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Impacts of extreme climate conditions due to climate change on the energy system design and operation

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Abstract

Extreme climate events occur more frequently and stronger in the future due to climate change. Maintaining the energy security during extreme conditions is essential to reduce the impacts of extreme climate and avoid disasters. Resilient design of the energy system to resist against extreme climate events are investigated considering four scenarios, namely, typical demand (TD), extreme demand (ED), extreme renewable energy generation (ER) and, extreme demand and renewable generation (EDR). A regional climate model is used to develop the four scenarios with the assistance of a building simulation model. Subsequently, multi-energy hub is optimized for each scenario considering net present value (NPV) and grid integration (GI) level as the objective functions. A significant difference in objective function values is observed when analyzing the four scenarios. Similarly, a significant difference in the energy system design is observed when moving from one scenario to another. The results of the study reveal that a energy system design is strongly influenced by extreme climate scenario considered which will make the energy system to be a sub-optimal when operating at a different climatic condition with a significant performance gap. Therefore, improving the climate flexibility of energy systems is an essential task which is challenging at the early design process.

Selection and peer-review under responsibility of the scientific committee of the Applied Energy Symposium and Forum, Renewable Energy Integration with Mini/Microgrids, REM 2018.

Keywords: Climate change; extreme climate events; energy hub; optimization; regional climate model

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1. Introduction

Climate change has adverse influences on various sectors such as energy, agriculture, urbanization etc. [1]. New research frontiers have been formed at different levels to mitigate the adverse effects due to the climate change. Rapid changes that take place in the energy sector can be considered as one main frontier in the fight against climate change [2]. Large scale integration of renewable energy technologies is taking place in order to facilitate the energy transition. Distributed energy systems such as energy hubs have shown the potential to integrate more renewable energy technologies when compared to direct integration [3–5]. Climate change can have a notable adverse impact on the design process of integrated energy systems creating a vicious cycle.

Extreme climate conditions such as cold and heat waves are considered as consequences of climate change. These extreme scenarios will result in extreme increase in the cooling or heating demand [6]. At the same time, extreme climate events will lead into situations having very low renewable energy generation. Simultaneous increase demand and drop in renewable based power generation might lead to blackouts. Hence, it is important make the energy systems to be climate resilient. Hence, it is important to quantify the influence of extreme climate on the demand pattern and subsequently on the energy system design.

Towards achieving this objective the manuscript is organized as follows. Section 2 presents the methodology followed to create time series whether data and subsequently demand data using the regional climate models considering four scenarios (considering extreme energy demands as well as generation). Subsequently, energy system is designed considering the extreme climate scenarios. The design tool used to optimize the energy system is explained in Section 3. A Pareto multi objective optimization is conducted to optimize the system design and operation strategy. Life cycle cost of the system and the autonomy level of the energy system are considered as the objective functions. Finally, Section 4 presents the results and the discussion. A significant drop in operating performance can be expected when energy systems that are designed to operate at extreme conditions operate at normal conditions. Hence, energy systems obtained considering extreme weather conditions are compared with the ones obtained using TDY (typical day year) method.

2. Estimating energy demand and renewable for future climate

Future climate conditions are simulated by means of global climate models (GCMs), forced by several representative concentration pathways (RCPs) [7]. Climate data from GCMs are coarse and not suitable for energy simulations, therefore their outputs are dynamically downscaled using regional climate models (RCMs). Outputs of RCA4, which is the 4th generation of the Rossby Centre RCM, have been used in this work [8]. RCA4 downscaled four GCMs to the spatial resolution of 12.5km: CNRM, ICHEC, IPSL and MPI. The first two GCNs are forced by RCP4.5 and RCP8.5 and the other two by RCP8.5. In this way, six future climate scenarios for the 30-year span of 2070-2099 with the hourly time resolution were synthesized [9]. This results in 180 years of weather data for the considered time span, which were used to create a representative weather data group, containing three one-year data sets: typical downscaled year (TDY), extreme cold year (ECY) and extreme warm year (EWY) [6]. These three data sets were used to generate energy demand profiles for future typical and extreme conditions. The numerical model for calculating the energy demand is a lumped system energy model in Simulink toolbox of Matlab [10] [11] [9]. The energy demand of 40 statistically representative buildings in Lund, Sweden for 2070-2099 using the three synthesized weather data sets. A similar approach as generating TDY, ECY and EWY was adopted to generate typical and extreme data sets for renewable energy generation; for wind turbine capacity, three sets of data for typical and extreme wind conditions were generated and for solar radiation, three data sets for global solar radiation. The method for creating typical and extreme conditions has been described thoroughly and verified in some previous works [6] [12] [13].

