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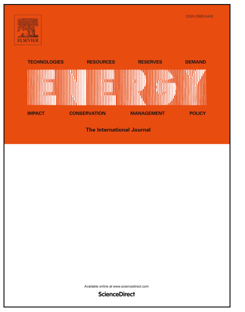

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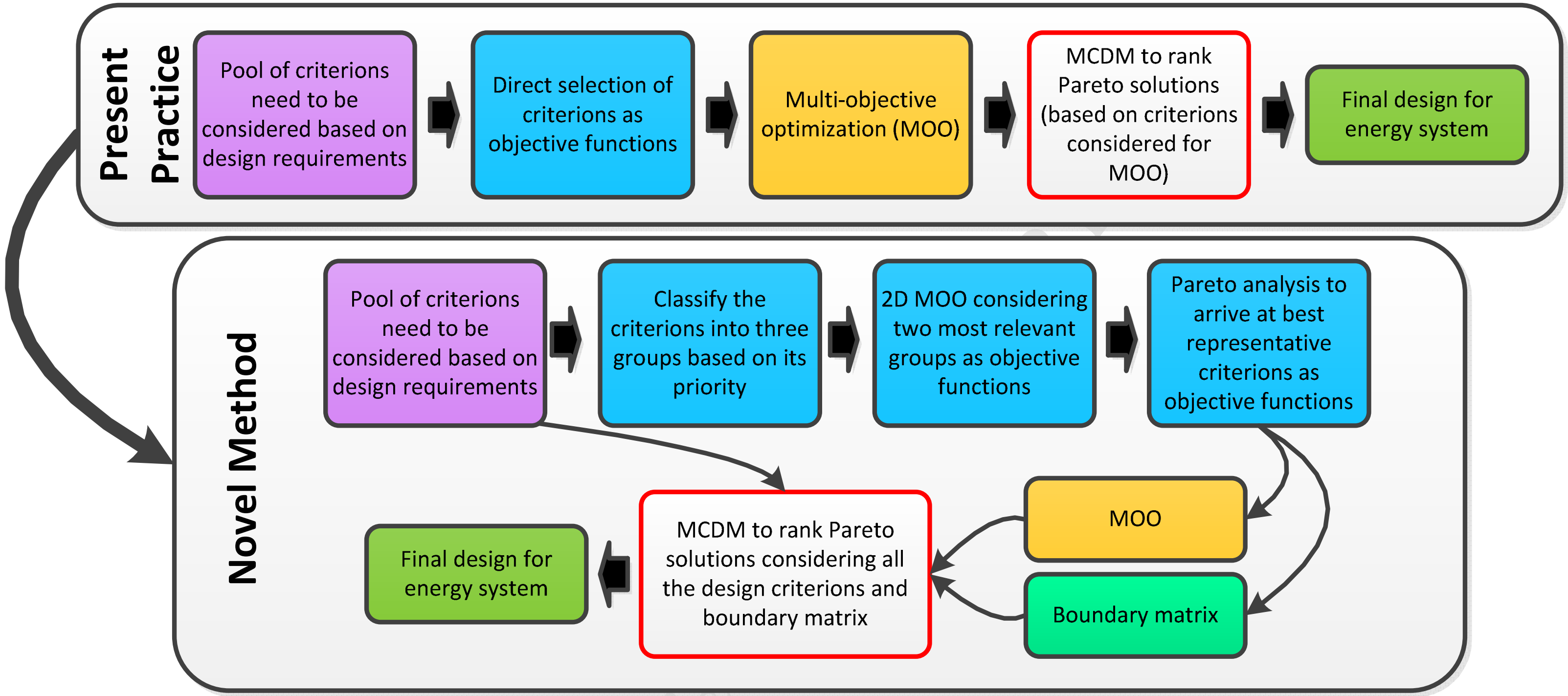

Graphical Abstract

An integrated approach to design site specific distributed electrical hubs combining optimization, multi-criterion assessment and decision making

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Abstract

An integrated approach is presented in this study to design electrical hubs combining optimization, multi-criterion assessment and decision making. Levelized Energy Cost (LEC), Initial Capital Cost (ICC), Grid Integration Level (GI), Levelized CO2 emission (LCO2), utilization of renewable energy, flexibility of the system, loss of load probability (LOLP) are considered as criteria used to assess the design. The novel approach consists of several steps. Pareto analysis is conducted initially using 2D Pareto fronts to reduce the dimensions of the optimization problem. Subsequently, Pareto multi objective optimization is conducted considering LEC, GI and ICC which were identified as the best set of objective functions to represent the design requirements. Next, fuzzy TOPSIS and level diagrams are used for multi-criterion decision making (MCDM) considering the set of criteria and the boundary matrix that represents the design requirements of the application. Pareto analysis shows that 5D optimization problem can be reduced to a 3D optimization problem when considering LEC, ICC and GI as the objective functions. Finally, results obtained from the case study shows that the novel method can be used design distributed energy systems considering a set of criteria which is beyond the reach of Pareto optimization with different priority levels.

Key words: Distributed Energy System; Multi-objective Optimization; Multi-criterion Assessment; Decision Making, Electrical Hub; Fuzzy TOPSIS

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1) Introduction

Integrating renewable energy technologies is important to make energy systems sustainable and face the challenges due to escalating prices of fossil fuel resources, Green House Gas (GHG) emissions and security problems due to nuclear energy. Wind and solar energy are becoming more promising choices in this regard. However, stochastic nature of these energy sources limits the direct integration of these energy technologies up to 40% of the demand in order to maintain the stability of grid [1,2]. Smart micro grids [3–5], virtual power plants [6–8], grid integrated and stand-alone hybrid energy systems [9–11] are getting popular on this regard as methods to integrate higher fractions of Solar PV (SPV) and wind energy. These systems consist of dispatchable energy sources and storage which can absorb the fluctuations of SPV and wind energy while maintaining the reliability of the power supply. However, a number of aspects (technical, environmental, economic, social) need to be considered in the designing process especially considering site specific requirements [12].

Multi objective optimization of distributed energy systems have been amply taken into discussion in recent literature in order to consider wider spectrum of aspects related to the design, moving beyond simple cost optimization. A number of diversified factors such as cost, environmental impact [13–15], utilization of renewable energy [16], system reliability [10,17,18], social impact [19], exergy efficiency [20] etc., have been considered in the optimization depending upon the requirements when designing distributed energy systems. A detailed list of different objective functions considered in multi objective optimization of energy systems is presented by Tan et-al [21], which is quite extensive. One cannot use an extended list of criteria as objective functions for the design optimization. On the other hand, according to Fadaee and Radzi [12], research studies on multi objective optimization of energy systems should focus more on catering site specific requirements when designing distributed energy systems. This makes it essential to consider a number of sites and design specific requirements beyond objective functions used for multi-objective optimization. Hence, multi-objective optimization should be a part of decision making process instead of being the only step; as it is practiced in most of the instances at present [10,13–18].

Recent research work on multi objective optimization of energy systems can be classified into two main classes depending upon the way it considers multiple attributes; i.e. weighted sum method and Pareto method [22]. In the former, different attributes that need to be considered are weighted and formulated as a single objective function.

This method is used in energy domain whenever designer is having a better understanding of objective space [23–25] (in order to weight the objective functions) which is not common in most of the instances. The latter is used to obtain entire set of Pareto solutions considering all the objectives which is frequently used in designing distributed energy systems, especially considering the Pareto front of cost and reliability[10,17,18] or cost and CO2 emissions [13–15]. It is important to continue energy system design beyond multi-objective optimization as suggested by Bhattacharyya [26] where multi criterion assessment and decision making needs to be combined with the designing process in order to rank the set of Pareto solutions obtained from multi-objective optimization. Selecting appropriate objective functions for Pareto optimization (as discussed before) and linking the Pareto optimization with multi-criterion decision making is still challenging.

Multi criterion assessment and decision making plays a vital role in both planning and designing energy systems. A number of different techniques have been used in this context which are reviewed in detailed in Ref. [27,28]. Multi-criterion decision making has been amply used in various applications related to locating energy systems [29–31], performance evaluation of energy systems [32–34], configuration selection etc [35–38]. However, most of these applications are different from energy system designing.

When it comes to design of distributed energy system, non-dominant set of solutions used for multi criterion decision making needs to be obtained using Pareto optimization. This is a lengthy process compared to most of the previous examples. Sayyaadi et-al [20], Perera et-al [39] and Mazza et-al [40] have used multi criterion decision making following multi objective optimization to design energy systems. Sayyaadi et-al [20] et-al used fuzzy Bellmane-Zadeh approach to rank Pareto solutions for a design application of co-generation system. Shirazi et-al [41] used LINMAP method to arrive at the most suitable design solution from the Pareto front. A similar approach based on fuzzy TOPSIS was used by Perera et-al [39] and Luo [42] when ranking Pareto solutions for a stand-alone energy system and Sterling engine. Objective functions used for Pareto optimization are directly used as the criteria for multi-criterion decision making process in these studies. Finding the most appropriate objective functions for the Pareto optimization is one of the main challenges in this context (Fig. 1). This approach cannot be used whenever set of criteria used to assess the energy system increases notably; especially for practical applications of distributed energy systems where much diversified criteria are expected to be evaluated (Fig. 1). In such instances, it is important to have an integrated approach consisting of several steps in order to identify the criteria that need to be considered in the assessment, select most the appropriate criteria as objective functions for Pareto optimization and support multi-criterion decision making considering all the criteria used to assess the system.

This study presents an integrated approach that can be used to design grid integrated electrical hubs [43,44] (simplified version of a multi energy hub [45,46] only considering the electrical parts) consisting of SPV panels, wind turbines, battery bank and an Internal Combustion Generator (ICG). Eight criteria are considered to assess a grid integrated electrical hub extending the number of criteria used to asses distributed energy systems in recent literature. A novel integrated approach consisting of several steps is introduced to design the electrical hub depending upon the importance of each criterion. A Pareto analysis is conducted with different combinations of objective functions to reduce the dimensions of the optimization problem and select the most suitable objective functions. Decision making process is extended beyond the Pareto optimization (values of the objective function) considering all the aspects of the design using a boundary matrix to present the boundaries of the customer expectation. These all are discussed thoroughly in the following sections: Section 2 provides a brief overview about the system considered in this study. Section 3 provides a detail description about the criteria used to assess the system and optimize. Section 4 presents a concise description about the dispatch strategy. Section 5 optimization algorithm and different combinations of objective functions considered. A detailed description about the novel integrated approach is presented in Section 6. Finally, application of the novel method is taken into discussion in Section 6.

2) Computational model for the electrical hub and assessment criteria

A computational model is developed in this study to formulate criteria that are used to assess the electrical hub. Some of these criteria are directly used as objective functions in the optimization process and some other are considered in the decision making process. This section presents a brief overview about the energy system configuration and the functionality

2.1) Overview of the Electrical Hub

An Electrical Hub operating as a distributed energy system connected to the grid is considered in this study. The Electrical Hub discussed in this paper is related to a rural electrification project for a small model village (peak demand of 29 kWh) in Hambanthota district. Rural electrification projects are an amply discussed case study related to distributed energy systems [47–52]. A detailed review of rural electrification projects based on hybrid systems can be found in Ref. [53].Hambantota is situated in the southern coastal belt in Sri Lanka which is having significant solar and wind energy potential according to the surveys carried out in Sri Lanka (Fig. 2). Hence, an energy system configuration consisting of SPV panels, wind turbines, ICG and a battery bank is considered for the Electrical Hub (Fig. 3).

A steady state hourly simulation is used to assess the energy flow in the system. Hourly wind speed and global horizontal solar irradiation are taken from meteorological databases which were available through local weather stations. An isotropic model is used calculate the tilted solar irradiation on the SPV panel [11]. Finally, power output from the solar panels is calculated using Durisch model [54]. The main advantage of this model is its capability to consider cell temperature, air mass, tilted solar irradiation when evaluating the efficiency of Solar PV panels which provides a better accuracy in modeling SPV panels [55]. Similarly, the power low approximation is used to convert the wind speed from anemometer to hub level height. Cubic Spline interpolation technique [56] is used to represent the power curve provided by the manufacturer of the wind turbines. Finally, renewable power generated (P_{RE}) using SPV panels and wind turbines are computed on hourly basis. A detailed description about the model used to compute the energy flow through the renewable energy components can be found in Ref. [11].

3) The criteria for the formulation

Eight criteria are used to assess the energy system covering a wider spectrum of interests by the users of the energy system; including economic, environmental, energy efficiency and reliability. A concise description about the each criterion is presented in this section.

