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A multi-stage optimisation-based decision-making framework for sustainable hybrid energy system in the residential sector

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ABSTRACT

Integrating renewables into existing energy infrastructure to construct hybrid energy systems (HES) plays a vital role for advancing energy sustainability. While various approaches, such as energy systems analysis and linear or non-linear optimisation, have been employed to achieve energy sustainability mainly at the national or city level, there has been a lack of focus on achieving energy sustainability in the residential sector through a holistic optimal decision-making approach for efficient HES design. This study focuses on developing a multi-stage optimisation-based decision-making framework that models, quantifies, and optimises the performance indicators of HES, allowing for an assessment of the trade-off between benefits and systems costs under various design scenarios. The initial step involves designing the HES model and constructing scenarios that cater to the electrification requirements of water, energy, and food elements in the residential sector by using a systematic thinking approach. Then, a preliminary evaluation of the modelled scenarios is conducted to assess energy sustainability in terms of technical and economic aspects. Afterwards, an optimal decision-making setup is established by integrating a multi-objective HES model into the NSGA-II algorithm, which approximates the Pareto optimal solutions. These solutions are then ranked by using a multi-criteria decision-making method. According to the findings, the Quetta region in Pakistan contains the best optimal solution. The results underscore the utility of the developed framework in facilitating the optimal design of renewables-integrated HES for the residential sector. Furthermore, intergovernmental organizations can leverage this framework to formulate effective policies aimed at encouraging residents to invest in HES installation.

1. Introduction

The concept of sustainable development (SD) has gained considerable attention and has been associated with various aspects of our planet in recent decades. Resultantly, the United Nations established 17 sustainable development goals (SDGs) in 2015 as successors to the Millennium Development Goals, aiming at achieving sustainability. amongst these SDGs, the provision of sustainable, abundant, and affordable water, energy, and food resources is considered crucial for the well-being of humanity [1]. Despite efforts spanning many years, more than a billion people still lack access to safe drinking water, one billion suffer from hunger, and 2.5 billion lack access to modern energy sources [1,2]. The water, energy, and food elements are interconnected, and their interdependencies significantly impact each other, as well as climate change [3,4]. Energy, in particular, plays a critical role amongst these sectors [5,6]. Moreover, the predicted increase in global energy demand by 2050 is estimated to be 80%, surpassing the projected increase for water and food, which are 55% and 60%, respectively [1]. Given the existing deficiencies and the mounting pressure on energy sources owing to population growth and increasing needs, it is imperative to restructure strategies for achieving energy sustainability, especially in the aftermath of the Covid-19.

Achieving energy sustainability necessitates a gradual transition from a fossil fuel-dominated culture to a high proportion of renewable energy (RE) in the energy mix [2], which in turn requires substantial investments in RE systems [7]. However, stakeholders may perceive investing in large-scale RE projects as risky due to the transitioning nature of RE technologies, the requirement for relatively expensive infrastructure, and their dependence on meteorological conditions [8]. Consequently, constructing hybrid energy systems (HES) by integrating the RE technologies with existing energy sources, such as grid and genset, has demonstrated a significant potential owing to reliability for

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energy supply [9]. Amongst various renewables, solar photovoltaic (PV) has emerged as a promising substitution for fossil fuels [10–13], with its global share in the energy mix experiencing exponential growth over the past decade [14].

Numerous studies have been conducted on the design and performance assessment of solar PV integrated HES. For instance, Liu et al. [15] performed techno-economic assessment of solar PV integrated HES for rural households in Africa to determine the optimal option amongst different PV module tracking scenarios by considering the net present cost as a decision indicator. Babatunde et al. [16] evaluated the techno-economic-environmental viability of HES, integrating solar PV, wind, and battery energy sources, for a household in sub-Saharan Africa, and suggested interest-friendly loans for low-income households. Li et al. [17] designed distributed HES, integrating solar PV and wind sources, for residential, commercial, and industrial sectors in Singapore by employing peer-to-peer energy exchange approach and blockchain technologies for efficient system operation. Barzegkar-Ntovom et al. [18] assessed the economic feasibility of the hybrid solar PV combined with battery storage energy source for a residential building in six Mediterranean countries, considering levelized cost of use as a decision indicator to quantify the competitiveness of various HES sizes. Das et al. [19] examined the techno-economic feasibility of HES, integrating solar PV, wind, battery, and gas boiler, to meet electric and thermal demands of a remote community in the western Australia by using HOMER software. Kumar and Tewary [20] proposed multiple configurations of standalone HES, integrating solar PV, wind, diesel generator, and battery storage, for meeting electricity needs in residential units. The authors examined the techno-economic feasibility of these configurations by using HOMER software and reported the potential for generating 19.3% excess electricity.

Optimisation of performance and system sizing characteristics of HES present challenges owing to the stochastic nature of energy sources and various influencing factors, such as location, meteorological parameters, efficiency values of energy system components, PV module slope angle, dust accumulation, and shading effects, which require optimal selection by considering technical and economic limitations [21]. Literature reports the application of various optimisation techniques focusing on different objective functions, such as power generation, renewable fraction, energy system cost, net present value, greenhouse gas (GHG) emissions, etc. The optimisation techniques commonly used can be classified into three categories: classical techniques, artificial intelligence approaches, and software tools [22]. Classical optimisation techniques, including numerical, analytical, graphical, and probabilistic approaches, have been widely employed in previous studies [22]. However, due to the limitations of classical techniques in solving advanced optimisation problems, artificial intelligence-based approaches have gained prominence for their effectiveness, flexibility, speed, and efficiency [23]. Artificial intelligence-based optimisation techniques are categorised into swarm intelligence, physics-based, human-inspired, and evolution-based algorithms [22]. Another type of optimisation techniques involves the use of software tools that facilitate pre-feasibility analyses and decision-making before implementing an energy system. Several software tools are available for conducting feasibility assessments of RE integration, such as ARES, INSEL, HYBRID, PVF-Chart, PV-DESIGN-PRO, HOMER, RETScreen, TRNSYS, PVSYST, RAPSIM, amongst others. RETScreen and HOMER are widely used by researchers and professionals, with RETScreen having the highest number of installations [22]. A recent trend in engineering optimisation is the hybridization of different optimisation methods into one single approach, combining their strengths to solve complex optimisation problems [22]. Hybrid optimisation techniques are predominantly developed by combining the artificial intelligence-based algorithms [22]. However, there has been relatively less exploration of hybrid approaches that combine optimisation techniques and multi-criteria decision-making (MCDM) methods.

Hence, the analysis of the extensive published research and review literature summed up the following research gaps:

- The lack of adopting a holistic system thinking approach for modelling HES specially for meeting the electrification requirements of the residential sector in terms of sustainable, abundant, and affordable water, energy, and food supply.
- The absence of a systematic scenario-based, data-driven hybrid optimisation approach, especially for the residential sector, to approximate and prioritize the optimal solutions for HES aiming at achieving better energy sustainability.

To address the highlighted knowledge gaps, this study is focused on following objectives: (1) to employ a holistic system-thinking approach in modelling HES and developing scenarios that can effectively meet the electrification requirements of the residential sector, (2) to examine the significance of preliminary assessment of modelled HES scenarios for energy sustainability and investigate the impact of considering load-shedding factor, (3) to optimise the HES scenarios for performance indicators enhancement and achieving better energy sustainability, (4) to conduct post-Pareto analysis, highlighting the impact of employing the MCDM method on the selection and classification of optimal solutions, for better utilization of optimisation outputs. To achieve these objectives, our study proposed a multi-stage optimisation-based decision-making framework that includes systematic HES design, preliminary techno-economic assessment, and optimal decision-making under various design scenarios, with the goal of achieving better energy sustainability in the residential sector.

The subsequent sections of this paper are organized as follows: Section 2 describes the developed multi-stage optimization-based decision-making framework; Section 3 highlights the study-related regions; Section 4 presents the results, and the corresponding discussion and recommendations are presented in section 5; and finally, Section 6 outlines the conclusions of this study.

