if the price of such generation increases.

4. Discussion

In the previous section, we analyzed the impact of different load shifting policies when there is a dispatchable source in the system. Here, in Section 4.1 we first remove this source from the system and examine the role of load shifting to meet a predetermined portion of the agricultural demand. Then, we present another model to include energy storage as an alternative to demand response program in Section 4.2.

4.1. Effect of demand response on partial demand

When there is only intermittent renewable sources in the system, it is not guaranteed to meet the demand completely. To understand the benefit of load shifting in this case, we develop a new model that aims to minimize the investment cost of the renewable system while meeting a pre-determined ratio of the demand. We compare the results of alternative load shifting cases and no load shifting case. In our model, the scenario dependent variables are
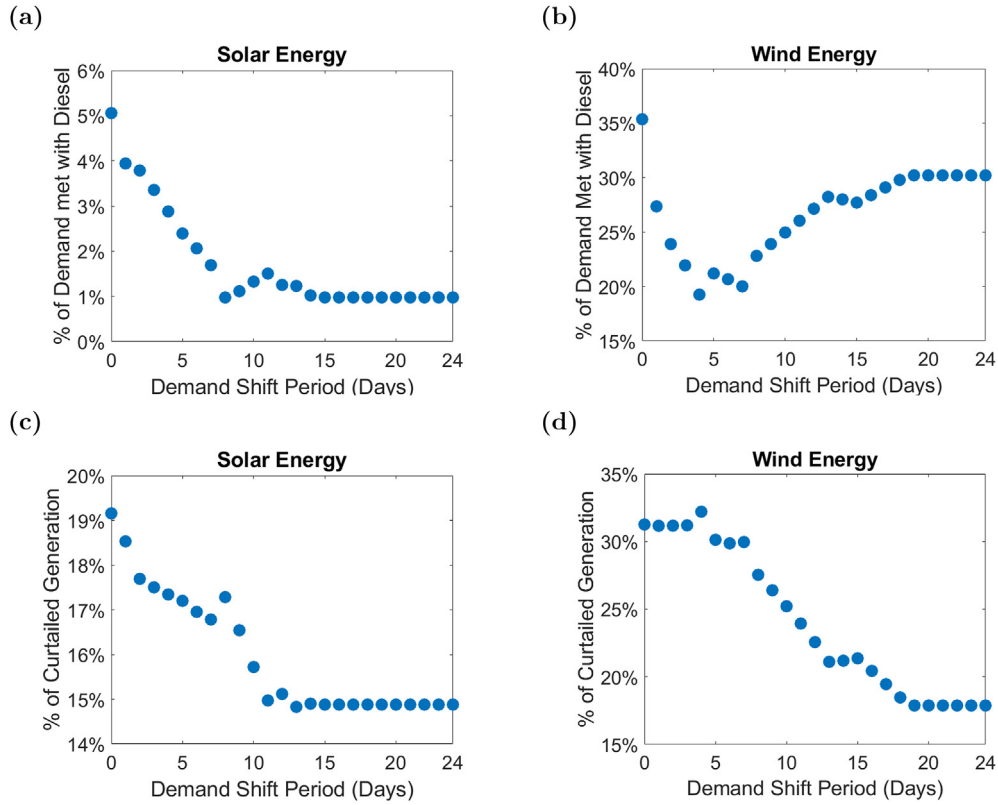
Fig. 4. The effect of demand response on (a,b) diesel usage and (c,d) curtailment amount observed in the system. Diesel energy decreases down to 1% from 5% of the total demand in the solar case as the demand shift period increases. This quantity reduces from 35% to 20% in the wind case. Demand response significantly help reduce the curtailment amount (from 31% to 18%) in the wind case, which is still higher than the curtailment amount of the solar case for all demand shift periods.
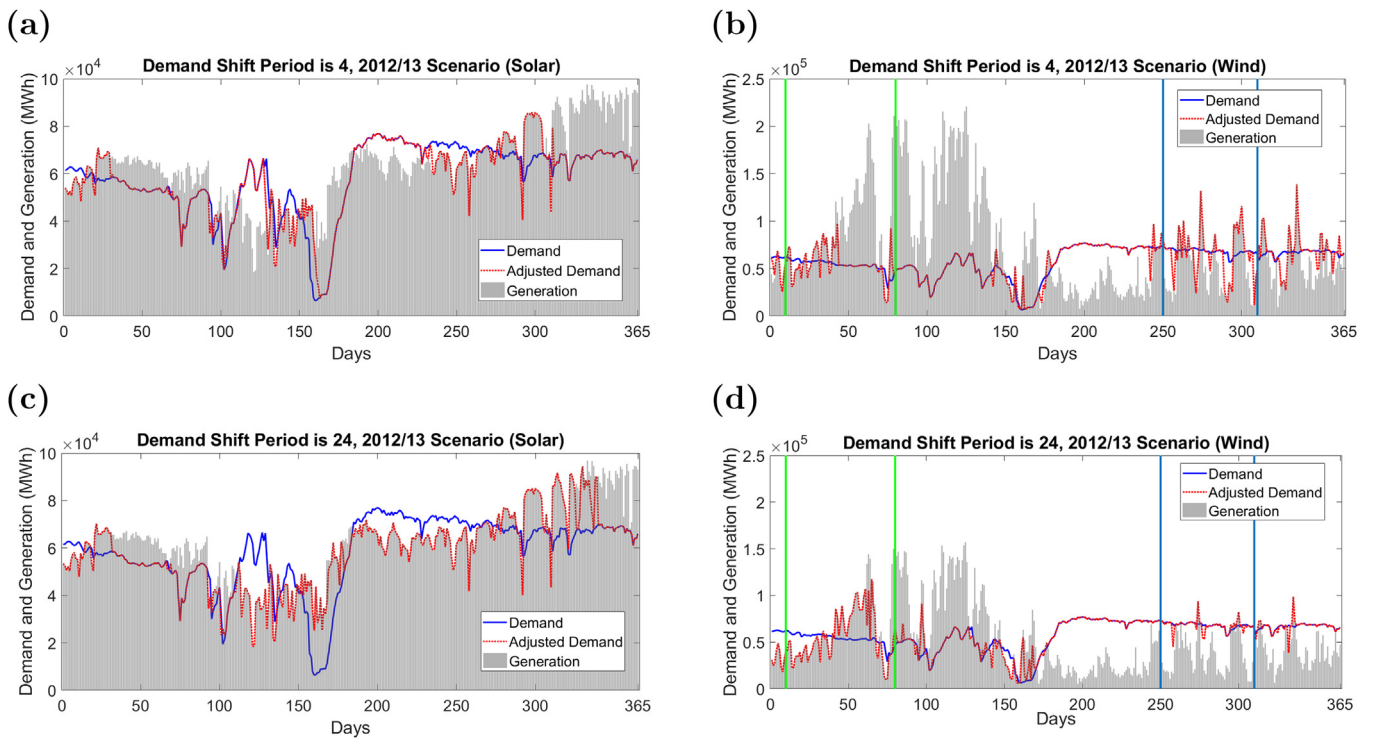