3.1) Power supply reliability

Power supply reliability becomes a vital factor to be considered in the designing process. Stochastic nature of the renewable energy potential, maintenance downtime of system devices as well as limitations in grid interactions and energy storage can result in breakdown in the power supply. Loss of power supply (LPS) due to downtime of system devices is not considered in this study. LPS is expected to be occurring (according to Eq. 1) for time step ‘t’ whenever renewable energy generation ($P_{RE}(t)$) is less than the demand and the mismatch cannot be fulfilled by the grid and the storage due to the limitations in the energy storage and the grid curtailments.

$$LPS(t) = ELD(t) - P_{RE}(t) - P_{ngen}(t) - P_{Bat\text{-}Max}(t) - P_{FG\text{-}Max}(t) \quad (1)$$

In this equation, ELD, P_{ngen}, $P_{Bat\text{-}Max}$ and $P_{FG\text{-}Max}$ denote electricity load demand of the application, nominal power of the ICG, maximum power flow from the battery depending upon the state of charge, and maximum power that can be taken from the grid considering the grid curtailments. All these terms are in kWh taken as input data/calculated each time step t [hour] for 8760 time steps. Finally, loss of load probability (LOLP) is calculated using LPS according to Eq. 2 which is used as the performance indicator to evaluate the power supply reliability.

$$LOLP = \frac{\sum_{t=1}^{8760} LPS(t)}{\sum_{t=1}^{8760} ELD(t)} \quad (2)$$

3.2) Grid integration Level

Autonomy of the system plays a major role in the renewable energy integration process. Strong interactions with grid will make the grid to be vulnerable to cascade failures. Hence, autonomy of the system is considered as a vital factor to be evaluated in renewable energy integration process especially in distributed generation. Instead of taking system autonomy (i.e. determines the percentage of demand generated within the system), grid integration level which is the complimentary to system autonomy is considered in this work. This will convert the maximization problem into a minimization problem that will make the decision making problem trouble free. Grid integration level can be defined in different methods. However, to be aligning with system autonomy defined in Ref. [57], GI is defined according to Eq. 3.

$$GI = \frac{\sum_{t=1}^{8760} PFG(t)}{\sum_{t=1}^{8760} ELD(t)} \quad (3)$$

In this equation, PFG denotes the energy units (kWh) taken from the grid during steady state operation in time step t.

3.3) Utilization of renewable energy

Various reasons such as stochastic nature of the demand and renewable energy potential, grid curtailments and limitations in energy storage makes it challenging to utilize renewable energy. This leads to a number of problems including poor energy efficiency, dependence on grid or dispatchable energy source which results in either poor autonomy or higher GHG emissions due to the combustion of fossil fuels. In order to rectify this issue, utilization of renewable energy is considered as a major criterion to be optimized in energy system design. This study uses Waste of Renewable Energy (WRE) as the performance indicator which should be minimized in the design process. WRE represents the energy losses that take place in system due to seasonal changes in demand, renewable energy potential, and limitations in the energy storage and grid curtailments that has been amply used in resent literature [16,39,58]. WRE is formulated as Eq. 4.

$$WRE = \frac{\sum_{t=1}^{8760}(P_{RE}(t) - P_{SB-Max}(t) - ELD(t) - P_{TG-Max}(t))}{\sum_{t=1}^{8760} ELD(t)} \tag{4}$$

In this equation, $P_{SB\text{-}Max}$ [kWh] denotes maximum energy that can be stored in time step t [hour], depending upon the state of charge and $P_{TG\text{-}Max}$ denotes maximum units [kWhs] that can be sold to the grid depending upon the grid curtailments.

3.4) Fuel Consumption of ICG

Dispatchable energy sources play a major role when integrating renewable energy technologies into integrated energy systems. However, reliance upon dispatchable energy sources based on fossil fuel resources makes the system to be vulnerable to dynamic pricing due to higher depletion of fossil fuel resources. In addition, Fuel transportation becomes challenging for places far from cities and the frequent use of ICG will lead to frequent maintenance. Minimizing fuel consumption will lead to minimize all the aforementioned limitations and make the system to become more sustainable. Fuel consumption (FC) of the ICG is calculated considering the operating load factor (LF) of the ICG which is taken as a fourth order polynomial function of ICG according to Eqn. (5).

$$FC = \sum_{t=1}^{8760}(a_{r,0} + a_{r,1}\,LF(t) + a_{r,2}\,LF^2(t) + a_{r,3}\,LF^3(t) + a_{r,4}\,LF^4(t)) \tag{5}$$

In this equation, $a_{r,0}$, $a_{r,1}$, $a_{r,2}$, $a_{r,3}$, and $a_{r,4}$ [liters per hour] are taken for each ICG using its performance curve.

3.5) Initial Capital investment

Two economical parameters are considered in this assessment: initial investment required and Levelized Energy Cost (LEC) considering lifecycle cash flow of the system. Initial Capital Cost (ICC) required consist of acquisition cost (I_{AC}), installation cost of the components (wind turbines, SPV panels, battery bank, ICG, power electronic devices etc) and other services charges that should be paid to the Energy Service Provider (I_{ESP} [$]) to operate as grid integrated energy system. I_{AC} [$] comprise of cash flows related to purchasing of system components considering present Sri Lankan market. Cash flows related to land clearance and installation costs are considered under I_{Ins} [$]. Investment for the land is not considered in this work. Finally, ICC [S] is calculated according to Eq. 6. S denotes set of system components

$$ICC = I_{ESP} + \sum_{\forall s \in S} (I_{AC,s} + I_{Ins,s}) \quad (6)$$

3.6) Levelized Energy Cost

Levelized Energy Cost (LEC) is calculated considering the total cash flows of the system. LEC mainly consist of three components i.e. ICC and operation and maintenance cost (OM), and cash flow due to grid interactions. OM consists of two main components, these are fixed (OM_{Fixed} [$]) and variable costs ($OM_{Variable}$ [$]). OM_{Fixed} considers recurrent annual cash flows for maintenance of wind turbines, SPV panels, fuel and operation cost for ICG etc. $OM_{Variable}$ considers the replacement cost for ICG and battery bank. Replacement time for the ICG is determined considering the operating hours and Rain-flow algorithm is used to determine the replacement time for the battery bank. Finally, present value of OM (OM_P [$]) costs is calculated using Eq. 7 combining both OM_{Fixed} and $OM_{Variable}$.

$$OM_P = \sum_{\forall s \in S} (OM_{Fixed,s} \, CRF_s) + \sum_{l=1}^{h} \sum_{\forall s \in S} p^l OM_{variable,s,k} \quad (7)$$

In this equation, CRF_s denotes Capital Recovery Factor for s^{th} component of operation and maintenance cash flow. P denotes the real interest rate calculated using both interest rates for investment and local market annual inflation ratio. The lifetime of the project is presented by h.

Net cash flow due to GIs (GICF) is computed considering cash inflow due to selling excess generated and buying the mismatch based on the real time price of the grid. Net cash flow of the system is calculated on annual basis according to Eq. 8.

$$GICF = \sum_{t=1}^{t=8760} (PFG(t)GCF(t) + PTG(t)GCT(t)) \quad (8)$$

In this equation GCF(t)and GCT(t) denote the real time price of grid electricity when purchasing form the utility grid and selling.

Subsequently, the present value of grid integrated cash flows $GICF_P$ is calculated.

Finally, Net Present Value (NPV) of all the three main cash flows is combined and NPV of the project is calculated according to Eq. 9. Finally, LEC [$/kWh] is calculated based on NPV.

$$\text{NPV} = OM_p + ICC + \text{CRF.GICF}_\text{P} \quad (9)$$

3.7) Levelized CO2 Emissions

Minimizing CO2 emissions in different phases of the project is considered as one of the objectives of the energy system designers. Levelized CO2 (LCO2) is taken as the performance indicator to evaluate this aspect in this work. Firstly, CO2 generation due to energy system components and their replacement is considered. Secondly, CO2 generated due to grid interactions (when purchasing electricity) and power generation in ICG is considered. Finally, total CO2 emission (TCO2 [kg]) of the system is calculated combining both these aspects which is subsequently used to calculate the LCO2 [CO2 kg/kWh] according to Eq. 10.

$$TCO = \sum_{\forall s \in S} ICO2_s + h \sum_{t=1}^{t=8760} (PFG(t)CGF(t) + CICG(t, LF)\, P_{ICG}(t)) \quad (10)$$

In this equation, $ICO2_s$ [kg] denote the lifecycle CO2 emission of system components including replacement for ICG and battery bank. CFG [kg/kWh] denotes the CO2 intensity for electricity unit taken from the grid and CICG [kg/kWh] denotes the CO2 intensity of each unit generated by ICG depending upon the load factor of the ICG.

3.8) Flexibility of the system

Flexibility of the system is defined as the ability of the system to adjust for the changes that take place in internal or external environment changes. Flexibility will make the system impervious to changes in the inputs and the outputs which are essential when it comes to distributed generation. Hourly time series for renewable energy potentials, demand, price of grid electricity etc., are considered as inputs to the computational model that are stochastic in nature. Hence it is important to consider the flexibility of the system to get adapted to the changes of these factors. In addition to these factors, flexibility of the system needs to be measured considering volatility of market prices in fuel, electricity, and energy storage. All the aforementioned factors can be considered as the external factors which system needs to be flexible. In addition, internal factors due to malfunctioning or maintenance of system components such as wind turbines, SPV Panels, ICG etc., need to be considered within the broad scope of flexibility. However, most of the recent studies in energy systems design did not consider all these aspects simultaneously due to the complexity and most of the studies limit their scope to power supply reliability, resilience (ramp rate) or cost [59–63]. This study also limits the scope to internal factors considering the changes in renewable energy potential, demand and grid curtailments.

In the field of energy system, many of the recent studies related to energy systems evaluate the flexibility based on one criterion either reliability, resilience (ramp rate) or cost [64]. However, flexibility needs to be defined considering all the criteria related to evaluate the system. In order to address the aforementioned limitations, four criteria are considered when evaluating the flexibility of the system (i.e. LEC, reliability, WRE and LCO2) using the method proposed in Ref. [65,66] for manufacturing systems. Performance change in each criterion due to the changes in the external factors is calculated first. Flexibility calculation is performed for the Pareto solutions obtained after multi objective optimization. k possible scenarios are considered in this context considering the changes in wind speed, solar irradiation, grid curtailments, and demand profile (three for each). Performance change ($PC_{q,p}$) in the p^{th} criterion in the design solution q is calculated according to Eq. 11.

$$PC_{q,p} = \sum_{i=1}^{k} (\varphi_i \,(CI_{i,p} - CI_{D,p}) / CI_{D,p}) \tag{11}$$

In Eq. 11, $CI_{D,p}$ denotes the criterion value under deterministic scenario and $CI_{i,p}$ denotes criterion value under external disturbances. Possibility of occurring each scenario (φ_i) can be obtained using a tree diagram. Relative change due to the changes take place in the system input is taken the measure to evaluate the flexibility. Coefficient of closure (CC) defined in Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is used to evaluate the flexibility of design solutions using decision matrix (q x p) defined based on $PC_{q,p}$. A detailed description about the Fuzzy TOPSIS method is given in Section 6.

4) Dispatch Strategy of the E-hub

A bi-level dispatch strategy combining fuzzy and finite state automata theory is used in this study to determine the operating load factor of the ICGs and the energy interactions with both battery bank and grid. Finite state automata have been amply used in representing dispatch strategy when designing hybrid energy systems [67,68]. Fuzzy rules are defined considering the state of charge level of the battery bank and the difference in Electric Load Demand (ELD) and generation. The fuzzy rules are optimized using the algorithm presented in Section 6. Interactions with the grid and energy storage are determined in the secondary level after determining the net power generation of the system, mismatch between demand and generation, real time electricity price in grid and state of charge of the battery bank. State transfer function is derived considering seven decision variables which are optimized using the optimization algorithm. Subsequently, the ten possible states that the system operates considering the SOC of battery bank, renewable energy generation, COE in grid, upper bounds to purchase ($P_{FG\text{-}Max}$ (t)) or sell electricity to grid ($P_{TG\text{-}Max}$ (t)) (grid curtailments).

5) Design optimization of the system and dispatch strategy

Optimum design and control of integrated energy systems combining renewable energy technologies for both stand-alone and grid integrated applications is a rich area of study. A number of publications have presented different techniques for optimization including heuristic, direct search, numerical methods where different objective functions are considered [12,69,70]. The response of the energy system to the changes in demand, renewable energy potential etc. needs to be considered where hourly simulation is required. Simulation of the system considering time series of demand, renewable energy potential and grid conditions result in objective functions neither linear nor analytical. Simultaneous optimization of design and control strategy makes mapping of decision space variable into objective space complicated. Lopez et-al [71] has shown that evolutionary algorithms are efficient in optimizing such integrated energy systems for stand-alone applications. Different architectures of algorithms have been adapted to optimize integrated energy systems which have shown to be promising for both grid connected and stand-alone operation [12,69,70].