2. Methodology

In this study, a multi-stage optimisation-based decision-making framework was developed, as illustrated in Fig. 1. The framework comprises the three main stages: (1) model development and data collection, (2) preliminary techno-economic assessment, and (3) optimal decision-making.

2.1. Model development and data collection

The initial stage of the framework development focused on designing the HES model, conceptualising different scenarios, and collecting the data by executing the conceptualised scenarios. The details of this stage will be discussed in the subsequent sections.

2.1.1. Hybrid energy system (HES) model

A holistic system-thinking approach, inspired by the Iceberg model [24], was employed in this study. The Iceberg model emphasizes understanding a system and exploring the relationships amongst its activities as a whole, rather than using a divide-and-analyse approach. Our adaptation of this model involved incorporating four levels of thinking [24,25], where the first three levels were utilised in designing the HES model, while the fourth level was employed in conceptualising the HES scenarios (Section 2.1.2).

During the initial level of HES model design, we identified the events (defined as concepts in the Iceberg model) related to power consumption for meeting the electrifications needs of abundant, affordable, and sustainable water, food, and energy supply in residential units. These events (see Table S-1 in the supplementary material (SM)) were determined based on existing literature [26] and insights obtained from stakeholder (details are mentioned in Table S-2 in SM) surveys. Secondly, we defined the operational patterns of these events, considering

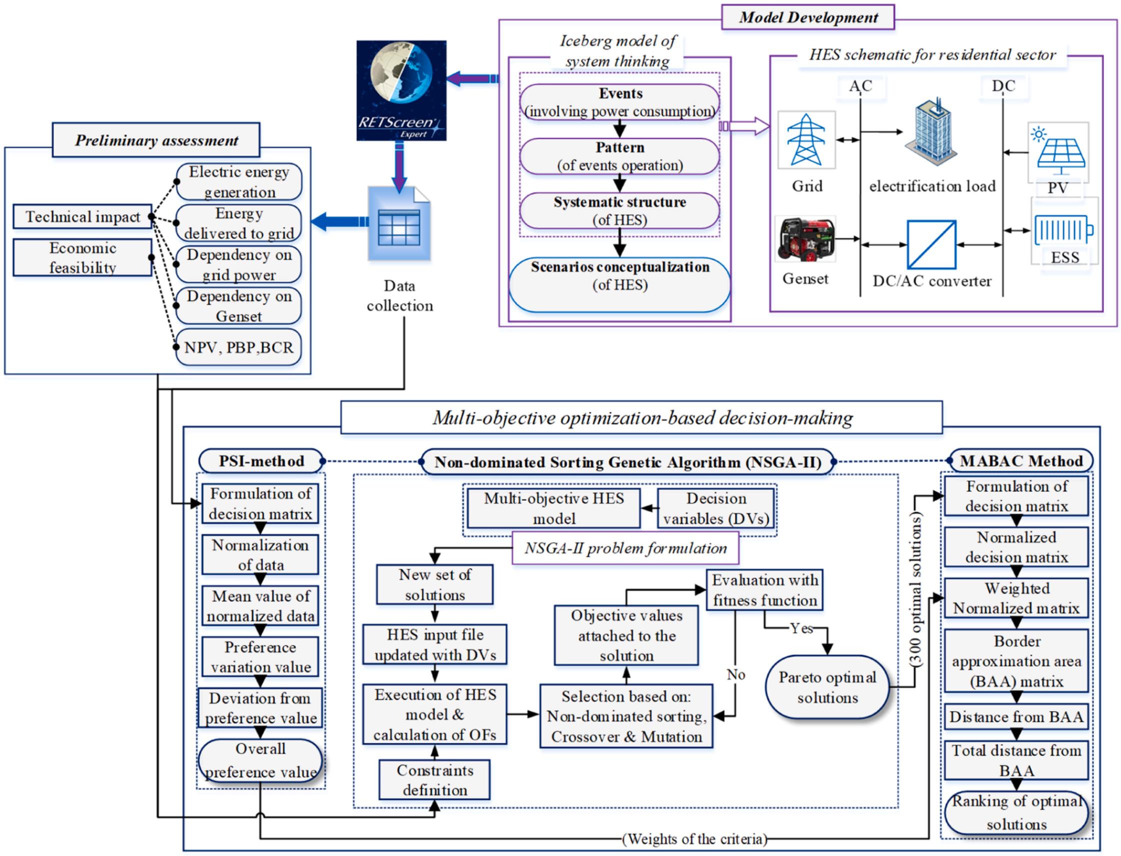

Fig. 1. Multi-stage optimisation-based decision-making framework.

factors such as intermittent resource-load correlation and the number of daily usage hours (see Table S-1 in the SM). Furthermore, we utilised the estimated optimal monthly energy demand with respect to variations in heating and cooling loads during winter and summer seasons (Table S-3 in SM) [27]. Thirdly, based on the identified events and their patterns, we modelled the systematic structure of the HES using the design variables for the baseline and proposed cases (see Fig. 1).

2.1.2. HES scenarios conceptualisation

Continuing the system-thinking approach, we applied the final level of the Iceberg model to conceptualise the HES scenarios. To achieve this, we conducted a workshop with experts (see Table S-2) to explore the

Table 1
The description of the conceptualised hybrid energy system (HES) scenarios.

HES Design scenario	Configuration type		Energy sources				Solar PV module type		PV module installation slope angle		ESS type	
HS-#	Off-grid	Grid-connected	RES	ESS	GES	GnES	mono-Si	poly-Si	Lat.	OSA	LA	DrC
1	√		√	√	√		√		√		√	
2	√		√	√		√	√		√		√	
3	√		√	√	√			√	√		√	
4	√		√	√		√		√	√		√	
5	√		√	√	√		√			√	√	
6	√		√	√		√	√			√	√	
7	√		√	√	√			√		√	√	
8	√		√	√		√		√		√	√	
9	√		√	√	√		√			√		√
10	√		√	√		√	√			√		√
11	√		√	√	√			√		√		√
12	√		√	√		√		√		√		√
13		√	√		√		√		√			
14		√	√		√	√	√		√			
15		√	√		√			√	√			
16		√	√		√	√		√	√			
17		√	√		√		√			√		
18		√	√		√	√	√			√		
19		√	√		√			√		√		
20		√	√		√	√		√		√		
21		√	√		√		√		√			
22		√	√		√	√	√		√			
23		√	√		√			√	√			
24		√	√		√	√		√	√			

current electrification sources in the study regions (as described in Section 3). Through this collaborative effort, we conceptualised HES scenarios that involved four energy sources: renewable solar PV energy source (RES), battery-based energy storage system (ESS), grid energy source (GES), and genset energy source (GnES). In line with the goal of achieving energy sustainability by integrating renewables into the energy infrastructure [12,28], RES was identified as the primary energy source. The conceptualised HES scenarios were classified into two main types: off-grid (OG) and grid-connected (GC) configurations. In the case of OG-type scenarios, RES was integrated with ESS, while GES served as a backup energy source. For GC-type scenarios, RES was integrated with GES. Additionally, GnES was integrated for electrification during load-shedding hours [29]. Consequently, twenty-four HES scenarios were conceptualised by considering five design variables, including configuration type, integrated energy sources, solar PV module type, solar PV module installation slope angle, and ESS type. A description of the conceptualised HES scenarios is provided in Table 1.

Once the technical structure of the HES scenarios was finalized, we gathered cost information for various parameters, including development costs, energy system costs, annual operation and maintenance costs, fuel costs, and periodic costs. This data was acquired through market survey, which helped complete the HES model. The details regarding the design variables, technical parameters, and cost parameters utilised in modelling the HES scenarios are summarized in Table S-4 in the SM.

2.1.3. Data collection

The conceptualised HES scenarios were modelled and evaluated for nine regions in Pakistan by using the RETScreen software [26,30]. RETScreen is an excel user interface-based clean energy project simulation tool developed and maintained by CEDRL (CANMET Energy Diversification Research Laboratory) under the supervision of the Ministry of Natural Resources of Canada. It is a well-established and validated software package widely utilised for the efficient evaluation of various RE-based projects [22,26]. The success and effectiveness of this modelling tool can be attributed to the collaborative efforts of multiple organizations, including the National Aeronautics and Space Administration, United Nations Environment Program, and numerous experts from academia, industry, and administrative sectors [26]. Therefore, leveraging the capabilities of the RETScreen tool, a total of 216 HES scenarios were modelled, enabling the collection of data with respect to a set of technical, economic, and environmental indicators. This data was crucial for preliminary assessment and facilitating the process of optimal decision-making.