Fig. 5. Generation and demand profiles for solar and wind in 2012/2013 scenario. High amount of curtailment occurs in the wind case between 10th and 80th days when the demand shift period is 4 days. When the demand shift period is extended to 24 days, demand is smoothed out to utilize the curtailed energy between 10th and 80th days, hence smaller system capacity suffices compared to 4 days shifting. However, the renewable energy generation between 250th and 350th days becomes scarcer due to declining installed capacity, resulting in more consumption of diesel energy.
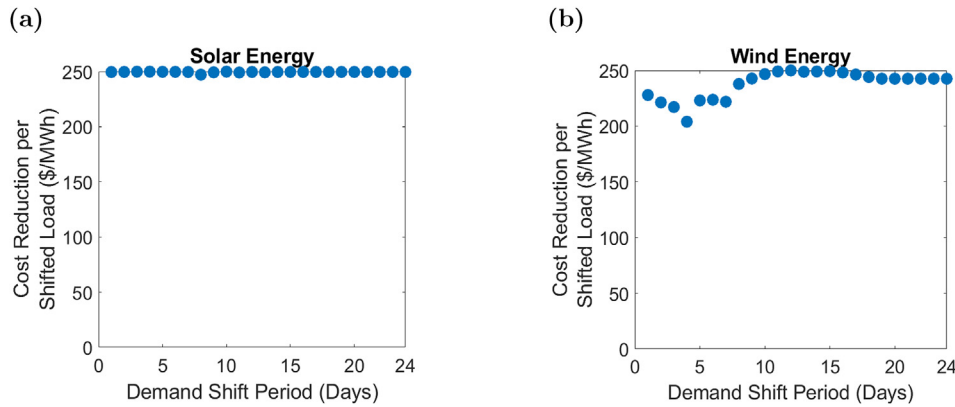
Fig. 6. Annual system cost reduction per shifted load compared to the case where demand shift period is zero. (a) Solar Energy (b) Wind Energy.