Evolutionary Algorithm based on Ɛ-dominance technique is used in this study for multi-objective optimization [72]. This method is a proven technique to maintain diversity of the Pareto front while reaching the best set of solutions. Optimization algorithm is combined with the computational model that formulates the objective functions. Hence, a simulation based optimization of the system is performed. Several combinations of the objective functions are considered as shown in Table 1 based on the formulations described in Section 3. Power supply reliability is considered as the constraint in all the optimizations.

6) Frame work for the multi criterion assessment and decision making

Optimum design and operation of Electrical Hubs is a multi-step process which consists of several phases as shown in Fig. 4. Multi-criterion assessment starts with understanding the main requirements that need to be met in the energy system designing project. This will help to understand and define criteria that need to be considered in the optimization, assessment and multi criterion decision making. As the second step, classifying these performance indicators based on the relative importance to the specific project is performed. In this study, performance indicators are classified into three groups i.e. Preference Indicators (PI), Basic Indicators (BI) and Critical Indicators (CI) depending upon its importance and relevance to the application. Power supply reliability and LEC are taken as the most influential factors to the design which cannot be waived to increase the performance of other indicators. Power supply reliability is considered as a constraint in the optimization process which is not considered further in the decision making process. LEC is carefully considered along with all the other criteria in the decision making process to ensure meeting the expected outcomes of the design.

BIs are selected from the pool of criteria considering the site specific information and the requirement of the applications. These criteria have a lower priority compared to CIs. In this work, ICC, LCO2, WRE, GI and system flexibility level are considered as BIs. These are considered as objective functions in the Pareto optimization and subsequently in the Pareto analysis (except system flexibility which is computed following the Pareto optimization considering the performance of the Pareto solutions). Finally, PIs are considered as other criteria need to be considered in the design. After the classifying the criteria, these criteria should be modelled to be used in the optimization. This is usually performed by an energy system designing tool box as explained in Sections 3, 4 and 5.

A number of techno-economic criteria can be suggested to consider in Pareto optimization. However, extending the dimensions of the objective space will make the optimization process more difficult and increase the set of Pareto solutions. Each and every solution in the Pareto front presents a unique system design, operation strategy or both. Hence, increasing the set of non-dominant solutions will make the ranking process more challenging. Hence, a 2D Pareto analysis is used to identify the performance indicators which can be promoted as objective functions to determine final set of solutions while reducing the dimensions of the optimization problem.

Selecting final system design by using the obtained Pareto front will limit the opportunity to fully consider the design requirements and the influence of the other criteria which are not considered for the Pareto optimization. Hence, decision making needs to be performed moving beyond the graphical analysis of the Pareto front obtained using CIs and few selected BIs where multi-criterion decision making technique is required. This will help to consider the pool of criteria including CIs, BIs and PIs with its relative importance. However, it is important to define the boundary matrix which gives the maximum value (for a minimization problem) that you can reach considering a specific criterion based on the design requirements. This is obtained considering the design requirements of the energy system, boundary values obtained in the 2D Pareto analysis and the boundary values of the 3D Pareto front. Finally, Fuzzy TOPSIS method is used with the support of Level diagrams for the multi criterion decision making process. Fuzzy TOPSIS have been amply used as a multi-criterion decision making technique for energy related applications [39,73–75] where a detailed explanation of this method can be found. A concise description about this method is presented in this section.

The fuzzy TOPSIS method consists of several steps:

Step 1: Performance criteria for all the design solutions are normalized using Eq. 12.

$$CN_{m,n} = \frac{c_{m,n} - c_{\min,n}}{c_{\max,n} - c_{\min,n}} \tag{12}$$

In this equation, $C_{m,n}$, denotes normalized value for *m*th criterion value for *n*th Pareto solution. $C_{m,n}$, $C_{max,n}$, and $C_{min,n}$ denotes respectively the value for *m*th criterion value for *n*th Pareto solution, maximum and minimum values obtained by the Pareto solutions for the same criterion.

Step 2: A positive ideal solution (I^+) and a negative ideal solution (I^-) is introduced which represents two ideal solutions considering best and worst performance for all the criteria.

Step 3: Weight matrix is developed which as a 1 x j matrix which present the relative weight for each criterion (for j criteria).

Step 4: Arrive at Ideal Positive Solution (I+) and Ideal Negative solution (I-) taking the best and worst criterion value under each criterion. Design solutions are expected to be close to the positive ideal solution and far from the negative ideal solution.

Step 5: Positive distance matrix (d+) is computed taking Euclidian distance between I+ and $CN_{m,n}$ for each Pareto solution as shown in Eq. 13.

$$d_m^+ = \sqrt{\sum_{i=1}^{n} w_i (I_i^+ - CN_{i,m})^2} \qquad (13)$$

Similarly, negative distance matrix (d-) is calculated.

Step 6: Coefficient of closure (CC) is defined as a minimization objective (most preferred solution is having the minimum value) which is calculated according to Eq. 14.

$$CC = \frac{d_m^+}{d_m^+ + d_m^-} \qquad (14)$$

7) Results and discussion

The path that needs to follow before reaching the final system design is quite lengthy. This section elaborates the final part of the design process which combines multi-objective optimization with multi-criterion decision making. As the first step, the role of each performance indicator in the assessment process is investigated considering the local conditions and specific design requirements. As discussed previously, energy system optimization process has turned from classical cost optimization to Pareto optimization where set of non-dominant solutions can be obtained considering conflicting objectives. The main advantage in this process is the system designer has the possibility of selecting the best solution considering the limitations of each criterion and its relative importance. This is an extensive task starting from selecting the best criteria to consider in the optimization process and subsequently the decision making process. This section elaborates how to address these issues using the novel method introduced in this paper through a case study. First part of this section is devoted on how to filter the best suited criteria for Pareto optimization. Second part of this section is dedicated to the selection of the design based on Pareto front obtained considering the objective functions identified in the first part.

7.1) Analyzing 2D Pareto fronts

Main challenge in the design process is to select most relevant criteria to assess the system design. This becomes more difficult when selecting several criteria for Pareto optimization from the pool of criteria selected to assess the system. In order to identify the criteria to be used in the optimization, 2D Pareto front is created considering the main objective as one objective function and the others respectively as the first step. In this work, LEC is considered as the main objective function and, LEC-CO2 emission, LEC-ICC, LEC-GI and LEC-WRE are taken for the design. Cross comparison of the values for objective functions are carried out to understand the limitations in improving each objective.

In order to analyze the Pareto fronts further, design solutions of four Pareto fronts are plotted for similar objectives in Fig. 5. When analyzing the objective space in Fig. 5, it is clear that design solutions of LEC-ICC Pareto front presents a non-dominant set of solutions since LEC and ICC are considered as the objectives. In addition, a notable increase in ICC is observed when moving from Pareto solutions of LEC-ICC Pareto front to LEC-WRE, LEC-GI and LEC-LCO2 accordingly. More importantly, design solutions of the four Pareto fronts can be clustered into two main clusters i.e. Cluster A and Cluster B as shown in Fig. 5. When considering the design solutions of two Pareto fronts in Cluster B, both are quite close to each other. Although it is not as close as Cluster B, design solutions of two Pareto fronts in Cluster A are quite close. Therefore LEC-ICC Pareto can be used to represent LEC-WRE Pareto front when considering LEC-ICC objective space.

In a similar manner, design solutions of the Pareto fronts are plotted in LEC-LCO2 objective space (Fig. 6). Similar to the previous case, LEC-LCO2 Pareto front presents the non-dominant frontier. When considering LEC-LCO2 and LEC-GI Pareto fronts both are located close to each other as these were clustered in Fig. 6. If we consider the scatter plot of design solutions of Pareto front considering all the five objectives; LEC-ICC and LEC-LCO2 Pareto fronts can be considered as the boundaries when considering its projections in LEC-LCO2 objective space.

Let us consider the possibility of replacing LCO2 by GI in the Pareto optimization process which will reduce the dimensions of the optimization problem. In this case, design solutions clustered in Cluster C will be lost which will result in loosing (dropping out) Pareto solutions marked in Region B. In addition, Pareto solutions marked in Region A will be lost. When considering most of the applications, the possibility that final design solution reaching Region B is quite less due to the higher LEC which is at least more than 50% larger when compared to the minimum. Comparing the region covered by LEC-ICC and LEC-GI Pareto fronts (area enclosed by light green and blue scatterplots, and light blue dash line) Region A is negligible. Hence, it can be concluded that GI level is a good indicator in representing LCO2 based on the projection in LEC-LCO2 objective space which will minimize the dimensions in the optimization process.

Scatter plots of four Pareto fronts are presented in LEC-GI objective space to analyze the system further (Fig. 7). The two main clusters observed since the beginning can be seen even in this case. LEC-WRE and LEC-ICC Pareto fronts meet each other; although the latter extends further. LEC-GI Pareto front presents set of solutions which are dominant as expected. LEC-GI and LEC-LCO2 are closely located to each other. However, when compared to Fig. 5 the difference in the solutions of two Pareto fronts are not uniform (Region C) in this case. In certain instances, it extends up to a 10% difference in grid integration level. Therefore, representing GI using LCO2 will lead to take away some important design solutions which are interesting to be considered in the multi criterion decision making process.

Utilization of renewable energy is considered as the fourth criterion to conduct Pareto optimization with LEC. The Pareto front obtained and the objective function values for the design solutions of the other Pareto fronts are plotted in Fig. 8. Clear separation of the LEC-CO2 and LEC-GI Pareto fronts are observed in this plot although LEC-WRE and LEC-ICC can be clustered together. When considering the renewable energy utilization of the design solutions of LEC-GI Pareto solutions, WRE is less than 15 % and majority of the solutions are clustered within 10% up to 15%. In contrast, majority of the design solutions are having WRE more than 20% when it comes to LEC-LCO2 Pareto front which is not preferred in usual system designing. Hence, LEC-GI can be considered as realistic upper bound.

After conducting the graphical analysis it is prudent to say that the four objectives considered to optimize the system design along with LEC can be classified into two groups in which one objective function can present the group. This will reduce the five dimensional optimization problem (including LEC) into a three dimensional optimization problem along with LEC. Further, this will improve both accuracy and efficiency while reaching the optimum set of results and sacrificing few design alternatives. When considering the first group (Cluster A in Fig 5) ICC can be considered as better alternative than WRE. ICC provides a better upper bound when considering LCO2 and GI along with an extended boundary considering LEC. Furthermore, LEC-ICC Pareto front overlaps with LEC-WRE Pareto front except for a small part in LEC and WRE objective space. Hence, it can be concluded that ICC is a better performance indicator to present both ICC and WRE. Similarly, GI can be used to represent the other group. Finally, LEC, GI and ICC gives a better representation of the five objective functions discussed while reducing the complexity of the optimization process.

7.2) 3D Pareto front considering LEC-ICC-GI

The 2D Pareto analysis helped to reduce the number of dimensions in the optimization problem. However, the four 2D Pareto fronts obtained in previous section only provided the boundaries of the objective space in which final design solution is located. In order to obtain non-dominant set of solutions, multi-objective optimization is carried out considering the objective functions identified in Section 7.1.

The Pareto front obtained from the optimization considering LEC, ICC and GI are presented in Fig. 9. Scatter plot clearly demonstrate that there exists a well distributed Pareto surface. Contour plot generated is using the scatter plot in order to help the system designer to visualize the distribution of Pareto solutions. Scatter plot and the contour diagram clearly delineates that the three objectives considered for the optimization are conflicting to each other in which it is difficult to optimize these three objectives simultaneously. It is simple to select one Pareto solution using both scatter and contour plot. Nonetheless, decision making is not straight forward since it is required to consider other factors such as LCO2, flexibility of the system, WRE etc., in the decision making process.

7.3) Multi Criterion Decision Making (MCDM) Process

In this work, seven criteria are used to assess the performance of the system. Direct graphical representation methods cannot be used to assess the solution space whenever the number of criteria used to assess the system increase beyond three. Hence coming up with the final system design is not straight forward. MCDM process helps the designer to arrive at the final design solution considering conflicting criteria as discussed in Section 6. The main challenge in using the multi-criterion decision making technique is deriving the weight matrix for Fuzzy TOPSIS considering relative importance of each criterion. This section presents path followed in order to achieve the final design solution.

MCDM process is sensitive to the specific application of the energy system. Prioritizing the criteria and identifying the expectations for the design plays a major role in this context. Identifying the upper bounds (since the design problem is formulated as a minimization problem) for the design requirements play a major role in this context. Whenever one or several criteria are improved performance of some other criteria will degrade. Hence, close comparison of each criterion is important in the multi-criterion decision making process. Normalized criterion values will be useful in such an ambiance to identify the upper limits for design requirements and the required changes. Finally, multi criterion decision making needs to be carried out considering the importance of each criterion specifically to the application within the boundary matrix.