2.2. Preliminary assessment of HES scenarios

The evaluation of the modelled HES scenarios encompassed an assessment in terms of technical and economic aspects. To conduct this assessment, the datasets obtained from evaluating the scenarios in the RETScreen tool were imported into Microsoft excel. This facilitated the quantification of the cumulative impacts of the modelled scenarios on energy sustainability. The technical aspect of the modelled scenarios was assessed by considering following indicators: electric energy (EE) delivered to the load by RES, EE exported to the grid by RES, power system capacity factor, power capacity of the system, area covered by solar PV modules, EE delivered to the load by GES and GnES, and fuel consumption in the baseline and proposed cases. The economic aspect of the modelled HES scenarios was assessed in terms of the net present value (NPV), benefit-cost ratio (BCR), payback period (PBP), and total investment required, whose calculations are defined in [26,31].

2.3. Optimal decision-making

The optimal decision-making stage comprised two main steps: (1) multi-objective optimisation utilising the non-dominated sorting genetic algorithm (NSGA-II), and (2) decision-making employing multi-criteria decision-making (MCDM) method. A comprehensive optimal decision-making setup was developed, incorporating NSGA-II to determine the Pareto optimal solutions for HES, while MCDM method was employed to make decisions regarding these solutions.

2.3.1. Multi-objective optimisation using NSGA-II

- ***Formulation of the multi-objective optimisation problem***

The multi-objective optimisation problem for HES was initially formulated to determine the optimal solutions by considering four objective functions. To execute the formulated objective functions, several decision variables were considered, including (1) H_T = incident solar radiations, (2) A_{PV} = the number of PV modules required to satisfy a desired load factor (0.9–1.0), (3) C_{res} = the cost of RES, and (4) e_{prop} = the GHG emissions factor for the proposed case. The incident solar radiations varied depending on changes in latitude. The number of PV modules required was influenced by factors, such as the type of PV module (mono-Si and poly-Si), the efficiency value of the PV module, and the frame area of the PV module. The cost of the RES was governed by the number of PV modules and the cost of the unit PV module. The GHG emissions factor was determined by the energy mix in the proposed case, with a higher percentage of RE resulting in a lower GHG emissions factor. The formulated four objective functions are defined as follows:

(1) Objective 1 (OF_1) = maximizing the output energy generated by RES (Eq. (1))

$$OF_1 = Max\,(Output\,energy\,from\,RES) = Max\,(E_{res}) \tag{1}$$

$$\text{where, } E_{res} = A^j_{PV_i}\,\eta_{PV}\,H^j_T \tag{2}$$

Eq. (2) presents the calculations for the output energy generated by RES [31,32] where, $A^j_{PV_i}$ represents the area required for PV modules for the i^{th} scenario in the j^{th} region, η_{PV} is the efficiency value of the solar PV module; and H^j_T is the total average incident solar radiations in the j^{th} region.

(2) Objective 2 (OF_2) = minimizing the retrofit cost (Eq. (3))

$$OF_2 = Min\,(\mathrm{Retrofit\ cost}) = Min\,\left(C_{retrofit}\right) \tag{3}$$

$$\text{where, } C_{retrofit} = C^j_{res_i} + C^j_{D_i} + C^j_{O\&M_i} \tag{4}$$

Eq. (4) presents the calculations for retrofit cost where, $C^j_{res_i}$ is the cost of RES, mainly of PV modules, for the i^{th} scenario in the j^{th} region; $C^j_{D_i}$ is the development cost of RES, which is a certain percentage value of $C^j_{RES_i}$; and $C^j_{O\&M_i}$ is the operation and maintenance cost of HES for the i^{th} scenario in the j^{th} region.

(3) Objective 3 (OF_3) = maximizing the benefit-cost ratio (Eq. (5))

$$OF_3 = Max\,(Benefit - \mathrm{cost}\ ratio) = Max\,(BCR) \tag{5}$$

$$\text{where, } BCR = NPV^j_i \Big/ C^j_{retrofit_i} \tag{6}$$

Eq. (6) presents the calculations of BCR where, NPV^j_i is the net present value for the i^{th} scenario in the j^{th} region; and $C^j_{retrofit_i}$ is the retrofit cost for the i^{th} scenario in the j^{th} region.

(4) Objective 4 (OF_4) = maximizing the reduction of GHG emissions (Eq. (7))

$$OF_4 = Max\,(GHG\,emissions\,reduction) = Max\,(GHG_r) \tag{7}$$

$$\text{where, } GHG_r = \left(e_{base} - e^j_{prop_i}\right) E^j_{res_i} \left(1 - \lambda_{prop}\right)\left(1 - e_{cr}\right) \tag{8}$$

Eq. (8) presents the calculations for GHG emissions reduction [31] where, $e_{base}$is the GHG emissions factor for baseline case, which was same for all scenarios in studied regions; $e^j_{prop_i}$ is the GHG emissions factor for the proposed case for the i^{th} scenario in the j^{th} region; $E^j_{res_i}$is the output energy generated by RES for the i^{th} scenario in the j^{th} region; λ_{prop} is the factor represents transmission and distribution losses, which was taken 17.5% [33]; and e_{cr} is credit transaction fee for GHG emissions reduction that was taken zero as this is not applicable in the studied regions.

The above-formulated objective functions were subjected to following constraints:

$$H^j_{T_{i,\min}} \le H^j_{T_i} \le H^j_{T_{i,\max}} \tag{9}$$

$$A^j_{PV_{i,min}} < A^j_{PV_i} \le A^j_{PV_{i,max}} \tag{10}$$

$$e^j_{prop_{i,min}} \le e^j_{prop_i} \le e^j_{prop_{i,max}} \tag{11}$$

where, $H^j_{T_{i,\min}}$ and $H^j_{T_{i,\max}}$ are the minimum and maximum incident solar radiation values for the i^{th} scenario in the j^{th} region; $A^j_{PV_{i,min}}$ and $A^j_{PV_{i,max}}$ are the minimum and maximum values for the area covered by PV modules for the i^{th} scenario in the j^{th} region, which also influences the cost of RES for the i^{th} scenario in the j^{th} region; $e^j_{prop_{i,min}}$ and $e^j_{prop_{i,max}}$ are the minimum and maximum GHG emissions factors for the proposed case for the i^{th} scenario in the j^{th} region.

- ***Optimisation algorithm***

The formulated multi-objective optimisation problem was executed using the NSGA-II algorithm in a python environment. NSGA-II is widely recognized as a highly effective multi-objective evolutionary algorithm for design and optimisation tasks owing to its ability to handle complex problems efficiently and with computational speed [34]. It has been successfully applied in various domains, including estimating carbon emissions for green vehicles routing [35], optimising hybrid RE systems under uncertainties [36], identifying optimal management practices for minimizing nutrients pollution in the Lincoln lake watershed [37], sensor placement optimisation [38], optimal stormwater management for reducing flooding risk [34], and operational optimisation of hybrid distributed energy system [39], amongst others.

To determine the Pareto optimal solutions for HES by executing the multi-objective optimisation problem, the NSGA-II generated an initial set of solutions for the decision variables of HES, which was then used to calculate the objective functions [34,40]. This process was iteratively performed for a suitable number of iterations to reach a set of non-dominated Pareto optimal solutions by following the procedural steps described in Section I in SM. Finally, the execution of the optimisation problem by using the NSGA-II resulted in a set of Pareto optimal solutions for the objective functions.