3.0 Overview of the energy system

A multi energy hub consisting of wind turbines, SPV panels, battery bank, internal combustion generator, heat pump that interacts with the grid is considered in this study (Fig. 1). The energy hub concept is amply taken into discussion in recent literature as a better option to integrate renewable energy technologies [3,4,14,15]. Hourly wind speed, solar irradiation, energy demand for heating and electricity are considered for each climate scenario. The energy hub is expected to be connected to the electrical grid which maintains energy interactions by purchasing and selling electricity. Real time pricing scheme is considered for both purchasing and selling electricity. Grid curtailments are introduced to limit the maximum amount of energy injected to the grid. The dispatch strategy is used to determine the energy interactions with the grid.

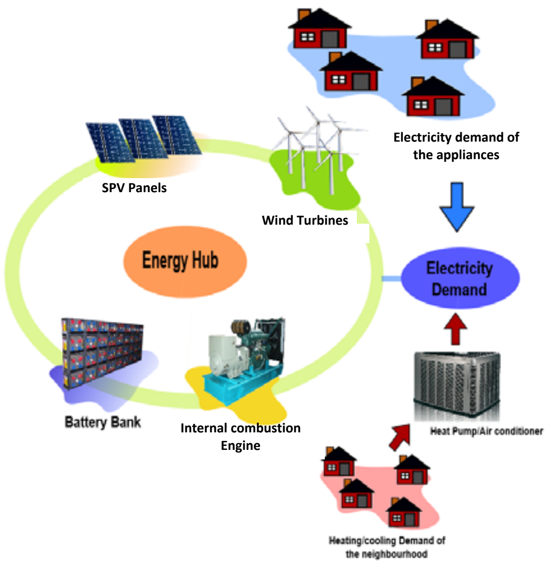

Fig. 1 Outlook of the energy system

Hourly, solar irradiation and wind speed data are taken as the input to the energy system model. Based on that, renewable power generation is computed on hourly scale combining the power generation of wind turbines and SPV panels. Eq. 1 is used to compute the power generation in SPV panels.

$$P_t^{SPV} = G_t^{\beta}\, \eta_t^{SPV}\, A^{SPV}\, x^{SPV}\, \varsigma, \quad \forall t \in T \tag{1}$$

In this equation, G_t^{β}, η_t^{SPV}, A^{SPV}, x^{spv} and ς denote the global solar irradiation on the tilted PV panel, the efficiency of the SPV panel, the number of PV panels obtained using the optimization algorithm.
Eq.2 is used to compute the power generation using wind turbines.

$$P_t^{Wind} = \tilde{P}_t^{W}(\mathrm{v_t})\ \mathrm{x^w}\ \eta^{\mathrm{Losses}}, \forall t \in T \tag{2}$$

In this equation, $\tilde{P}_t^{W}(\mathrm{v_t})$, X^{w} and η^{Losses} denote, power generation of a single wind turbine for wind velocity v_t the number of wind turbines in the system (which is obtained using the optimization algorithm) and the power losses.
Energy storage and internal combustion generator are used as the dispatchable storage and energy source that withstand the fluctuations in renewable energy potential and demand with the support of the grid. Life time of both battery bank and internal combustion generator depends on the operation style adapted. Frequent operation of both battery bank and internal combustion generator might lead to shorter lifetimes. Hence, minimum depth of discharge is optimized using the optimization algorithm. A bi-level dispatch strategy is used to determine the operation conditions of the internal combustion generator and the state of charge of the battery bank. The primary level of the dispatch strategy determines the operating load factor of the internal combustion generator using fuzzy automata. The secondary level of the dispatch strategy determines the interactions with storage and the grid. A detailed description about the dispatch strategy can be found in Ref. [3].
Net present value (NPV) and Grid integration level are used as the objective functions for the Pareto optimization.