The application of the suggested method is tried on the case of a small, model rural village in Hambanthota, a district in southern coastal belt of Sri Lanka. Reliability of the system is considered vital which is taken as a constraint in the optimization as discussed in Section 6. The village is already connected to the grid which requires having a competitive electricity price after designing the new system (compared to the grid) and is considered as a special design requirement. Initial capital investment plays a vital role since it is challenging to go for bank loans for community based energy systems. Flexibility of the system had to be considered seriously since coastal weather changes rapidly which results in notable changes in wind and SPV energy potentials. In addition, minimizing grid the integration level is one main objective that is expected to be achieved through the design. However, it is a difficult task to provide a quantitative value regarding the importance of each criterion.

Decision making is all about for what extent one would be ready to sacrifice the performance of one or few criterion to improve the performance of one or several criteria where a qualitative and quantitative understanding about the relative importance of each criterion is important. Lack of a quantitative understanding about the importance of each criterion makes it difficult to go through the MCDM process. A small change in one criterion may result in a notable change in the other criterion. This relative importance need to be obtained considering values obtained for different criteria by the non-dominant set of solutions and design requirements of the application. Inter dependence on each criterion makes this process more tedious. Hence, an iterative approach is required on this regard. The process is initiated by defining the boundary matrix which gives the upper bounds (for minimization problem) for each criterion in the decision making process. The upper bound is merely taken observing the upper and lower bound values of each criterion obtained through Pareto optimization along with design requirements. Hence, there is no guarantee that designer could reach it. The boundary matrix can be changed whenever the designer understands that it is too tight or maintain similar ratios whenever it is too loose. Finally the boundary matrix which presents the boundary for each criterion where the customer is ready to accept the design is created which is presented in Table 2.

7.3.1) Analyzing the Level Diagrams

MCDM process starts after understanding the boundary for the final design with an initial guess for the weight matrix. Results obtained for each weight matrix is evaluated while improving the weight matrix in order to cater the objectives. Level diagrams are used in this context to identify the possible directions that can be taken in improving the weight matrix. An intermediate (Case A) and the final weight matrix arrived (Case B) in the decision making process are presented in Table 3. Best six design solutions corresponding to both Case A and Case B (obtained using fuzzy TOPSIS method) are presented in Table 4 and 5. 2D and a set of 3D contour plots obtained for both Case A and B are presented in Fig. 10, 11 (a) and (b).

Table 2. Boundary matrix for the criteria based on the requirements of the customer. Green denotes acceptance and red denotes rejection for different regions of normalized value for criteria. Green color denotes acceptable and red denotes not acceptable

3D contour plots are helpful in understanding the impact of changing the weight of one criterion over the others. Contour plots are presented in Fig. 11 (a) and (b) considering different criteria used for MCDM. When analyzing the contour plots for two cases, several local optimums are observed in Case A (plots in left hand for both Fig. 11 (a) and (b)). However, when moving to Case B one global optimum is observed in most of the instances except in normalized flexibility and LEC which shows complicated variation with several local maximums. This agrees with the previous observation in 2D scatter plot. In order to analyze the 3D contour plots further, two contour plots from Fig. 11(a) (Normalized LEC (NLEC)- Normalized GI (NGI) and NLEC-Normalized Fx. (NFx)) are taken for Case A and illustrated in detailed in Fig. 12.

Analyzing the 2D scatter plot is considered as the first step in the decision making process which provides a better representation of all the criteria simultaneously as in Fig. 10. In addition, 2D scatter plots supports the decision makers at the early stage of decision making process to bring all the global optimums close to the boundary matrix (or into the boundary matrix). When considering the two scatter plots in Fig. 10 it is clear that the surface of the scatter plots for Case A is rough except ICC. As a consequence, global maximum moves significantly (interchange with local maximum) with a marginal change in the weight matrix. This makes it difficult to analyze the possibility to improve the specific criteria. When moving to Case B in the same diagram (left to right) much smoother surface is observed for most of the criterion except flexibility. This makes it easy to analyze the systems further. However, 2D scatter plots can be used only at the beginning where major changes in weight matrix is performed in order to bring the criteria considered closed to the boundary matrix. Sensitivity of changing the weight for one criterion over the other cannot be evaluated directly using 2D contour plots which make it difficult to be used as a method to fine tune the weight matrix. This can be visualized further using 3D contour plots considering two criteria along with CC.

When analyzing the NFG-NICC contour plot for Case A in Fig. 12, best ranked solutions (red colored region) are distributed in P and Q regions. The distribution of these two regions forms a frontier with a negative gradient. This demonstrates that these objectives are conflicting to each other and a significant reduction in N-FG can be obtained with a marginal increase in N-ICC. A similar pattern is observed when analyzing NFX and NLEC Pareto front (Fig. 12 (right hand)). Best ranked solutions are distributed in region R and S. These two objectives also produce a Pareto front in which it is difficult to improve both simultaneously. However, this indirectly implies both GI and flexibility improves with a marginal sacrifice in LEC in which improvements in GI is more significant compared to flexibility as observed in P and Q regions in left plot in Fig. 12 and R and S regions in right plot (numerical values are later presented in Table 4 and 5). In a similar manner, it can be shown that a significant improvement in GI with a marginal sacrifice of ICC when analyzing the NGI-NICC contour plot for Case A in Fig. 11 (a). Therefore, it is clear that a notable improvement in GI can be achieved while sacrificing the criterion values for ICC and LEC.

The analysis can be extended further to evaluate the possibility of improving the other criteria and the consequences of improving them. In order to analyze the consequences of improving LCO2, NLEC-NLCO2 plot for Case A (Fig 11 (b): first left one from the top) is taken. The set of high ranked solutions is distributed within (marked in red) linearly with a positive gradient. This reveals that LEC and LCO2 are parallel objectives in which one will increase with the increase of the other. When analyzing the contour plots for Case A, it is observed that GI can be improved which will convert existing distributed maximas into a global maximum (or merge both together) resulting an increase in LEC as shown in regions P and Q in Fig. 12. However, a major improvement in flexibility will interchange global maximum and local maximum which will increase the LEC beyond the expectations (from R to S) since this will increase N-LEC beyond 0.25 which is the boundary. Improvement in flexibility and grid integration levels is required to meet the expectations of the customer according to the boundary matrix. When analyzing the contour plot it is clear that increasing the weight of grid integration and marginally increasing the weight of the system flexibility will drive towards the expectations. The observations of the contour plot analysis is used to improve the weight matrix and finally arrived to a weight matrix for Case B which is given in Table 3.
Contour plots obtained after revising the weight matrix are plotted in the same diagram (Fig. 11 (a) and (b)) in order to make the comparison simple. When analyzing the contour plots for Case B it is prudent to say that most of the contour plots are quite smooth with one global maximum for most of the instances. This makes the analysis and decision making easier. Local minimums located at different locations of the contour map makes it challenging to analyze the consequence changing the weight of one criterion. Hence, decision makers should go back and forth again and again from one plot to another as discussed before in order to find the promising directions to change the weight matrix. Contour plot for Case B clearly shows that all the criteria are within the boundary and a notable improvement in criteria is not possible.

7.3.2)Analyzing the best candidates for each weight matrix

2D and 3D Level diagrams help the decision makers to reach towards the best fitting weight matrix. However, final system design should be arrived after closely examining the best ranked design solutions. On the other hand, analyzing the best set of solutions obtained after revising the weigh matrix, helps the decision maker to get a quantitative understanding about the promising changes that should be made in weight matrix especially for very small changes in the weight matrix. Hence, analyzing the contour plots and best set of solutions are complimentary tasks which help the system designer to come up with final system design.

Assessing the best ranked solutions, started with selecting the best six design solutions for Case A (see Table 4). When analyzing the design solutions, it is prudent that most of the design solutions perform well when considering several criteria. A1 adheres to most of the design criteria except with GI. A1 maintains a normalized grid integration level of 0.57 which is greater than the accepted limit of 0.4 which is the same for A2 and A5. These two design solutions are having normalized grid integration level of 0.64 and 0.62 respectively which is higher than 0.4. A4 and A6 design solutions performs close to each other for most of the criteria being within the boundary matrix including grid integration level. However, A6 is marginally outside the boundary matrix when considering the expectations of the design. Therefore, A4 becomes the only design solution within the design requirements.

Contour plots provide the possible directions to improve the weight matrix further. After several iterations weight matrix for Case B (see Table 3) is obtained in order to see the possibility of improving the design further. A significant change in the weight matrix is not performed when moving to Case B. Hence, four design solutions that appeared in the best six alternatives are appearing in Table 5 (B1, B3, B4 and B5). B6 does not fulfill the design requirements since LEC is beyond the critical LEC defined in the boundary matrix. Both B1 and B2 meet the design requirements. B2 outperformed B1 when it comes to grid interactions and B1 outperformed B2 when it comes to LEC, LCO2, fuel consumption and waste of renewable energy. System configuration will change when considering the capacities of SPV panels and wind turbines. When moving from B2 to B1, the final decision solution arrived is highly subjective to the decision maker whether the designer appreciates the notable improvement in grid integration level in B2 or the overall improvement B1. In this case B1 is considered as the best design solution.

7.3.3) Comparison of different approaches

Single objective optimization is used in most of the instances when designing distributed energy systems. However, multi-objective optimization is followed by multi criterion decision making using the same set of criteria used as objective functions in certain instances. It is interesting to compare these two approaches with the novel approach presented in this study.

First, we compare the novel approach with the results obtained through single objective optimization. Two cases are considered for the comparison as presented in Table 7; i.e. design solution with the minimum LEC (BLEC) and ICC (BICC). LEC can be reduced by 27% while LCO2 emission can be reduced by 46% when moving from B1 to BLEC. However, when analyzing the system design we can understand that system tends to depend more on the grid when considering BLEC. Furthermore, flexibility of the system drops notably. More importantly both these performance indicators are below the expectations of the users when considering the boundary matrix. When moving into BICC, system flexibility, ICC and WRE are way above the expectations. However, LEC, LCO2 and grid integration level are way above the expectations of the design. When considering both BLEC and BICC we can conclude the optimum design ends up in extremes where system performs way better considering certain criteria while it performs extremely poor for the other critera.

In most of the instances, decision making is performed based on the criteria considered for Pareto optimization. This will omit several important criteria from the decision making process. It is important to assess the consequences of limiting the decision making process into few criteria that are considered in the Pareto optimization process. In order to achieve this, four cases are considered (i.e., Case C, D, E and F) removing one or two criteria in the weight matrix from the decision making process. The ratio among the weights for the other criteria remained same as for Case B in the weight matrix. Case C does not consider System flexibility, Case D does not consider grid integration level, Case E does not consider LCO2 and fuel consumption and finally Case F does not consider initial capital cost. Weight matrix for each case is tabulated in Table 6. The best design solution obtained under each weight matrix is presented in Table 7.

When analyzing the design solutions for Cases C, D, E and, F it is clear that removing a criterion from the weight matrix will results in a notable increase of the performance indicator (considering a minimization problem) of the specific criterion removed from the weight matrix. For example, the N-Flex increases from 0.499 to 0.678r and N-

GI level increases from 0.373 to 0.887 for Cases C and D which respectively remove flexibility and grid integration level from the weigh matrix (Table 7). The same can be observed in Case F. This will result in poor performance under these criteria which are outside the decision matrix in this case which will not be preferred by the end users. However, due to the weaknesses (over simplification of the design space) in the existing methods used for multi-criterion decision making system designers will end-up in such designs.

The sensitivity of each criterion considered for the multi-criterion decision making is different depending upon the weight matrix, the considered criterion, its relationship with the other criteria and the boundary matrix. For example, when considering Case E, increase in N-LCO2 after taking away from the weight matrix is insignificant when compared to Case C, D and F. This can be justified by assessing the level diagrams, LCO2 and LEC are parallel objectives (as discussed in 6.3.1) within the close proximity of the weight matrix selected (as shown in Fig. 12.(a) NLEC-NLCO2 diagram). Hence, both these objectives can simultaneously be minimized within the proximity of the weight matrix selected with strong coupling. Higher, weight matrix on both LCO2 and LEC results in lower emissions as well as LEC. Removing LCO2 from weight matrix does not influence in a similar manner to Case C and D. This is due to the weight imposed by LEC. However, a notable reduction in LEC is observed due to the removing of weight in LCO2. This coupling makes it difficult to fine tune the weight matrix where Contour Level diagrams are extremely useful to find the proper directions to improve the weight matrix. However, the coupling between LEC-LCO2 is limited to one part of the decision space as observed when analyzing Fig. 5, 6 and 7. Hence, a notable change in LCO2 can be observed for a different setting of the weight matrix.

When considering both approaches practiced in present it is clear that multi-objective optimization followed by multi criterion decision making performs better that single objective optimization. However, the limitation in considering a number of criteria in the optimization process and subsequently in multi-criterion decision making process is still one of the main challenges in literature. This will lead to system designs that are performing extremely badly for the criteria not considered in the optimization process. The integrated approach proposed in this study can address the aforementioned limitations by appropriately selecting the objective functions for the Pareto optimization and subsequently considering the criteria not considered for the optimization in the decision making process.