2.3.2. Multi-criteria decision-making

The outcome of the multi-objective optimisation process is a set of non-dominated solutions known as Pareto optimal solutions, based on the defined objective functions, decision variables, and constraints. Typically, the generated sets usually contain numerous Pareto optimal solutions. However, decision makers cannot simply select a single optimal solution from this set, as each optimal solution provides the best value of one objective function while compromising others. Therefore, a post-optimisation process is necessary to comprehensively evaluate the optimal solutions and facilitate the decision-making process of selecting and utilizing the optimal system sizes and locations for stakeholders [40]. In this concern, the application of MCDM methods can be instrumental in analysing and ranking the optimal solutions, enabling decision-makers to choose designs that strike optimal compromise between performance indicators [8,40]. We employed four performance indicator criteria, denoted asE_{res}, $C_{retrofit}$, BCR, andGHG_r, representing the technical, economic, and environmental aspects of the HES and were evaluated during optimisation process, to facilitate the decision-making process.

Amongst the various MCDM methods, the Multi-attributive Border Approximation area Comparison (MABAC) is a latest and widely used approach that ranks the multiple solutions based on predefined indicator criteria by considering their distance from the border approximation area (BAA) value. The MABAC method is governed by five steps: (1) normalizing the decision matrix, (2) formulating the weighted normalized decision matrix, (3) constructing the BAA matrix, (4) calculating the distance of solutions from the BAA, and (5) determining the total distance of solutions from BAA, which are represented by Eqs. (12-16), respectively [13,41].

$$\overline{x_{ml}} = \frac{x_{ml} - best\,(x_m)}{\max\,(x_m) - \min\,(x_m)} \tag{12}$$

where, x_{ml} is the decision matrix containing l^{th} criteria and m^{th} solution; $\overline{x_{ml}}$ is the normalized decision matrix; and $\max\,(x_m)$ and $\min\,(x_m)$ are the maximum and minimum values of the l^{th} criteria.

$$v_{ml} = w_l.(\overline{x_{ml}} + 1) \tag{13}$$

In Eq. (13), v_{ml} is the weighted normalized decision matrix; and w_l is the weight of the criteria.

$$g_l = \left(\sum\nolimits_{m=1}^{M} v_{ml}\right)^{1/M} \tag{14}$$

where, $g_l$is the BAA matrix.

$$q_{ml} = v_{ml} - g_l \tag{15}$$

In Eq. (15), q_{ml} represents the distance of the m^{th} solution for the l^{th} criteria from corresponding BAA value.

$$R_m = \sum\nolimits_{l=1}^{L} q_{ml} \tag{16}$$

In Eq. (16), R_m is the total distance of the m^{th} solution from BAA. Finally, the solutions can be ranked based on the R_m, and a solution with higher R_m score is preferable than a solution with lower R_m value. Additionally, based on the $R_m = \sum_{l=1}^{L} q_{ml}$ score, the solutions can also be classified as ideal solutions (with R_m+ score) and anti-ideal solutions (with R_m- score) from the perspective of all indicator criteria collectively [13,41].

The weights of the criteria are crucial for conducting MCDM analysis. Various methods can be utilised to calculate the weights of the criteria; however, we employed the Preference Selection Index (PSI) method, which is one of the latest methods that assigns weights to criteria based on their relative importance [42]. The procedural steps of the PSI method that can assist in calculating the weights of the indicator criteria are outlined in Section II in SM.

3. Case study

Pakistan is strategically located to achieve energy sustainability, with significant potential for solar, wind, and hydropower generation (rationale of choosing case study country is mentioned in Section III of SM). To achieve the objectives, the modelled HES scenarios were evaluated for nine metropolitan regions in Pakistan. These regions cover various geographical dimensions of the country and account for over 20% of the total population [43], with a majority of residents having a stable financial status. The metropolitan regions for this study include Islamabad/Rawalpindi (ISL/RWP), Karachi (KHI), Lahore (LHR), Peshawar (PEW), Quetta (QTA), Faisalabad (FSD), Gujranwala (GRW), Multan (MTN), and Hyderabad (HYD). Detailed geographical and meteorological information, along with the calculated optimal slope angles for these regions, are provided in Table S-5 in SM.

4. Results and analysis

The findings of the study are presented and analysed as follows: preliminary assessment of the modelled HES scenarios in terms of technical and economic aspects, Pareto configurations of HES scenarios, and post-Pareto decision-making for optimal solutions.

4.1. Preliminary assessment of modelled HES scenarios

The preliminary assessment of the modelled HES scenarios focused on evaluating their technical impacts and economic feasibility for achieving better energy sustainability in the residential sector. To accomplish this, the technical and economic indicators obtained from evaluating the modelled HES scenarios in RETScreen tool were imported into Microsoft excel for quantifying the cumulative impacts and feasibility. The results are presented in Figs. 2-4.

The prime focus of integrating RE sources into the existing electrification system is to reduce reliance on GES and the usage of GnES. The technical impact of the modelled HES scenarios was evaluated based on various factors, as shown in Figs. 2-3. Fig. 2 demonstrates the technical evaluation of HES scenarios in terms of EE delivered directly to the load by RES, EE exported to the grid by RES, and the area covered by PV modules. Fig. 3 depicts the technical evaluation in terms of the EE delivered to the load by GES and GnES for backup and electrification during load-shedding hours, respectively, and the fuel consumption in the baseline and the proposed cases.

The analysis of the outcomes presented in Figs. 2-3 revealed that the HES scenarios generated EE ranging from 10 to 28.5 MWh, with variations primarily based on latitude and HES configuration type. To generate this amount of EE, the required area for solar PV modules ranged from 87 to 127 m^2, which could be accommodated in over 50% of the residential units in the studied regions. The generated EE satisfied 82–99% of the load requirements, with the remaining load being fulfilled by GES or GnES. The modelled HES scenarios resulted in a reduction of 4.0–7.7 thousand liters of conventional fuel consumption compared to the baseline case. The impact assessment of HES scenarios based on configuration types revealed that GC configurations generated 123–145% more EE compared to OG configurations with the same PV modules area. However, OG configurations met a slightly higher percentage of direct load requirements due to the ESS integrated with RES. GC configurations exported a significant amount of EE to the grid, addressing fewer direct load requirements but requiring more energy supply from GES compared to OG configurations.

The integration of RES resulted in a significant reduction of 64–99% in conventional fuel consumption for electricity generation. However, integrating GnES for load-shedding hours led to much higher fuel consumption compared to GES when generating equivalent kWhs. For instance, in the modelled HES scenarios, integrating GnES increased fuel consumption by 316–342% and 233% for OG and GC configurations, respectively, while attempting to meet 1–2% and 13–17% of EE demand for OG and GC configurations, respectively. The technical assessment considering different types of solar PV module revealed that mono-Si PV modules required 6–9.5% less area but generated approximately 0.35–0.36% less EE compared to poly-Si PV modules. The analysis also showed regional variations in EE generation, with the highest EE generation values observed in GRW, QTA, PEW, and KHI, and the lowest in ISL/RWP.

The economic feasibility of the modelled HES scenarios was assessed using financial indicators such as net present value (NPV), payback period (PBP), BCR, and total investment, as presented in Fig. 4. The analysis revealed a range of feasibility, with total investments ranging from 6.9 to 18.5 thousand USD, PBP from 3.1 to 23.1 years, NPV from