the amount of generation used or spilled and the amount of demand unmet or shifted at each time period for each scenario. The model that we propose for the aforementioned system is the following:

$$\min c^l Cap \qquad (11)$$
$$s.t.$$

$$(d_{t\omega} - D_{t\omega}^{net}) - g_{t\omega}Cap \leq D_{t\omega}^{unmet} \qquad \forall t, \omega \qquad (12)$$

$$\sum_{t \in T}\sum_{\omega \in \Omega} \pi_\omega D_{t\omega}^{unmet} \leq \alpha^{unmet}\sum_{t \in T}\sum_{\omega \in \Omega}\pi_\omega d_{t\omega} \qquad (13)$$
$$(6) - (8)$$

$$D_{tk\omega}^{shift}, Cap, D_{t\omega}^{unmet} \geq 0, \qquad D_{t\omega}^{net} free \qquad \forall t, k, \omega \qquad (14)$$

The model minimizes the cost of required installed capacity. Constraint (12) finds the amount of unmet demand for each day in each scenario. Constraint (13) states that the total expected unmet demand in a year cannot exceed the specified percentage of the total expected demand. Constraints (6)–(8) are used for demand shift. Lastly, constraint (14) provides the domain constraint.

Fig. 7 shows the installed capacity level in (a,b), and curtailment amounts in (c,d) for solar and wind energy alternatives. Here, we present the results for a maximum shift period of 7 days as the

results do not chance significantly after that period. We observe that if at least 75% of the demand has to be met and demand shift period is 7 days, a solar system with a capacity of 11,070 MWp is installed and 4.5% of the generation would be curtailed. For the wind case, to meet the same amount of demand, the system size and the curtailment ratio become 12,910 MWp and 27%, respectively.

If we require that 100% of the demand be met and specify the demand shift period as 7 days, curtailment reaches 30% in a 19,879 MWp solar system and 70% in a 41,803 MWp wind system, a finding which demonstrates that solar energy can meet the demand with less capacity and less curtailed energy when no backup source is used. Fig. 8 (a,b) show the annual cost savings due to flexible demand, savings which are defined as the decrease in instalment cost compared to the case where demand shift period is zero, i.e. when load shifting is not possible. Since Fig. 8 (a,b) are concave, we can conclude that the marginal cost savings (the difference in between the annual cost savings when demand shift period is k days and $k - 1$ days) decreases as the demand shift period increases for both solar and wind cases (i.e. we realize decreasing marginal returns from increasing demand flexibility). Therefore, large initial annual cost savings can be obtained from shifting agricultural demand over a relatively small portion of time. For a system with only solar generation, annual cost savings with a demand shift period of one day are 40% of the savings when the demand shift period is seven days.