Conclusions

A decision support tool to design distributed electrical hubs consisting of wind turbines, SPV panels, battery bank and an ICG operating connected to the grid is taken into discussion in this study. Selecting the objective functions for Pareto optimizing and subsequently multi-criterion decision making, considering a set of criteria in order to meet the design requirements is focused. Eight criteria are defined covering wider spectrum of interests including cost, environmental impact, energy efficiency etc in the designing process. A novel method is introduced to evaluate the flexibility of the energy system based on several criteria. Flexibility of the system is evaluated considering the uncertainty of external factors such as renewable energy potential, price of grid electricity and grid curtailments. Optimum set of solutions obtained from the Pareto optimization is simulated considering 27 different operation scenarios. Flexibility is used to evaluate the robustness on the design solutions under varying operating conditions.

A bi-level multi criterion decision making process is introduced to reach to the final design solution. 2D Pareto optimization is used to select the best representative objective functions to be considered in the Pareto optimization. Subsequently, LEC, grid integration level and initial capital cost found out to be the best representative objective functions reducing the dimension of the problem up to a 3D optimization problem without losing a large number of possible solutions. Pareto front obtained considering three objective functions are ranked using seven criteria. Fuzzy TOPSIS is used to rank the non-dominant solutions using 2D and 3D level diagrams. Boundary matrix is used to assure that the design requirements of the distributed energy system are met and the relative importances of the criteria are maintained while reaching the final design solution.

Design solution arrived using the novel decision support system is compared with the design alternatives obtained considering single objective optimization (considering LEC and ICC) and weight matrices neglecting some of the criteria not considered for Pareto optimization (methods practiced in present). Optimum design solutions obtained considering LEC and ICC as objective functions perform better compared to the final design solution obtained using the novel method when considering the specific objective function. However, the performances with respect to the other criteria are extremely poor. Furthermore, final design solution obtained from the novel method was compared with design solutions obtained using a weight matrix neglecting the criteria that were not considered in the Pareto optimization. The comparison shows that neglecting the criteria that were not considered for Pareto optimization will lead to design solutions with poor performances under those criteria. This can be addressed by the novel method introduced in this study through appropriate selection of objective functions and extending the criteria considered in the decision making process.

This study considers eight criteria at different levels of the decision making process. The criteria used in this study can be directly used or extended further depending upon the requirements of the application. Similarly, objective functions can be selected in a similar manner based of the classification considering the importance of each criterion. This study uses a Pareto analysis as the dimension reduction method. However, it is difficult to guarantee that dimensional reduction can be achieved in a similar level or the system designer will end up with the same set of objective functions. This process solely depends upon the application. Other methods such as Principle Component Analysis (PCA) can be looked for possibility of dimension reduction. However, extending the multi-criterion decision can be followed as it is which is essential to bring the sensitivity of other criteria.

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Table 4: Best six solutions ranked based on weight matrix for Case A

System	Criterion Values							Normalized criterion values							CC	System configuration			
	LEC[1]	LCO2[2]	FC[3]	GI[3]	WRE[4]	ICC[5]	Flex.	NLEC	NLCO2	NFC	NGI	NWRE	NICC	NFlex		SPV[6]	Wind[7]	Battery[8]	ICG[9]
A 1	0.155	0.261	0.038	27.9	1.02	2.32	0.362	0.05	0.15	0.09	0.57	0.06	0.32	0.56	0.685	12.9	50	2880	27.5
A 2	0.179	0.356	0.063	31.4	0.18	1.80	0.309	0.14	0.27	0.19	0.64	0.01	0.18	0.47	0.684	10.9	35	960	30
A 3	0.161	0.270	0.043	25.7	0.95	2.33	0.372	0.07	0.16	0.11	0.52	0.05	0.32	0.57	0.683	12.9	50	2880	30
A 4	0.197	0.363	0.079	18.5	0.42	2.33	0.327	0.21	0.28	0.26	0.37	0.02	0.32	0.49	0.683	13.6	40	1920	30
A 5	0.148	0.219	0.022	30.7	1.50	2.34	0.367	0.02	0.09	0.02	0.62	0.09	0.32	0.56	0.681	15.6	50	2880	30
A 6	0.185	0.312	0.065	17.4	1.52	2.51	0.372	0.16	0.21	0.20	0.35	0.09	0.36	0.57	0.677	13.6	55	1920	30

Table 5: Best six solutions ranked based on weight matrix for Case B

System	Criterion Values														CC	System configuration			
	LEC[1]	LCO2[2]	FC[3]	GI[3]	WRE[4]	ICC[5]	Flex.	NLEC	NLCO2	NFC	NGI	NWRE	NICC	NFlex		SPV[6]	Wind[7]	Battery[8]	ICG[9]
B1	0.197	0.363	0.079	18.5	0.42	2.33	0.327	0.21	0.28	0.26	0.37	0.02	0.32	0.49	0.680	13.6	40	1920	30
B 2	0.203	0.374	0.087	14.3	1.17	2.50	0.326	0.23	0.29	0.29	0.29	0.07	0.36	0.50	0.678	10.9	55	1920	30
B 3	0.185	0.312	0.065	17.4	1.52	2.51	0.372	0.16	0.21	0.20	0.35	0.09	0.36	0.57	0.676	13.6	55	1920	30
B 4	0.161	0.270	0.043	25.7	0.95	2.33	0.372	0.07	0.16	0.11	0.52	0.05	0.32	0.57	0.675	12.9	50	2880	30
B 5	0.155	0.261	0.038	27.9	1.02	2.32	0.362	0.05	0.15	0.09	0.57	0.06	0.32	0.56	0.675	12.9	50	2880	27.5
B 6	0.222	0.381	0.094	9.6	1.33	2.70	0.296	0.31	0.30	0.32	0.19	0.08	0.41	0.45	0.674	12.2	55	1920	27.5

Table: 7 Best six solutions ranked based on weight matrix for Case B, C, D, E and F

System	Criterion Values														CC	System configuration			
	LEC[1]	LCO2[2]	FC[3]	GI[3]	WRE[4]	ICC[5]	Flex.	NLEC	NLCO2	NFC	NGI	NWRE	NICC	NFlex		SPV[6]	Wind[7]	Battery[8]	ICG[9]
B1	0.197	0.363	0.079	18.5	0.42	2.33	0.327	0.210	0.277	0.256	0.373	0.024	0.318	0.499	0.680	13.6	40	1920	30
C	0.166	0.254	0.043	21.1	2.06	2.51	0.439	0.089	0.137	0.109	0.425	0.119	0.364	0.678	0.746	16.32	55	1920	30
D	0.186	0.397	0.062	43.7	0.00	1.23	0.301	0.167	0.321	0.186	0.887	0.000	0.042	0.458	0.750	4.76	25	960	30
E	0.251	0.406	0.108	3.1	1.94	2.87	0.191	0.420	0.333	0.377	0.059	0.112	0.454	0.281	0.677	12.92	60	1920	30
F	0.227	0.303	0.078	2.7	3.14	3.40	0.277	0.326	0.200	0.252	0.051	0.181	0.587	0.419	0.724	19.04	65	3840	27.5
BLEC	0.143	0.196	0.021	25.3	3.43	2.82	0.502	0.000	0.061	0.017	0.512	0.198	0.441	0.781	NA	16.32	65	3840	30
BICC	0.281	0.715	0.172	28.5	0	1.44	0.130	0.536	0.731	0.643	0.579	0.000	0.000	0.182	NA	0.68	0	2880	30

[1]LEC in \$, [2]LCO2 in kg/kWh, [3]fuel consumption in l/kWh, [3]grid integration level (%), [4]WRE (%), [5]ICC (x10^5\$), [6]SPV capacity in kW, [7]wind turbine capacity in kW Battery [8]bank size in kWh and [9]ICG capacity in kW

666 **Nomenclature**

BI Basic Indicators

CC Coefficient of closure

CFG CO2 intensity for electricity unit taken from the grid

CI Critical Indicators

CICG CO2 intensity of each unit generated by ICG

$CI_{D,p}$ criterion value under deterministic scenario

$CI_{i,p}$ criterion value under i^th^ scenario with disturbances

$C_{m,n}$, normalized value for *m*th criterion value for *n*th Pareto solution

$C_{min,n}$ minimum value for *m*th criterion value for *n*th Pareto solution

$C_{max,n}$ maximum value for *m*th criterion value for *n*th Pareto solution

CRF Capital Recovery Factor

d+ Positive distance matrix

d- Negative distance matrix

ELD electricity load demand

FC Fuel consumption

Fx. Flexibility

GCF(t) real time price of grid electricity when purchasing

GCT(t) real time price of grid electricity when selling

GHG Green House Gas

GI Grid Integration Level

GICF Net cash flow due to GIs

GICFP present value of grid integrated cash flows

I- negative ideal solution

I+ Positive ideal solution

I_{AC} acquisition cost

ICC Initial Capital Cost

ICG Internal Combustion Generator

ICO2s lifecycle CO2 emission of the system components

I_{ESP} services charges to Energy Service Provider

I_{Ins} installation costs

LCO2 Levelized CO2

LCO2 Levelized CO2 emission

LEC Levelized Energy Cost

LF operating load factor of the ICG

Lim_{BC} limit cost for battery charge

Lim_{BD} limit cost for battery discharge

Lim_{BTG} limit cost for battery discharge to grid

Lim_{GTB} limit cost for battery charge from grid

LOLP loss of load probability

MCDM multi-criterion decision making

NFC normalized fuel consumption

NFx. Normalized flexibility

NGI Normalized Grid Integration Level

NICC Normalized Initial Capital Cost

NLCO2 Normalized Levelized CO2 emission

NLEC Normalized Levelized Energy Cost

NPV Net Present Value ()

NWRE Normalized Waste of Renewable Energy

OM operation and maintenance cost

OM_{Fixed} fixed operation and maintenance cost

OM_P present value of OM

$OM_{Variable}$ variable operation and maintenance cost

P the real interest rate

$P_{Bat-Max}$ maximum power flow from the battery

P_{ngen} nominal power of the ICG

P_{FG-Max} maximum power that can be taken from the grid

PI Preference Indicators

P_{RE} renewable power generated

P_{SB-Max} maximum energy stored in battery

P_{TG-Max} maximum units that can be sold to the grid

SOC_{min} minimum state of charge

$SOC_{Min,G}$ minimum state of charge when discharging to grid

SOC_{Set} maximum state of charged to be reached when charging from grid

SPV Solar PV

TCO2 total CO2 emission by the system

TOPSIS Technique for Order of Preference by Similarity to Ideal Solution

WRE Waste of Renewable Energy

φ_i Possibility of occurring ith scenario

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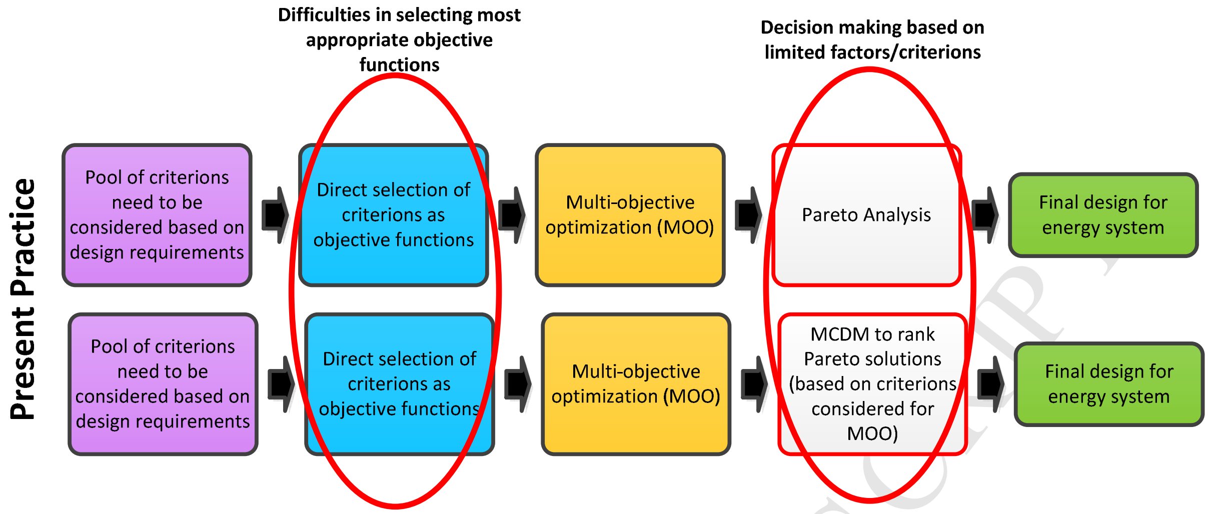