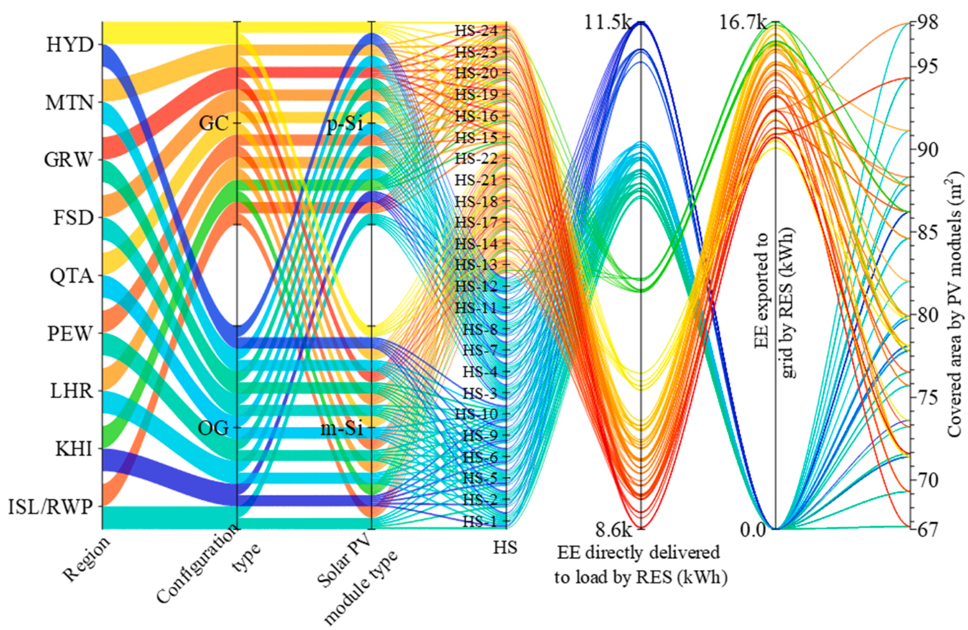

Fig. 2. Technical impact assessment in the terms of EE delivered to the load, EE exported to the grid, and covered area for modelled HES scenarios for the studied regions.

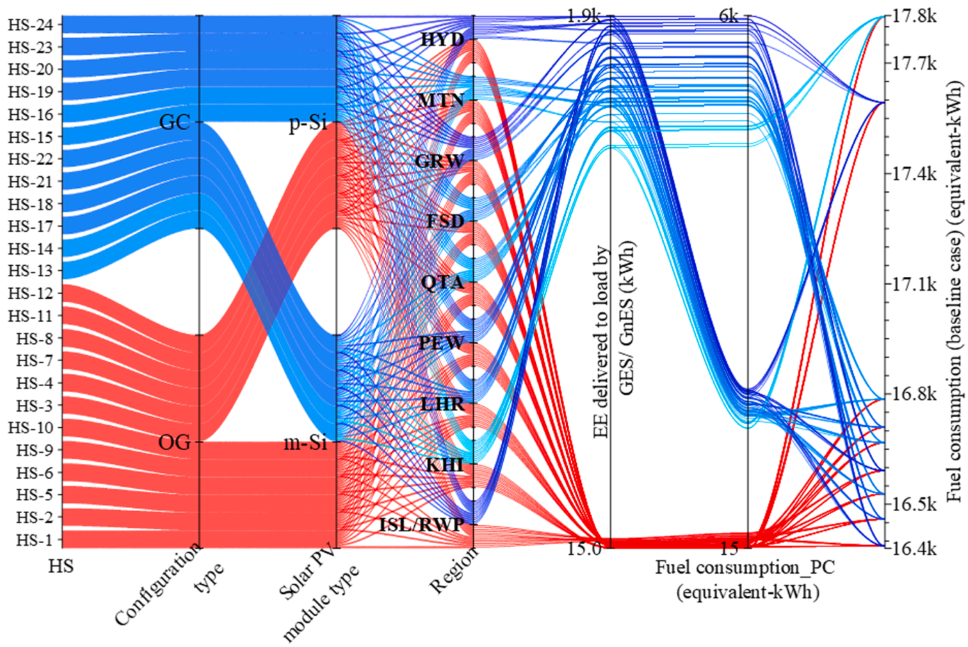

Fig. 3. Technical impact assessment in the terms of EE delivered to load by GES/ GnES and conventional fuel consumption in the baseline and proposed cases (PC) of modelled HES scenarios for the studied regions.

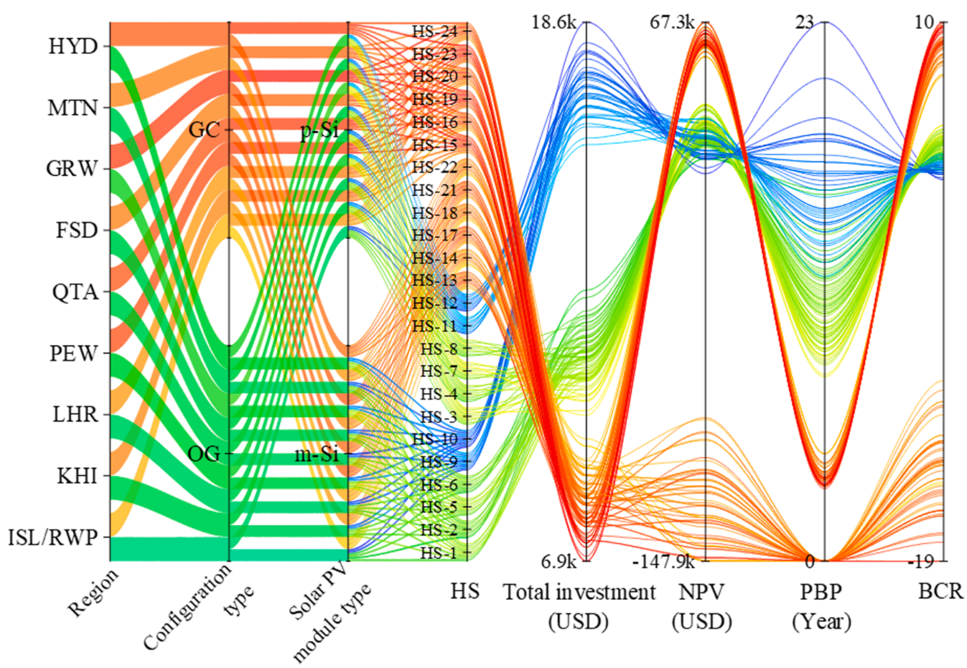

Fig. 4. Economic feasibility assessment of the modelled HES scenarios for the studied regions.

6.7 to 67.2 thousand USD, and BCR from 1.4 to 9.8. However, when considering load-shedding factor and integrating GnES, the economic feasibility was significantly reduced. GC configurations were found to be more economically feasible compared to OG configurations due to shorter PBP, higher NPV, and BCR values. However, when integrating GnES, the economic assessment revealed negative NPV, BCR, and undefined PBP for GC configurations. Poly-Si PV modules were somewhat more economically feasible than mono-Si modules, primarily due to their lower price. From the regional perspective, KHI exhibited the highest economic feasibility, while ISL/RWP demonstrated the least economic feasibility.

Overall, the integration of RE into the existing electrification system showed potential for reducing conventional fuel consumption and improving energy sustainability. However, the economic feasibility varied depending on factors such as HES configuration, PV module type, and regional considerations.

4.2. Pareto configurations of modelled HES scenarios

The optimisation of HES involved the exploration of various design scenarios for multiple regions utilising the procedure outlined in Section 2.3.1. This multi-regional optimisation approach offers improved decision-making opportunities for stakeholders. It proves particularly beneficial when the resources required for replacing conventional sources with renewables, such as area, budget, stakeholder preferences, and risk attitudes, differ across regions. Moreover, this approach is useful for stakeholders seeking a comprehensive understanding of the trade-offs between costs and benefits at varying scales. It facilitates informed decision-making by providing a thorough and comparative analysis of integrating renewables into existing energy infrastructures in different regions.

The approximate Pareto optimal solution designs for modelled HES scenarios in nine different regions under defined objective functions are presented in Figs. 5 and S-1 (Pareto optimal designs for KHI are presented as an example in Fig. 5, while Pareto optimal designs for remaining eight regions are presented in Figure S-1 in SM). The vertical axis of these figures demonstrates the objective function, while horizontal line represents non-dominated Pareto optimal solutions (in total of 300 solutions for each region). To reduce the randomness factor in Pareto optimal solutions, we executed the optimization algorithm ten times for each region and aggregated the average of the Pareto optimal solutions to generate the final set of solutions for each region, as demonstrated in Figs. 5 and S-1. The corresponding optimal values for decision variables are presented in Figs. 6 and S-2 (optimal decision variable values for KHI are presented as an example in Fig. 6, while optimal decision variable values for remaining eight regions are presented in Figure S-2 in SM).