NPV represents the financial aspect of the project. NPV is computed considering initial capital cost (ICC) of the system components i.e. wind turbines, SPV panels, battery bank, and internal combustion generator, grid integration cost and the operation and maintenance cost (OM_p denotes present value of operation and maintenance cost) according to Eq. 1.

$$\mathrm{NPV} = OM_p + ICC + \mathrm{CRF.GICF_P} \tag{3}$$

In Eq. 3, CRF and GICF respectively present grid integration cost factor capital recovery factor.
Strong interactions with the grid by both injecting and purchasing electricity to and from the grid may lead to instabilities in the grid. Hence, energy autonomy of distributed energy systems is considered as an important aspect in the design process of distributed energy systems. In this study, we use grid integration level to present the autonomy of the distributed energy system. However, to be aligning with system autonomy defined in Ref. [3], GI is defined according to Eq. 4.

$$GI = \frac{\sum_{t=1}^{8760} PFG(t)}{\sum_{t=1}^{8760} ED(t)} \tag{4}$$

In this equation, PFG and ED denote the energy units (kWh) taken from the grid and electricity demand of the energy hub during steady state operation in time step t.
Energy system is optimized considering four scenarios i.e. typical hour model (TD), extreme scenario for renewable energy potential (ER), extreme scenario for demand (ED) and extreme scenario for both demand and renewable (EDR) generation. Subsequently, energy system is optimized considering both system design and operation strategy. A heuristic algorithm is used in this study to conduct Pareto optimization. A Pareto optimization is conducted considering Net Present value of the System and Grid integration level as the objective functions. Steady state ε-dominance method is used to conduct the Pareto optimization [16]. A detailed description about the optimization algorithm used can be found in Ref. [17,18].

4.0 Results and discussion

Four Pareto fronts are taken which include one typical scenario based on TDY and three extreme scenarios. Among the three extreme scenarios first two represent extreme demand and generation scenarios. Finally, the fourth scenario considers concurrent extreme conditions in both demand and generation at the same time. A notable cost reduction is observed for all the Pareto fronts when increasing the grid interaction levels. Permitting higher grid interactions makes it easy to incorporate more renewable energy technologies while depending less on the energy storage and dispatchable source which results in reduction in the NPV. The four Pareto fronts clearly show that designing energy system considering the extreme scenarios will have a notable impact on the NPV (Fig. 2). Three Pareto fronts that present extreme climate conditions are having a higher NPV when compared to the moderate scenario. Considering the extreme conditions in both demand and generation will result in a significant increase in the NPV.

Four Pareto solutions (which are having GI levels close to each other (TD-A is having a closer GI level to ED-A, ER-A and so on)) are taken from each Pareto front in order to further discuss the influence of extreme climate conditions. NPV, GI, ICC and renewable energy capacity of the design solutions are tabulated in in Table 1. In addition, percentage change in ICC with respect the corresponding Pareto solution in scenario TD is also included in-order to get a better understanding. When analysing the TD (moderate scenario) and ED (extreme demand scenario) sets, a significant increase in initial capital cost can be noticed (more than 20%). For example, initial capital cost has increased by 33% when moving from TD-C to ED-C. The increase in the initial capital cost can be understood when considering the increase in the renewable energy capacity. When moving from TD to ER (extreme renewable energy potential scenario), initial capital cost has reduced along with the reduction in REC. However, when compared to the reduction in renewable energy capacity, the reduction in ICC is trivial. This can be explained when considering the increase in dispatchable generator capacity, the change in renewable energy mix (ratio of SPV panels to wind turbines), and the increase in storage capacity. In addition to that, the ratio between NPV to initial capital cost increase when moving from TD to ER. This variation shows that the recurrent cost will increase as a result of frequent usage of dispatchable generator and the battery bank. When moving from TD set to EDR (extreme demand and renewable energy), the optimum design solutions shows the characteristics of both ED and ER upto a certain extent. When analysing the Pareto fronts of the four scenarios, it can be concluded that a notable changes in system design and operation should be taken place in to face extreme climate conditions. However, the most challenging thing is these changes are not quite similar to each other.