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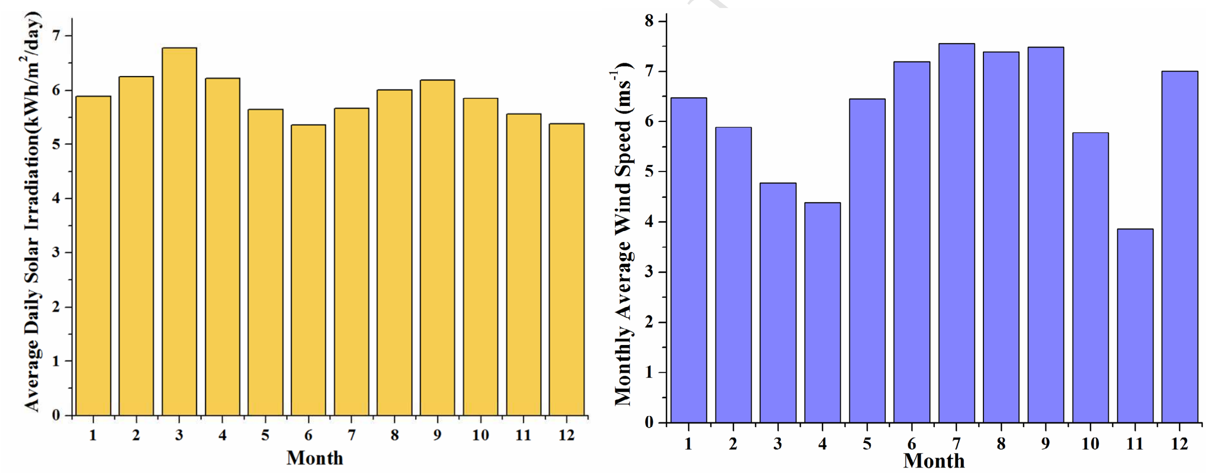


Fig. 2 Renewable energy potentials for the location selected.

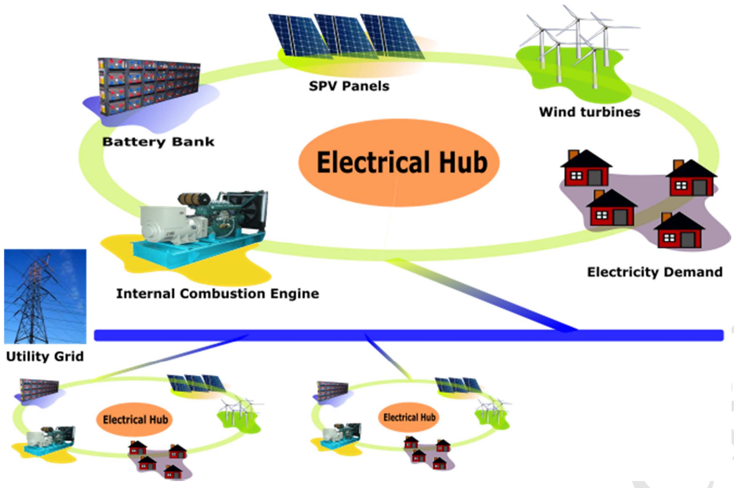
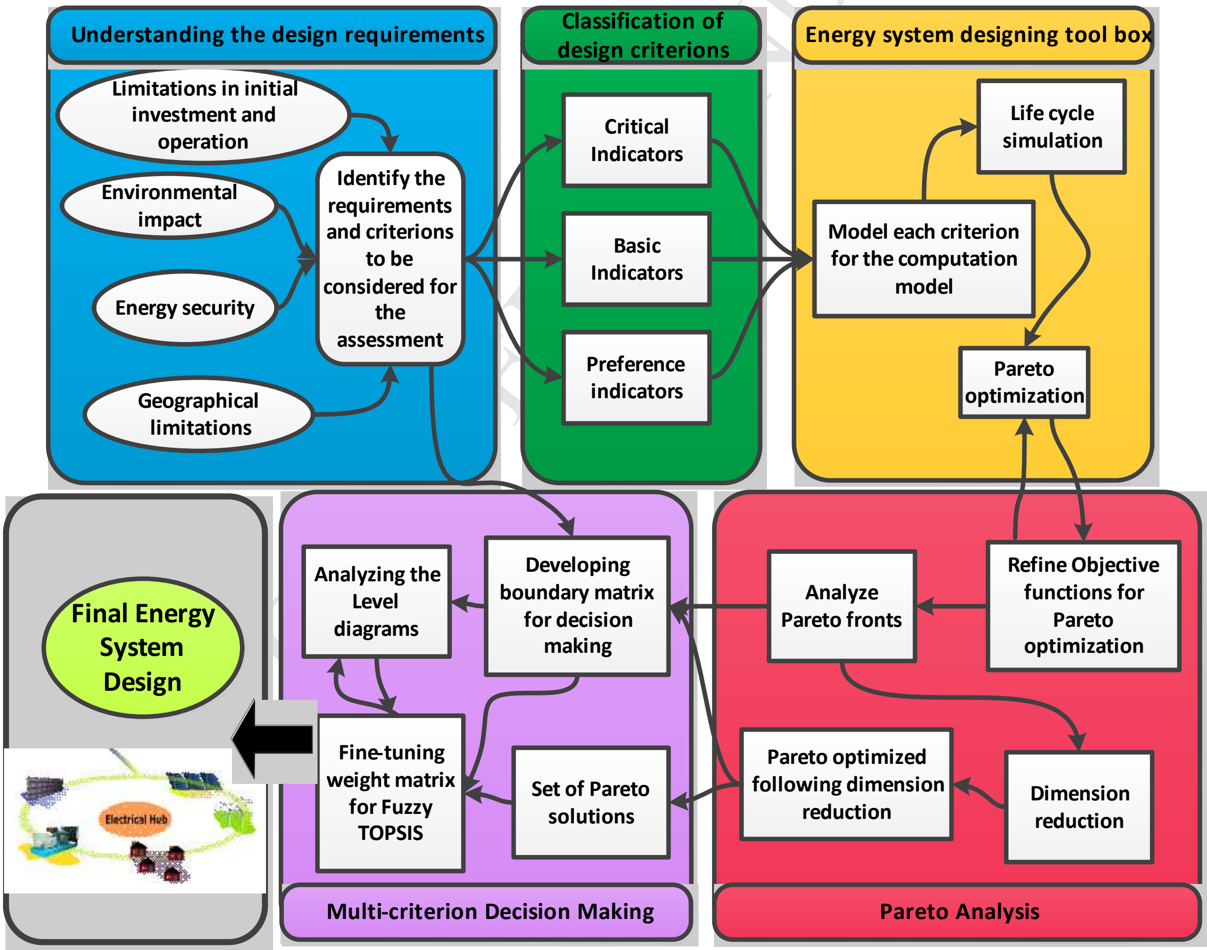


Fig. 3 Overview of the electrical Hub



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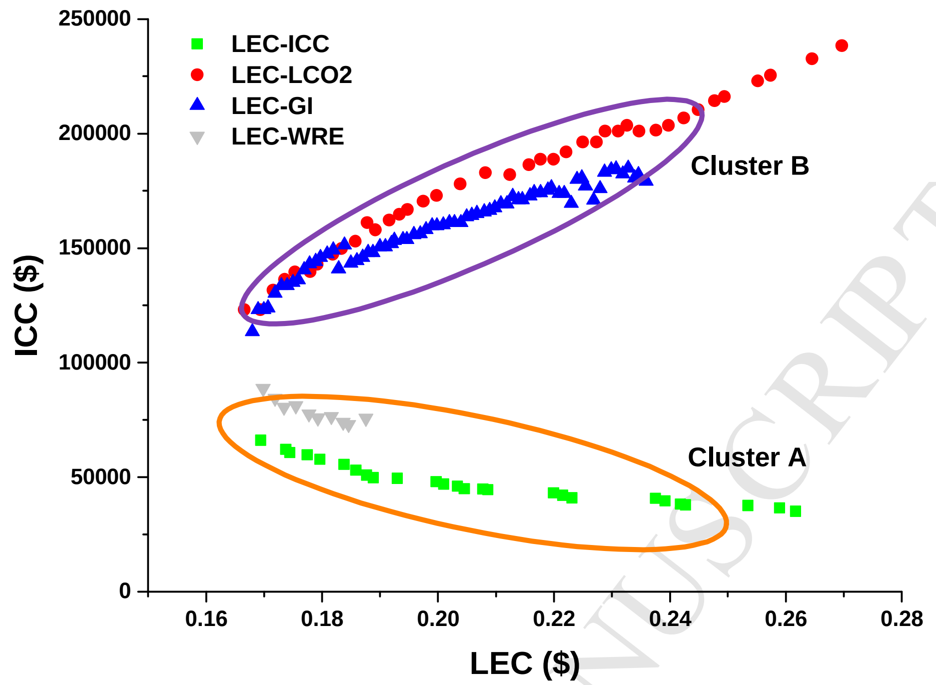

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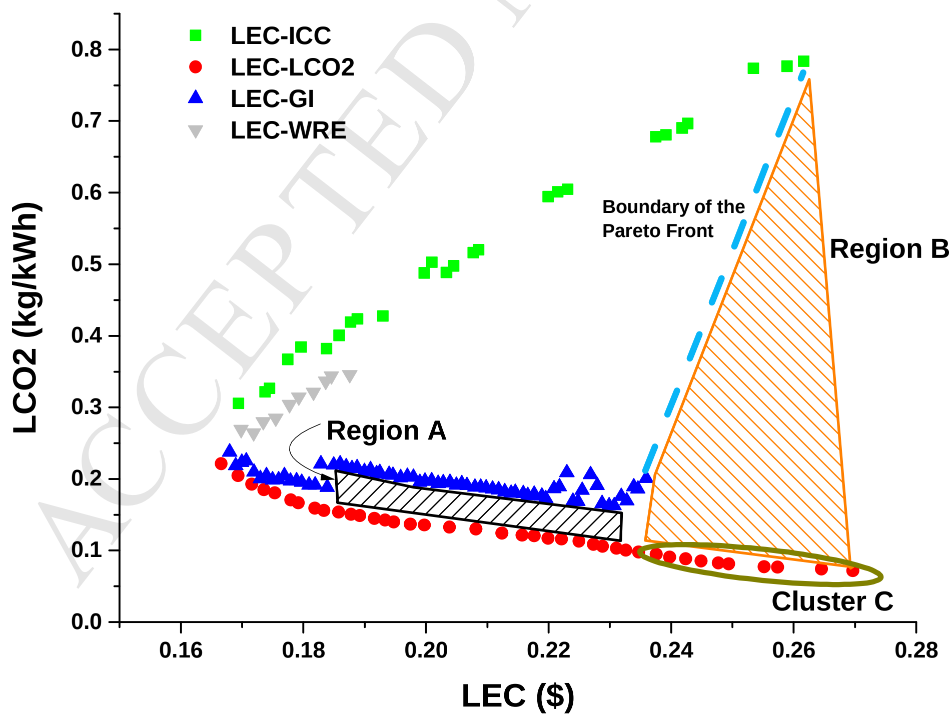

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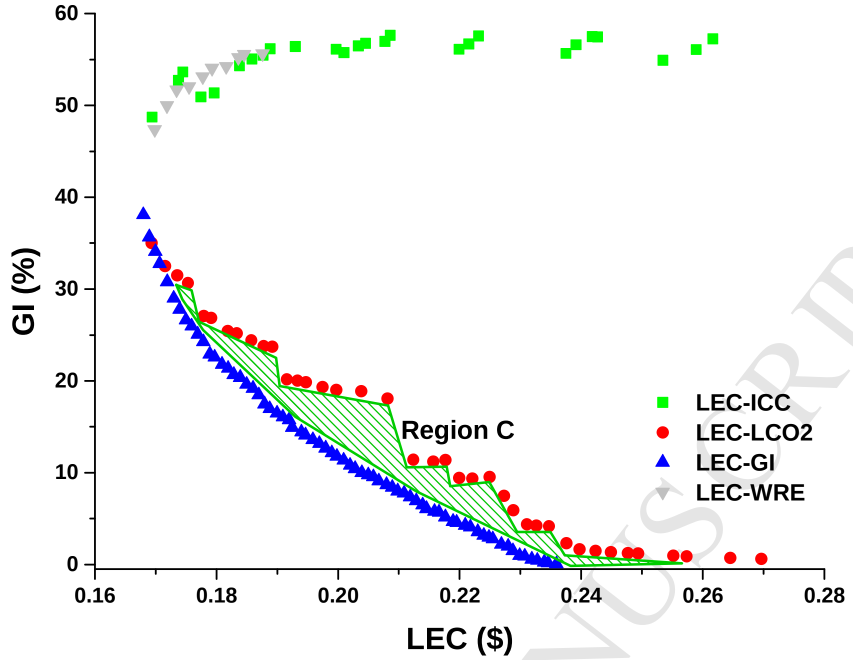