The complete spectrum of colors in Figs. 5 and S-1 indicates the retrofit costs in relation to the output energy from RES, BCR, and reduction in GHG emissions, with blue being the highest and red being the lowest. The analysis of the spectrum revealed a general trend: as retrofit costs increased, the output energy from RES and GHG emissions reduction increased, while BCR decreased. Take KHI as an example to elaborate the outcomes, optimising the retrofit cost to be between 4.96 and 6.69 thousand USD led to a reduction in grid power consumption in the residential sector by 12.8 to 17.36 MWh through the use of RES. This optimal power generation from RES was supported by the incident solar radiations of 9.28 to 9.36 kWh/m^2 on 38 to 51 number of PV modules, resulting in a reduction of 5.69 to 7.68 thousand tCO_2 GHG emissions with a BCR 4.27 to 5.42, as shown in Figs. 5 and 6.

The multi-regional analysis of Pareto optimal solution designs (Figs. 5 and S-1) revealed that KHI exhibited the highest potential for generating energy from RES and reducing GHG emissions within the retrofit cost range of 4.96 to 6.69 thousand USD. This retrofit cost value was 1.4 to 9.6% greater compared to FSD, MTN, LHR, and ISL/RWP, while it was 10.7 to 17.5% lesser compared to GRW, PEW, QTA, and HYD. On the contrary, ISL/RWP exhibited the least potential for generating energy from RES, amounting to 7.4 to 10.1 MWh, and reducing GHG emissions by 3.2 to 4.4 thousand tCO_2, with a retrofit cost of 5.4 to 7.4 thousand USD and a BCR of 1.9 to 2.3.

Amongst the corresponding decision variables (presented in Fig. 6 and Figure S-2 in SM), the number of PV modules and incident solar radiations are critical decision variables that primarily determine the total energy generated by RES and the associated retrofit cost parameters. The GHG emissions factor is influenced by the energy mix and exhibits an inverse relation with the total reduction in GHG emissions. The analysis of Figs. 6 and S-2 revealed that the regions of GRW, PEW, QTA, HYD, and KHI had the lower range of optimal number of PV modules, in that order, than KHI. Consequently, these regions had lower retrofitting costs compared to KHI. Conversely, FSD, MTN, LHR, and ISL/RWP had a higher range of optimal number of PV modules compared to KHI, but the energy generated by RES in these regions was 18.4 to 42.3% lower owing to low incident solar radiations.

Therefore, incorporating multiple optimal solution designs for HES with varying retrofitting costs and under different scenarios can enhance the understanding of decision-makers and stakeholders regarding the combined benefits for the studied regions. This approach facilitates the prioritisation and selection of the most suitable optimal solution designs for implementation by considering optimised parameters, such as the number of PV modules in light of factors such as available space, budget, stakeholders' preferences, and market availability. Additionally, weather parameters, such as incident solar radiations, latitude, air pressure, and wind speed, can also influence the decision of stakeholders.

4.3. Post-Pareto decision-making for optimal solutions

The post-Pareto decision-making analysis was performed to facilitate the selection of the best optimal designs for HES from a large set of approximated Pareto optimal solutions. This decision-making analysis was conducted in three phases, including prioritizing the Pareto optimal solutions, classifying the Pareto optimal solutions, and determining the most and least suitable regions. To accomplish the post-Pareto decision-making process, the MABAC decision-making method, combined with the PSI method, was employed, where the PSI method was initially employed to calculate the importance of the performance indicators.

To begin with the post-Pareto decision-making analysis, first, the 300 approximated Pareto optimal solutions were prioritized based on their

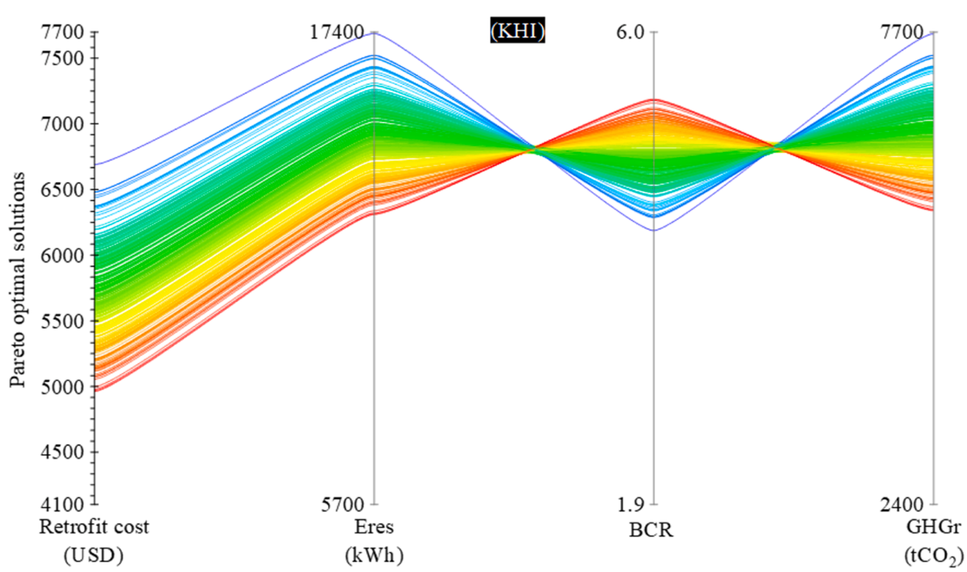

Fig. 5. Pareto optimal solutions for objective functions.

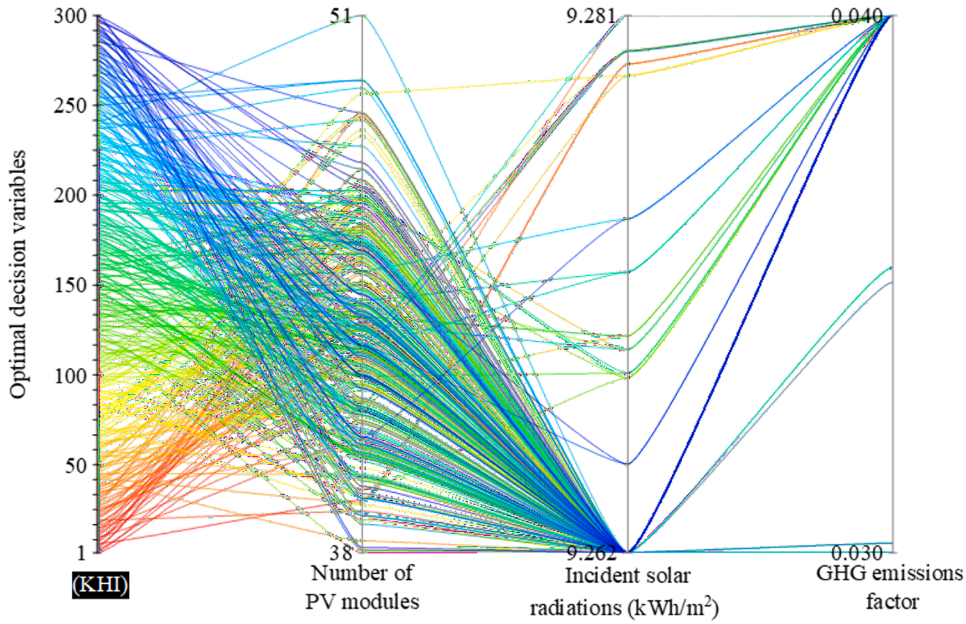

Fig. 6. Optimal values for decision variables.

composite MABAC scores. The decision analysis of Pareto optimal designs for KHI region is presented as an example in Fig. 7 and the analysis for the remaining eight regions is presented in Figure S-3, where the top ten ranked optimal solutions are highlighted, and their corresponding optimal solution values are listed in Table S-6. The results revealed that each region had a diverse range of best Pareto optimal solution designs, encompassing different retrofit costs and associated optimal benefits. This indicates the feasibility of implementing HES across a variety of options, considering the financial resources of investors.