Table 3
Sensitivity analysis for diesel generation cost in solar case when demand is shifted.

Cost Change	Demand Shift Period = 0			Demand Shift Period = 1			Demand Shift Period = 5			Demand Shift Period = 10		
	$c^D/2$	c^D	$2c^D$	$c^D/2$	c^D	$2c^D$	$c^D/2$	c^D	$2c^D$	$c^D/2$	c^D	$2c^D$
Cost of System (MM$)	1773	1995	2185	1743	1943	2076	1700	1859	1932	1682	1790	1809
Installed Capacity (MWp)	13,536	16,485	18,215	13,713	16,561	18,321	14,001	16,578	17,637	13,735	16,474	17,302
Curtailment % of Generation	11	19	25	10	19	24	9	17	21	7	16	19
% of Demand Met with Diesel	13	5	3	12	4	2	9	2	1	9	1	0

Table 4
Sensitivity analysis for diesel generation cost in wind case when demand is shifted.

| Cost Change	Demand Shift Period = 0			Demand Shift Period = 1			Demand Shift Period = 5			Demand Shift Period = 10		
	$c^D/2$	c^D	$2c^D$	$c^D/2$	c^D	$2c^D$	$c^D/2$	c^D	$2c^D$	$c^D/2$	c^D	$2c^D$
Cost of System (MM$)	2455	3702	5112	2439	3518	4606	2403	3347	4022	2363	3298	3864
Installed Capacity (MWp)	4409	11,716	18,121	4676	13,146	18,548	5021	14,041	18,827	5424	12,475	19,402
Curtailment % of Generation	9	31	46	8	31	43	6	30	40	4	25	40
% of Demand Met with Diesel	68	35	21	66	27	16	62	21	10	58	25	7
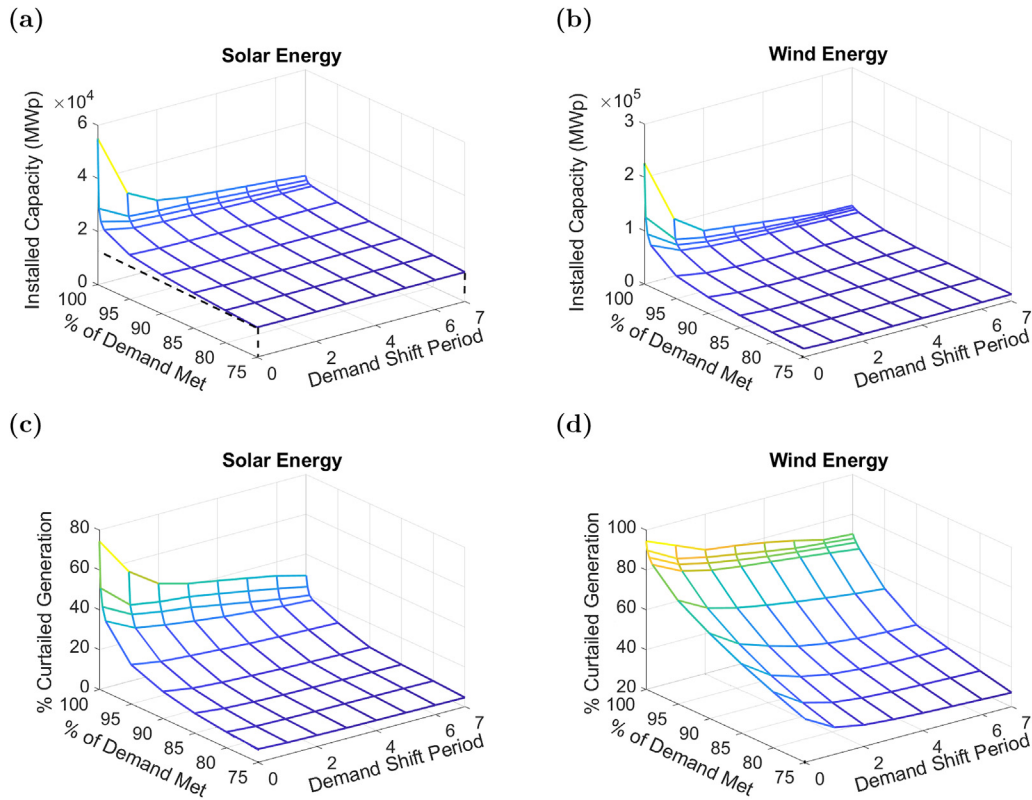
Fig. 7. Effect of demand response when demand is partially met without a backup source. (a,b) installed capacity (c,d) curtailed generation (% of total generation). Installed capacity and the curtailment values are higher in the wind case to meet the same amount of demand. The gap between solar and wind energy widens if the system needs to meet a larger portion of the demand or a lower demand shift period is imposed.