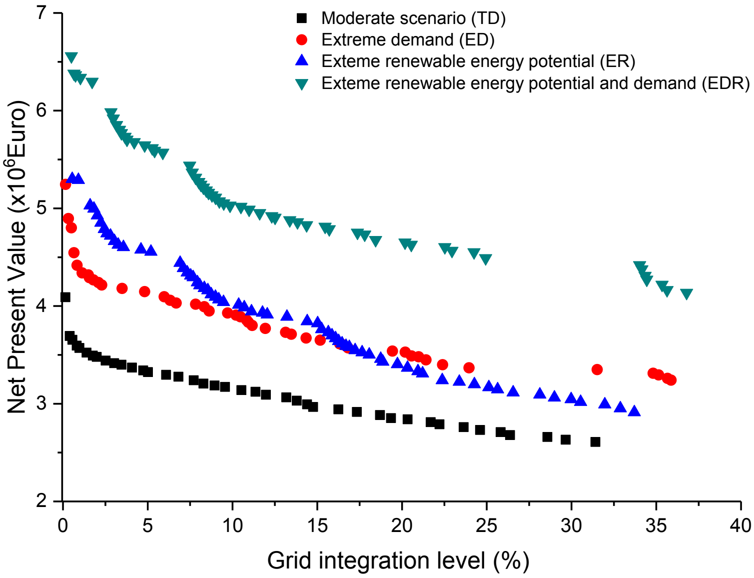

Fig. 2 Pareto fronts obtained for the four scenarios considering Net Present Value (NPV) and Grid Integration level as objective functions.

Table 1: A comparison of Pareto solutions extracted from the Pareto fronts

	NPV ($x10^6$ Euro)	GI (%)	ICC ($x10^6$ Euro)	Percentage increase in ICC	REC (kVA)
TD-A	3.48	2.00	2.41	-	1035
TD-B	3.34	4.73	2.31	-	970
TD-C	3.14	10.52	2.13	-	850
TD-D	2.84	20.33	1.96	-	715
ED-A	4.24	2.09	2.91	21	1390
ED-B	4.15	4.82	2.86	24	1360
ED-C	3.91	10.21	2.83	33	1360
ED-D	3.53	20.19	2.55	30	1145
ER-A	4.93	2.03	2.61	8	430
ER-B	4.58	4.60	2.28	-1	310
ER-C	4.01	10.37	2.06	-3	335
ER-D	3.37	20.32	1.83	-7	295
EDR-A	5.98	2.83	3.02	25	490
EDR-B	5.65	4.82	2.68	16	370
EDR-C	5.02	10.50	2.41	13	380
EDR-D	4.65	20.18	2.30	18	320

Conclusions

Extreme climate events occur quite frequently as a result of the climate change. Such extreme climate conditions can have a notable impact on both energy demand and generation. Extreme climate conditions can influence energy demand; renewable energy potential and certain instances both demand and generation. Considering extreme climate conditions is a difficult task especially during energy system optimization process. In this study, we considered four scenarios to evaluate the impact of extreme scenarios systematically. When analysing these scenarios it is revealed that there is a significant difference in the energy system configuration when moving from one to another. Therefore, energy system design obtained using all the four scenarios will end-up being sub-optimal when the system operates in a different scenario other than the specific conditions it is designed for. This makes it more important to consider moving into other optimization methods such as stochastic and robust optimization methods in order to improve climate flexibility of distributed energy systems.

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