Moreover, to identify the acceptability nature of the Pareto optimal solution designs, a unique feature of the MABAC method, which relies on the distance value of the alternatives from BAA value, was utilized [13]. According to this feature, solutions with positive distance values lie above the BAA line and are classified as acceptable solutions, while those with negative distance values lie below the BAA line and are classified as unacceptable. The outcomes elaborating the classification of Pareto optimal solutions are illustrated in Fig. 8. The analysis revealed that 1948 solutions out of total 2700 (73.5%) were classified as acceptable, indicating their potential for implementation in improving energy sustainability. Amongst the studied regions, QTA had the highest number of acceptable solutions (243 out of 300). Interestingly, the ISL/RWP region, which was found least feasible region in general, contained the second-highest number of acceptable solutions. Overall, each region had over 200 acceptable solutions, which is a significant number to consider for implementation, taking into account the affordability of investors in achieving better energy sustainability in the residential sector.

To rank the studied regions and determine the most and least suitable ones, a new scenario, indicated as an overall analysis scenario, was established based on insights from a recent work [8]. The overall scenario involved selecting the top ten ranked solutions for each studied region, whose details including performance indicator values, MABAC scores, and rankings, are listed in Table S-6. These all-selected solutions were also classified as acceptable owing to their positive distances from BAA value, as illustrated in Figure S-4. The MABAC scores of the selected solutions in overall scenario were calculated by employing the

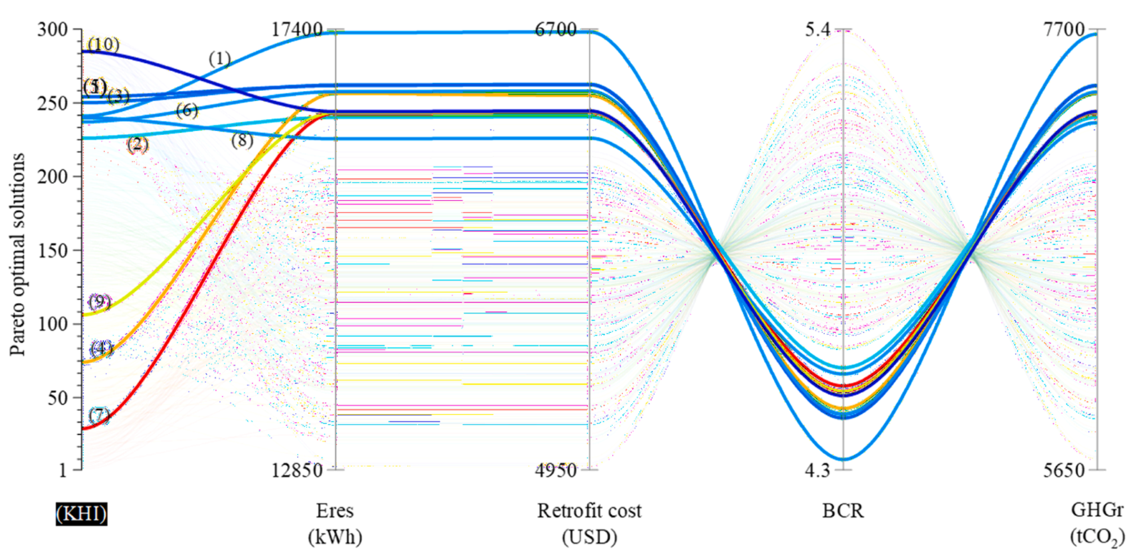

Fig. 7. Decision-making analysis of the Pareto optimal solutions (top ten are highlighted).

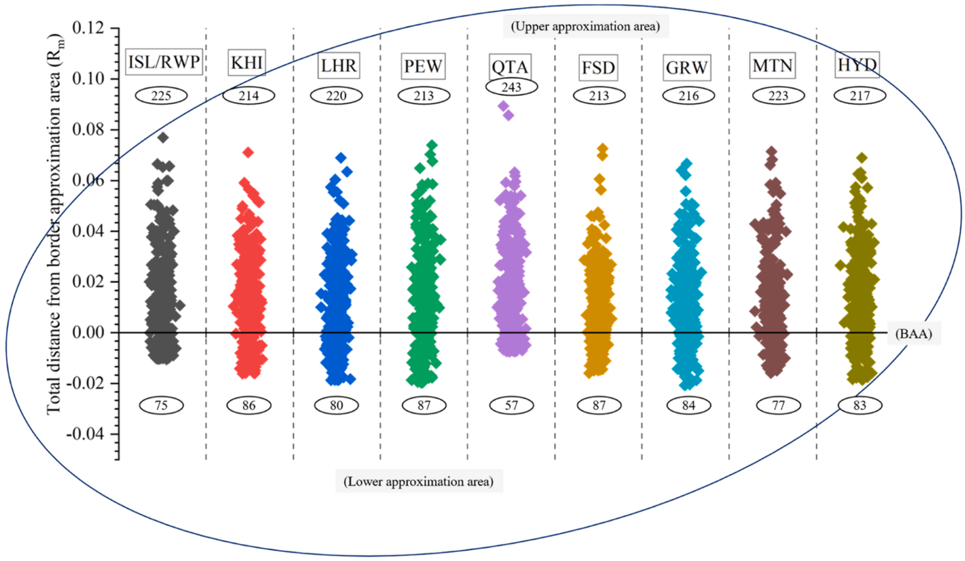

Fig. 8. The classification of the Pareto optimal solutions.

procedural steps of the MABAC method. Subsequently, the studied regions were ranked based on the aggregated MABAC score (as shown in Fig. 9), which was obtained by averaging the MABAC scores of the ten selected solutions for each region in overall scenario.

The analysis of the overall scenario (Table S-6 and Figure S-4) revealed that the best compromised Pareto optimal solution design belonged to QTA regions. This design offered a 13.2 MWh energy generation potential, a 5.97 thousand tCO_2 GHG emissions reduction potential, and a 3.24 BCR at a retrofitting cost of 5.75 thousand USD. On the contrary, the least compromised Pareto optimal solution design in overall scenario analysis belonged to FSD region, with 6.39 thousand USD retrofitting cost and resulted in a 13.7 MWh energy generation potential, a 6.0 thousand tCO_2 GHG emissions reduction potential and a 3.09 BCR. In general, the comparative analysis of the studied regions based on the overall scenario analysis revealed that the KHI region was the most suitable, offering cumulative greater benefits in terms of energy generation from RES and reduction in GHG emissions. It was followed by the HYD and QTA regions, and then the following descending order with fractional disparities: FSD > GRW > MTN > PEW. The LHR region was found to be the second-least feasible, while the ISL/RWP region as the least feasible, with minimal benefits in relation to the corresponding optimal retrofit costs.

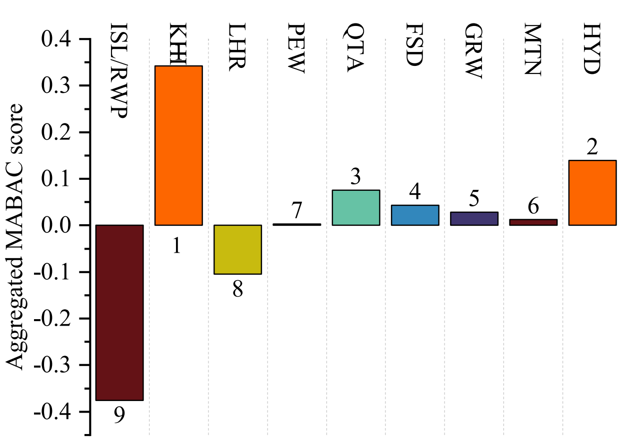

Fig. 9. Overall scenario-based decision-making analysis for the studied region.

5. Discussion and recommendations

The scenario-based analysis is a critical analytical tool that was applied to investigate the sustainability of HES in metropolitan regions of Pakistan. The preliminary examination of the modelled HES scenarios demonstrated the significant technical impact and economic feasibility of integrating RE sources to meet residential electricity needs. However, this techno-economic evaluation was primarily influenced by the integration of GnES into HES. In Pakistan, GnES are commonly used during load-shedding hours to generate emergency electricity. The scenario-based analysis revealed that integration of GnES resulted in an undefined PBP and a reduced NPV, consequently leading to higher levelized cost of electricity (LCOE). Notably, HES configurations that integrated GnES were found to be economically unfeasible and environmentally detrimental. GnES rely on conventional oil fuels, whose prices have risen significantly in recent months [44]. Considering the country's heavy reliance on imported fuels [45], and the prevailing severe inflation, it is anticipated that GnES will incur incrementally higher LCOE. This situation adversely impacts residents who experience spikes in LCOE, with further increase expected in the future.