4.2. Generation shift - storage

Demand response programs and energy storage are both considered as control mechanisms that help reduce the intermittency of the renewable energy systems [42]. Load shifting as a demand response program changes the pattern in the demand side and helps match supply and demand. The supply side counterpart of this effect can be achieved with energy storage. For this purpose, we examine the energy storage as a substitute for load shifting programs. The cost of the storage necessary to replace the flexibility provided by load shifting gives an upper bound for the demand response budget when the dispatchable generation is limited in the system. Therefore, in a new model provided below, we fix the renewable capacity and the amount of diesel used with the values

obtained from the dispatchable generation model for each demand shift period and minimize the size of the storage needed in the system.

$$\min c^s S \tag{15}$$
$$s.t.$$

$$g_{t\omega} Cap = P_{t\omega}^{used} + P_{t\omega}^{str} + P_{t\omega}^{spill} \qquad \forall t, \omega \tag{16}$$

$$d_{t\omega} = P_{t\omega}^{rls} + P_{t\omega}^{used} + P_{t\omega}^{diesel} \qquad \forall t, \omega \tag{17}$$
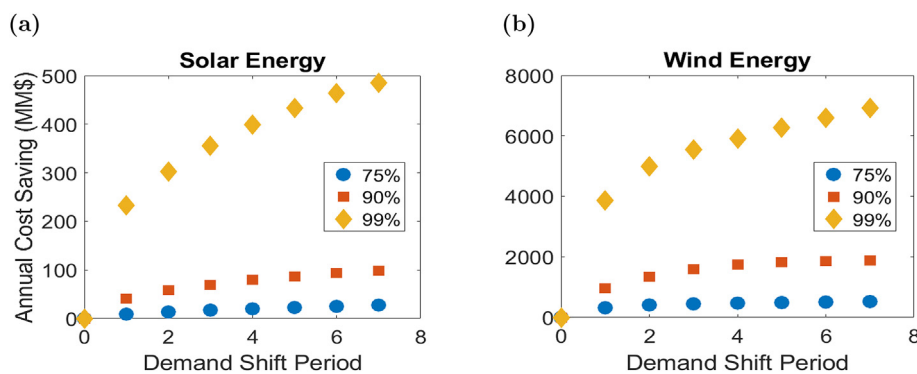

Fig. 8. Cost savings when demand is partially met without a backup source for (a) solar case, and (b) wind case. Decreasing marginal returns are observed from increasing demand flexibility.

Table 5
Lifetime and cost of storage types [43].