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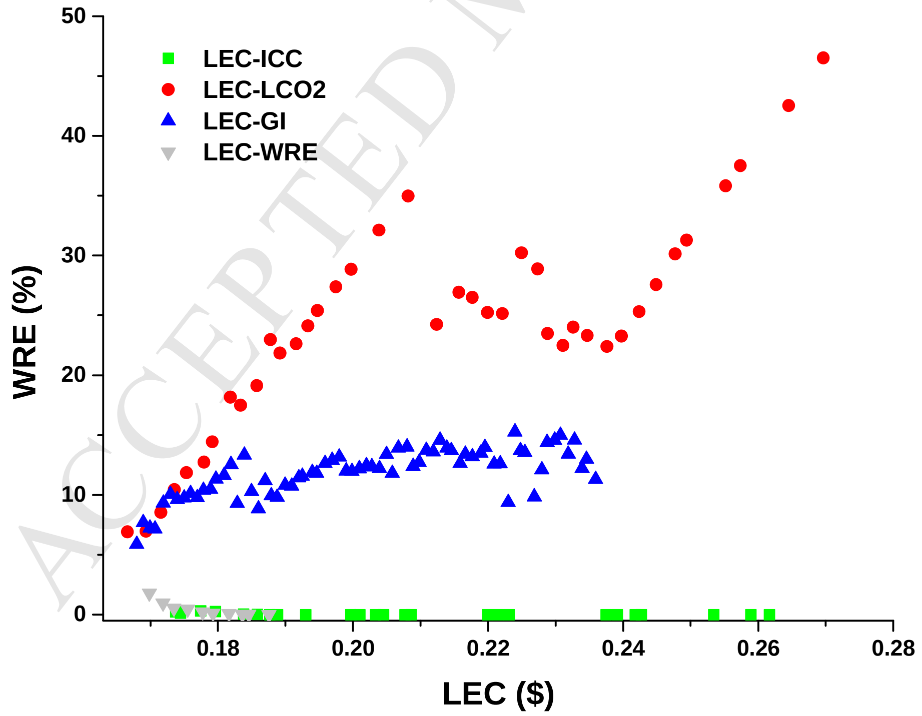

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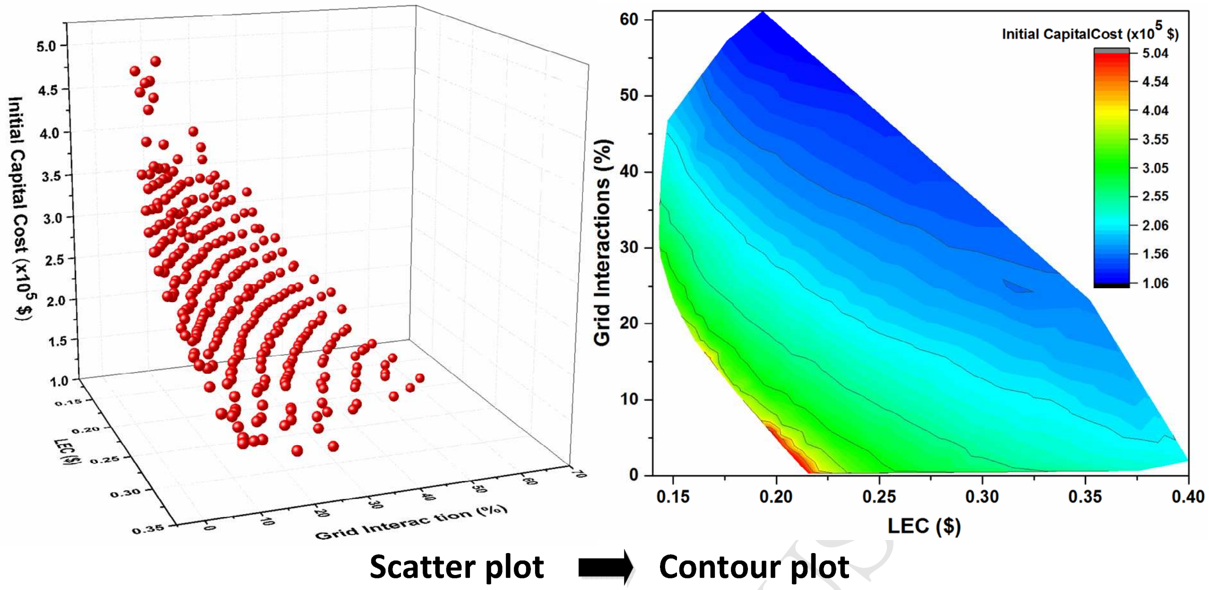

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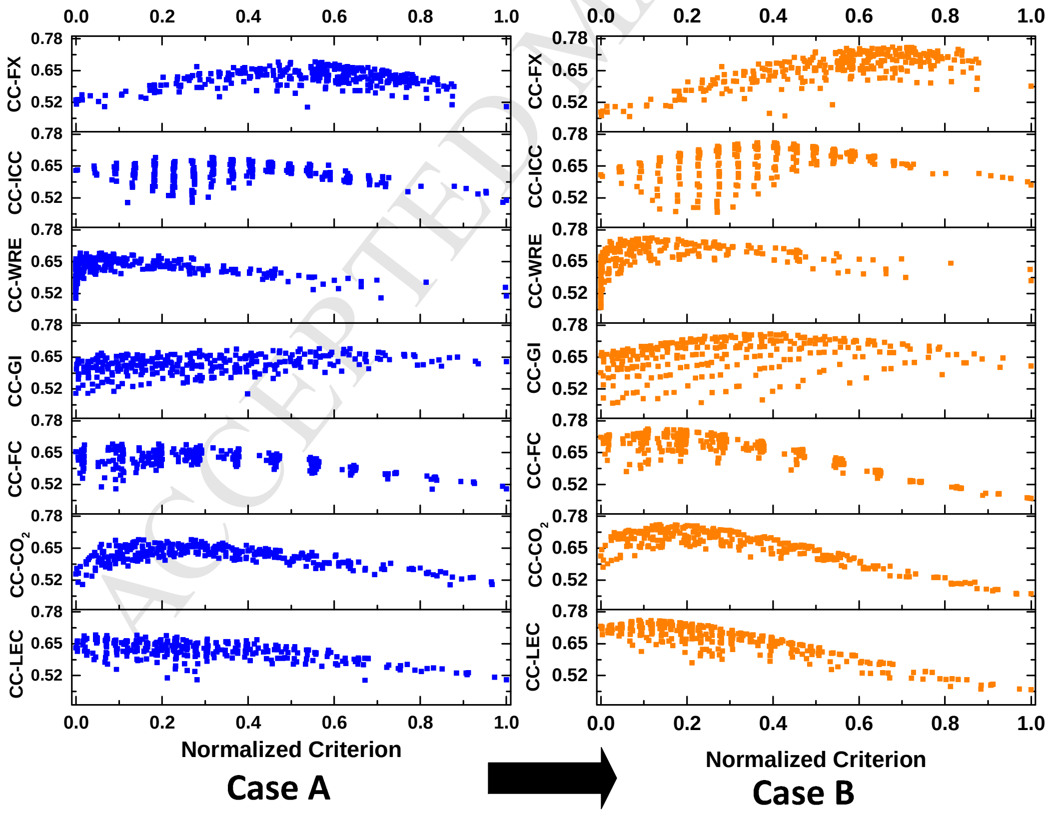

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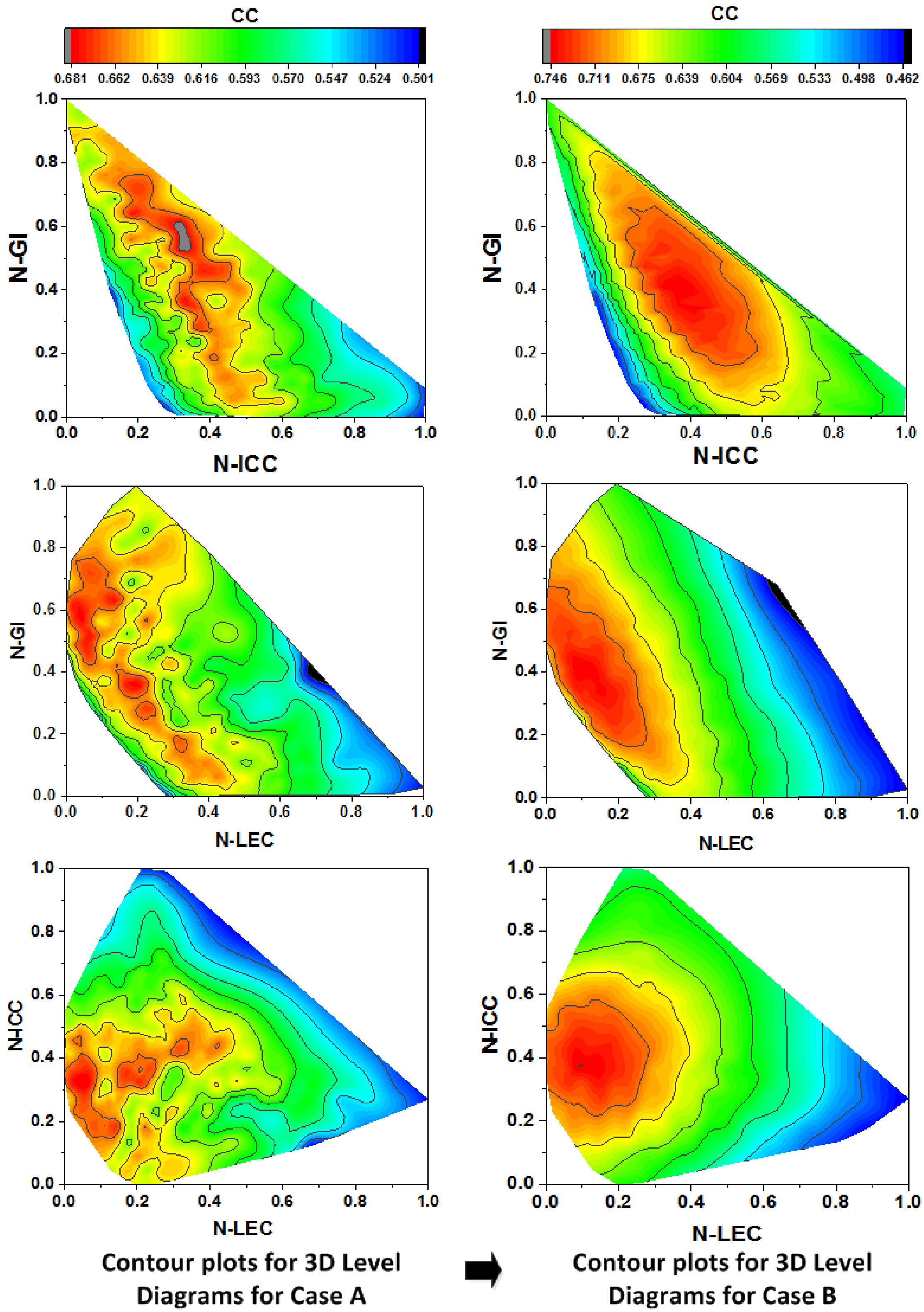

Fig. 11 (a): A comparison of 3D contour plots (normalized) considering coefficient of closure with different criteria