Storage Type	Investment Cost	Lifetime	Annualized Investment Cost
	(USD/kWh)	(Years)	(USD/MWh.year)
PHS	21	60	1109
CAES	53	50	2903
FloodedLA	147	9	20,681
VRLA	263	9	37,001
NaS	368	17	32,641

$$P_{t\omega}^s = P_{(t-1)\omega}^s - P_{t\omega}^{rls}\frac{1}{\gamma} + P_{t\omega}^{str}\gamma \qquad \forall t, \omega \qquad (18)$$

$$P_{t\omega}^s \leq S \qquad \forall t, \omega \qquad (19)$$

$$P_{0,\omega}^s = P_{365,\omega}^s = 0 \qquad \forall \omega \qquad (20)$$

$$\sum_{t \in T}\sum_{\omega \in \Omega} \pi_\omega P_{t\omega}^{diesel} \leq L^{diesel} \qquad (21)$$

$$S, P_{t\omega}^{diesel}, P_{t\omega}^s, P_{t\omega}^{str}, P_{t\omega}^{rls}, P_{t\omega}^{used}, P_{t\omega}^{spill} \geq 0 \qquad \forall t, k, \omega \qquad (22)$$

The objective function (15) minimizes the cost of the required storage capacity. Constraint (16) states that renewable energy generated can be directly used, stored or spilled at each time period and scenario. In constraint (17), demand is satisfied with directly used renewable energy, diesel, or from the storage at each time period and scenario. Constraint (18) defines the energy balance equation of the storage. Constraint (19) guarantees that the amount of energy stored at each time period cannot exceed the storage capacity. Constraint (20) defines the beginning and ending conditions of the storage. Constraint (21) limits the diesel amount used in the system and constraint (22) defines the domain constraints.

Table 5 shows the lifetime and investment costs of different storage systems taken from the literature [43]. The cost values are annualized with the same formula in Section 3.2. Fig. 9 (a,b) exhibit the additional annual storage cost that would be required to compensate for the absence of demand flexibility when the renewable generation capacity and the diesel amounts are fixed to the values obtained from the dispatchable model results. Here, the annual cost of storage can provide another benchmark for the incentive that can be offered to the farmers to adopt the demand response program. In Fig. 9 (c,d), the storage cost is divided by the amount of shifted demand obtained in the load shifting case for each demand shift period. In solar case, storage cost remains the same after the demand shift period is increased to more than 15 days. However, storage cost per shifted demand keeps increasing because the amount of shifted demand decreases. Although some storage types such as pumped hydro storage and compressed air storage may not be practical to use in the agricultural context, we included them into our analysis to have more variation among the available options in terms of cost and lifetime of the systems. If the planner wants to avoid investing on energy storage and allows 7 days period for demand shift, the amount of incentive that can be given is between $1.35/kWh and $4.05/kWh in solar systems and is between $2.68/kWh and $10.89/kWh in wind systems. Therefore, we observe that energy storage is an expensive substitute for demand response. Lastly, Fig. 9 (e,f) show the storage cost per expected demand, therefore are very similar to Fig. 9 (a,b).
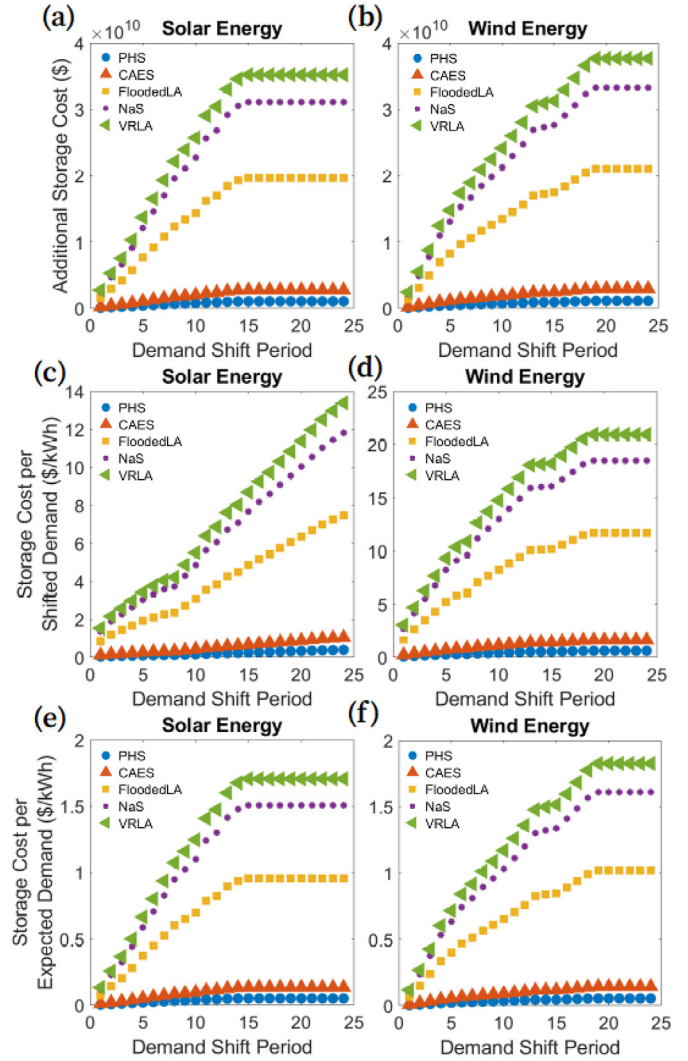