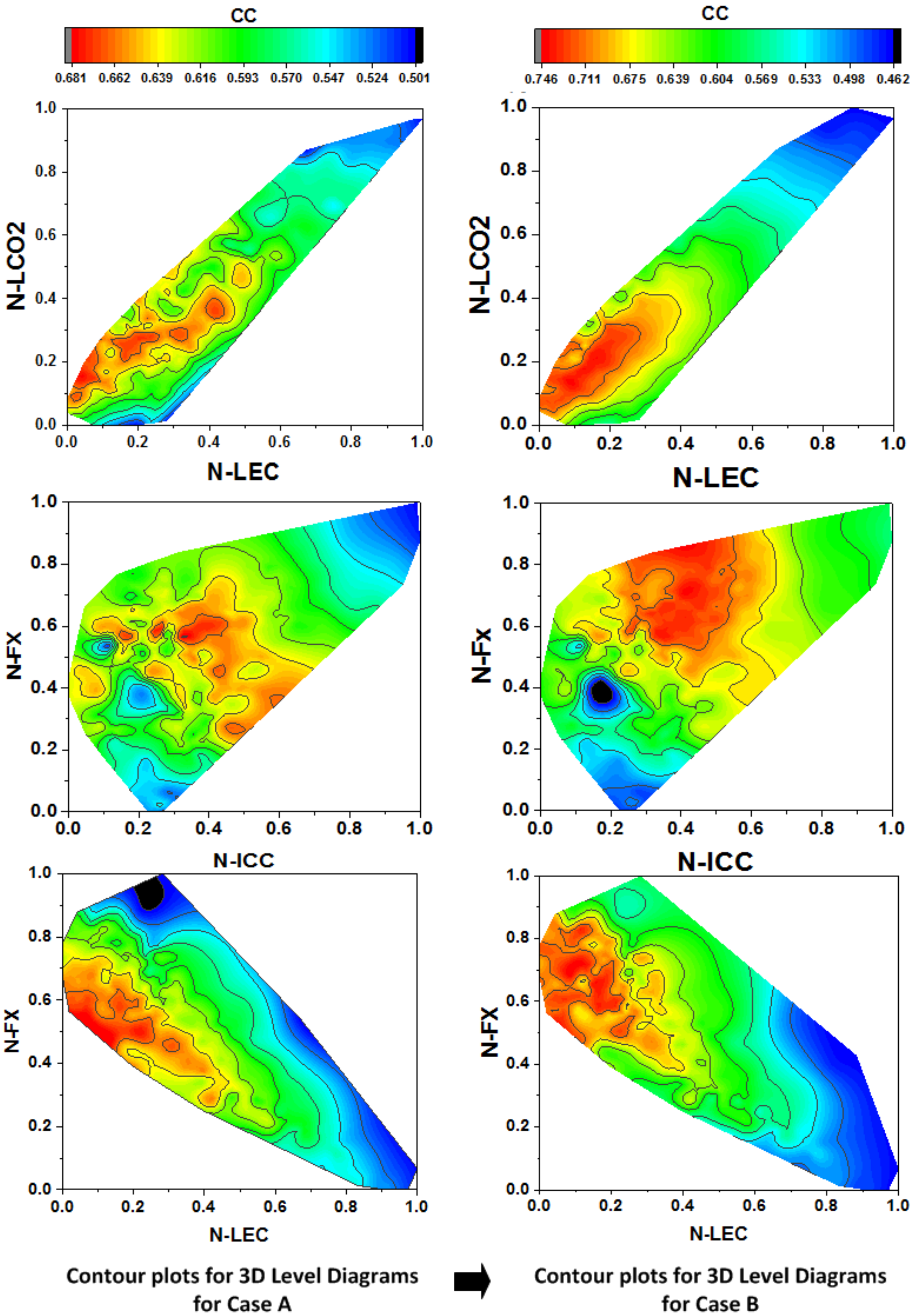

Fig. 11 (b): A comparison of 3D contour plots (normalized) considering coefficient of closure with different criterions for Case A and B

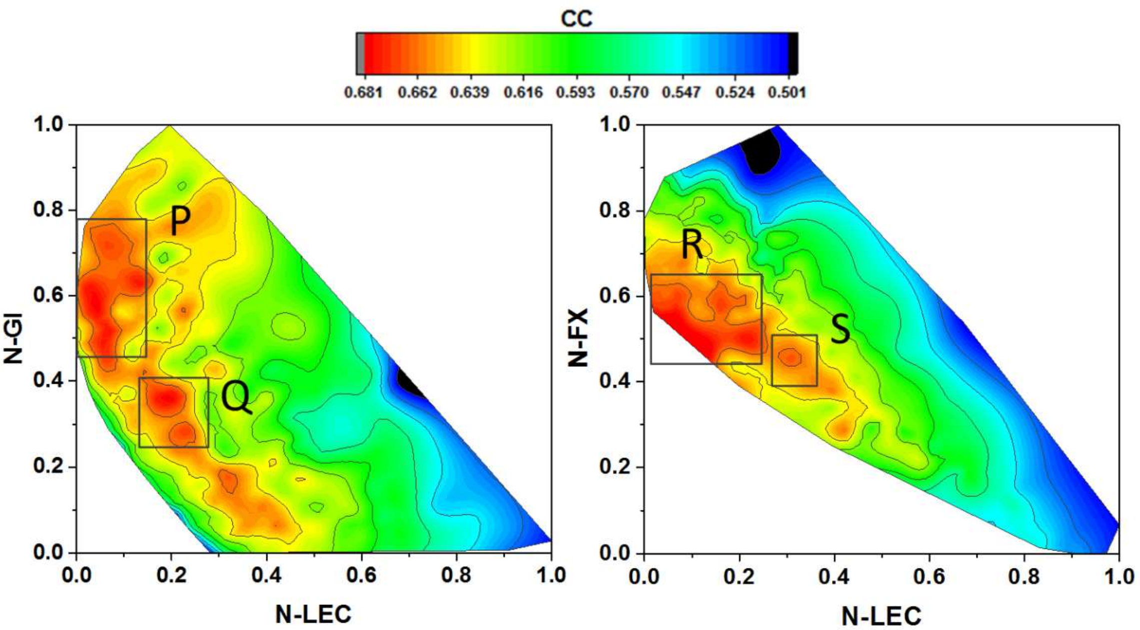

Fig. 12 Possible changes in contour plot with the changes in weight matrix

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Table 1: Different combinations of objective functions considered for optimization and decision space variables

Scenario[1]	Objective functions considered	Constraint function	Decision space variables
A	Case 1: LEC-ICC Case 2: LEC-LCO2 Case 3: LEC-GI Case 4: LEC-WRE	Loss of Load probability	• Number and type of SPV panels • Number and type of wind turbines • Size of Battery bank • Size of ICG • Variables for finite state machines • Variables of fuzzy controller
B	LEC-GI-ICC		

[(1)] Scenario A relates to Cases for Pareto analysis and B relates for multi-criterion decision making

Table 2. Boundary matrix for the criterions based on the requirements of the customer. Green denotes acceptance and red denotes rejection for different regions of normalized value for criterions. Green color denotes acceptable and red denotes not acceptable

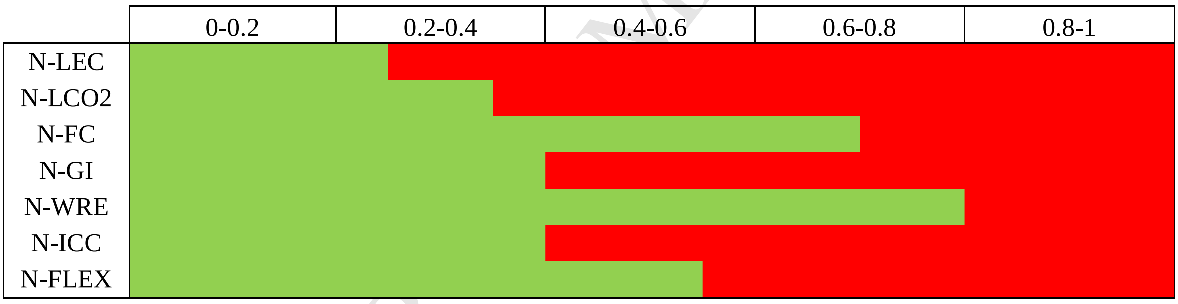

Table 3: Weight matrix considered for Case A and Case B

Case	LEC	LCO2	FC	GI	WRE	ICC	Fx.
A	0.255	0.136	0.043	0.128	0.064	0.187	0.187
B	0.245	0.131	0.041	0.163	0.061	0.180	0.180

Table 4: Best six solutions ranked based on weight matrix for Case A

System	Criterion Values							Normalized criterion values							CC	System configuration			
	LEC[1]	LCO2[2]	FC[3]	GI[3]	WRE[4]	ICC[5]	Flex.	NLEC	NLCO2	NFC	NGI	NWRE	NICC	NFlex		SPV[6]	Wind[7]	Battery[8]	ICG[9]
A 1	0.155	0.261	0.038	27.9	1.02	2.32	0.362	0.05	0.15	0.09	0.57	0.06	0.32	0.56	0.685	12.9	50	2880	27.5
A 2	0.179	0.356	0.063	31.4	0.18	1.80	0.309	0.14	0.27	0.19	0.64	0.01	0.18	0.47	0.684	10.9	35	960	30
A 3	0.161	0.270	0.043	25.7	0.95	2.33	0.372	0.07	0.16	0.11	0.52	0.05	0.32	0.57	0.683	12.9	50	2880	30
A 4	0.197	0.363	0.079	18.5	0.42	2.33	0.327	0.21	0.28	0.26	0.37	0.02	0.32	0.49	0.683	13.6	40	1920	30
A 5	0.148	0.219	0.022	30.7	1.50	2.34	0.367	0.02	0.09	0.02	0.62	0.09	0.32	0.56	0.681	15.6	50	2880	30
A 6	0.185	0.312	0.065	17.4	1.52	2.51	0.372	0.16	0.21	0.20	0.35	0.09	0.36	0.57	0.677	13.6	55	1920	30

Table 5: Best six solutions ranked based on weight matrix for Case B

System	Criterion Values														CC	System configuration			
	LEC[1]	LCO2[2]	FC[3]	GI[3]	WRE[4]	ICC[5]	Flex.	NLEC	NLCO2	NFC	NGI	NWRE	NICC	NFlex		SPV[6]	Wind[7]	Battery[8]	ICG[9]
B1	0.197	0.363	0.079	18.5	0.42	2.33	0.327	0.21	0.28	0.26	0.37	0.02	0.32	0.49	0.680	13.6	40	1920	30
B 2	0.203	0.374	0.087	14.3	1.17	2.50	0.326	0.23	0.29	0.29	0.29	0.07	0.36	0.50	0.678	10.9	55	1920	30
B 3	0.185	0.312	0.065	17.4	1.52	2.51	0.372	0.16	0.21	0.20	0.35	0.09	0.36	0.57	0.676	13.6	55	1920	30
B 4	0.161	0.270	0.043	25.7	0.95	2.33	0.372	0.07	0.16	0.11	0.52	0.05	0.32	0.57	0.675	12.9	50	2880	30
B 5	0.155	0.261	0.038	27.9	1.02	2.32	0.362	0.05	0.15	0.09	0.57	0.06	0.32	0.56	0.675	12.9	50	2880	27.5
B 6	0.222	0.381	0.094	9.6	1.33	2.70	0.296	0.31	0.30	0.32	0.19	0.08	0.41	0.45	0.674	12.2	55	1920	27.5

Table: 7 Best six solutions ranked based on weight matrix for Case B, C, D, E , F, BLEC and BICC

System	Criterion Values														CC	System configuration			
	LEC[1]	LCO2[2]	FC[3]	GI[3]	WRE[4]	ICC[5]	Flex.	NLEC	NLCO2	NFC	NGI	NWRE	NICC	NFlex		SPV[6]	Wind[7]	Battery[8]	ICG[9]
B1	0.197	0.363	0.079	18.5	0.42	2.33	0.327	0.210	0.277	0.256	0.373	0.024	0.318	0.499	0.680	13.6	40	1920	30
C	0.166	0.254	0.043	21.1	2.06	2.51	0.439	0.089	0.137	0.109	0.425	0.119	0.364	0.678	0.746	16.32	55	1920	30
D	0.186	0.397	0.062	43.7	0.00	1.23	0.301	0.167	0.321	0.186	0.887	0.000	0.042	0.458	0.750	4.76	25	960	30
E	0.251	0.406	0.108	3.1	1.94	2.87	0.191	0.420	0.333	0.377	0.059	0.112	0.454	0.281	0.677	12.92	60	1920	30
F	0.227	0.303	0.078	2.7	3.14	3.40	0.277	0.326	0.200	0.252	0.051	0.181	0.587	0.419	0.724	19.04	65	3840	27.5
BLEC	0.143	0.196	0.021	25.3	3.43	2.82	0.502	0.000	0.061	0.017	0.512	0.198	0.441	0.781	NA	16.32	65	3840	30
BICC	0.281	0.715	0.172	28.5	0	1.44	0.130	0.536	0.731	0.643	0.579	0.000	0.000	0.182	NA	0.68	0	2880	30

[1]LEC in \$, [2]LCO2 in kg/kWh, [3]fuel consumption in l/kWh, [3]grid integration level (%), [4]WRE (%), [5]ICC (x10^5\$), [6]SPV capacity in kW, [7]wind turbine capacity in kW Battery [8]bank size in kWh and [9]ICG capacity in kW

Table 6: Weight matrix for Case B, C, D, E and F

Case	LEC	LCO2	FC	GI	WRE	ICC	Flex.
B	0.245	0.131	0.041	0.163	0.061	0.180	0.180
C	0.299	0.159	0.050	0.199	0.075	0.219	0
D	0.293	0.156	0.049	0	0.073	0.215	0.215
E	0.296	0	0	0.197	0.074	0.217	0.217
F	0.299	0.159	0.050	0.199	0.075	0	0.219

- A novel integrated method to design distributed energy system
- Determine most suitable objective functions for Pareto optimization
- MCDM considering set of criterions with different priorities
- Combine optimization, Pareto analysis and MCDM