Fig. 9. (a,b) Annual storage cost, (c,d) storage cost per shifted demand and (e,f) storage cost per expected demand when storage is considered as a substitute for demand response.

5. Conclusion

In this study, we evaluate the value of demand response on sizing decision of solar and wind energy sources for agricultural energy demand. We present a framework for energy practitioners who might be interested in building decentralized systems operating mainly with renewable energy systems for water pumps. With this framework, which involves scenario based stochastic programming models, we evaluate the alternative load shifting policies depending on the flexibility of agricultural demand. We show that introducing load shifting programs for agricultural consumers not necessarily decreases the peak demand as opposed to many demand response programs and large savings can be obtained from shifting this type of demand over a relatively small portion of time.

We present a case study from Gujarat, India and run our models for wind and solar cases separately to observe which renewable source is more coherent with agricultural load. We show that solar energy is better aligned with the agricultural energy demand than wind throughout the year. Therefore, demand response is more helpful when it is used with the wind generation. More specifically,

the system cost can be reduced by 10% with a demand shift period of 10 days in solar case, whereas this number is 5 days in the wind case.

When the renewable systems are coupled with an expensive dispatchable source such as diesel, it is not very easy to predict the installed capacity of renewables and diesel usage. Therefore, an optimization model is needed to be solved with the existing renewable potential and demand data. If the aim is to reduce the contribution of dispatchable source in the system, the ideal demand shift period is 4 days in our wind case and 8 days in the solar case. Increasing the amount of time over which the agricultural load can be distributed does not help reduce the dispatchable source requirement; however, increasing the demand shift period up to 13 days in solar case and 20 days in wind case results in significantly better utilization of renewable sources. In the solar case, average shifted load in a month is 1% of the demand for demand shift period of 1 day, increases up to 4.5% for the period of 10 days and remains almost the same afterwards. In the wind case, average shifted demand amount in a month varies between 4% and 10% for the increasing number of demand shift periods. This number reaches up to 8% quickly for the demand shift periods of 4 days.

Finally, when solar and wind energy are installed without any backup source in order to meet portions of the agricultural demand, required installed generation capacity and curtailment are lower in the solar case compared to the wind case for all demand shift periods and all percentages of the demand met. We also show that energy storage can be a convenient control mechanism for the integration of renewables; however, is an expensive substitute for demand response programs for agricultural load.

Author contribution section

Ayse Selin Kocaman: Writing - original draft, Conceptualization, Formal analysis, Methodology, Writing, Supervision. Emin Ozyoruk: Writing - original draft, Data curation, Formal analysis, Writing. Shantanu Taneja: Data curation. Vijay Modi: Conceptualization, Supervision.

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