Optimising the selected performance indicators of HES resulted in determining 300 Pareto optimal solutions for each studied regions, totalling 2700 solutions. The analysis summarised in Fig. 10 showcased the substantial potential of these solution designs in achieving energy sustainability. The findings indicated a flexible range of retrofit costs, with the lowest cost approximately 30% lower than the highest cost, while still allowing for optimal benefits in terms of clean power generation. Moreover, the optimal ranges of performance indicators overlapped for all regions, implying the existence of solution designs that could have equally impactful outcomes across the studied regions without contradictions. Consequently, a majority of residents can invest in installing the optimal HES configurations based on their affordability, resulting in multiple benefits, such as alleviating strain on the grid infrastructure, supplying excess generated EE to the distribution system, and reducing dependence on imported fuel and its associated combustion, thereby promoting a healthier and cleaner environment.

It is worth noting that the government's capability to purchase essential resources, such as oil and gas, has been diminishing due to mounting foreign debt and low foreign reserves. Conversely, the growing population necessitates more housing units, leading to a significant influx of people into metropolitan regions, such as LHR, GRW, FSD, and MTN. As a result, the resident count in these areas is expanding at an alarming rate. Therefore, the increasing urbanization presents both

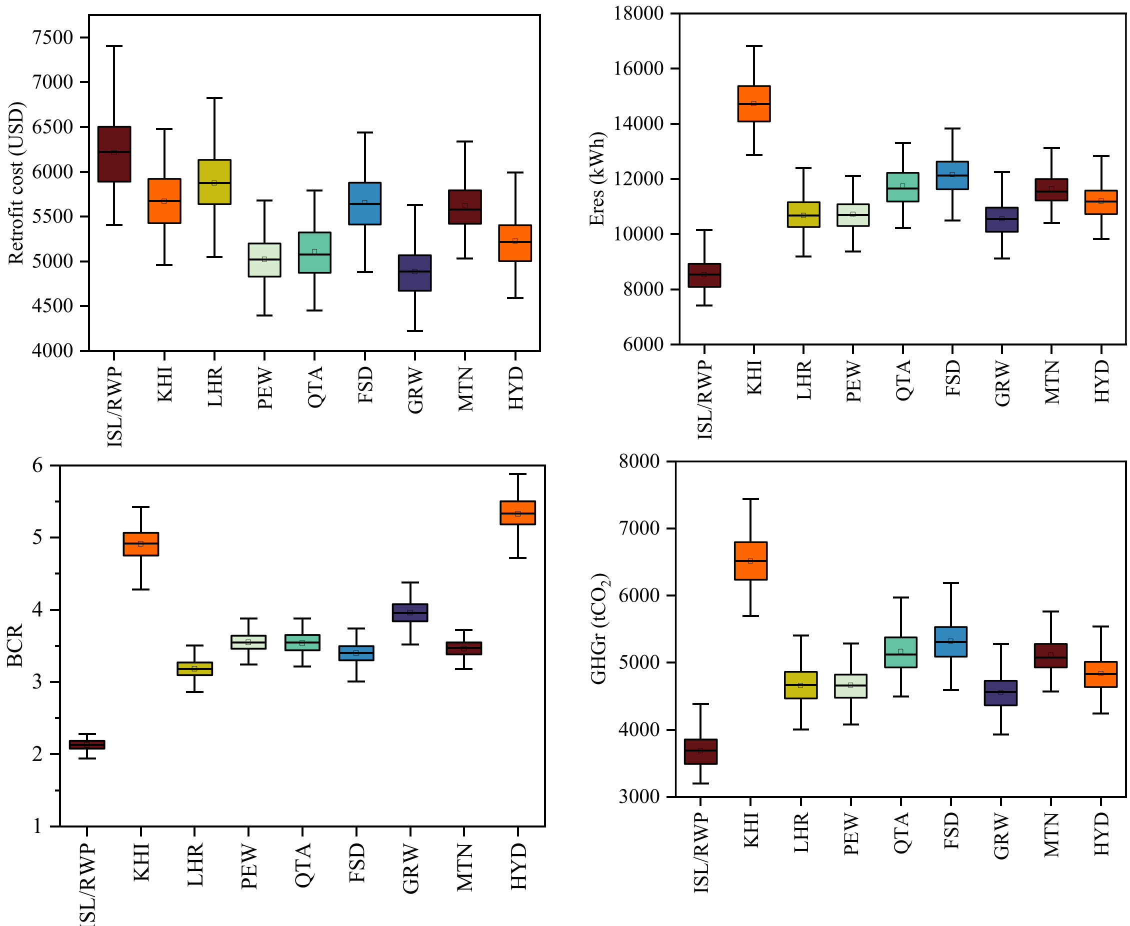

Fig. 10. Summary of the determined 300 Pareto optimal solutions for the studied regions.

an opportunity and a necessity to encourage residents to adopt optimal HES with integrated RE sources through appealing incentive schemes. This approach would help balance the rising energy demand and address the prevailing issues of load-shedding.

Based on the analysis and discussion of the results, some implications are made to assist governmental authorities in Pakistan's residential sector in formulating policies aiming at achieving better energy sustainability. The following recommendations are made:

- Considering the determined Pareto optimal solution designs for studied regions, the reginal policies should be developed by the government, specifically focusing on providing additional incentives and benefits for regions that exhibit relatively higher feasibility, such as Karachi, Quetta, and Hyderabad.
- The government should actively discourage the use of GnES in the domestic sector to lessen the demand for imported fuels. Conversely, a clear policy framework should be established to promote the integration of RE sources into existing infrastructure, including incentives for cleaner production and carbon credits.
- In addition to the energy consumption billing system, measures such as imposing taxes on excessive energy consumption for luxuries and energy waste should be introduced. These measures would contribute to a decrease in overall EE demand. Furthermore, efforts should be made to control power theft by utilising theft-detection smart devices [46].

6. Conclusions

This study developed a multi-stage optimisation-based decision-making framework for HES aiming at achieving better energy sustainability in the residential sector. In the developed framework, a HES model was initially designed, and various electrification scenarios were modelled for metropolitan regions in Pakistan by using a holistic system-thinking approach. These scenarios were then analysed and optimised through three stages, including (1) a preliminary assessment of technical and economic aspects, (2) optimisation of the HES size by utilising the NSGA-II algorithm, and (3) selection of optimal solution designs and locations based on system performance indicators by employing the MCDM method. The key findings of this study are summarised as follows:

- The preliminary evaluation of 216 modelled HES scenarios indicated that GC configurations were more plausible compared to OG configurations. However, the inclusion of GnES with GC configurations to address load-shedding reduced their feasibility significantly.
- A total of 2700 non-dominated Pareto optimal HES designs were determined for nine regions, with 300 designs for each region. These designs offered a flexible range of retrofit costs and associated benefits for each region. KHI had the best range of optimal benefits, while ISL/RWP had the lowest range of optimal benefits.
- The comparison of Pareto optimal designs across all the studied regions showcased competition amongst the designs to excel in specific ranges of optimal solution values, with the highest energy generation and GHG emissions reduction values in KHI, the highest BCR values in HYD, and lowest retrofit cost values in GRW.
- The decision-making analysis of Pareto optimal solutions concluded with the identification of the best compromised optimal solution in QTA. Overall, 73.5% (1948 out of 2700) of the Pareto optimal

solutions were deemed acceptable, with over 200 acceptable solutions for each of the studied regions.
- The region-based ranking of Pareto-optimal solutions demonstrated that all studied regions had a wide and flexible range of objective functions for Pareto optimal HES designs, which encourages residents to invest in HES installations based on their affordability.
- The analysis of Pareto optimal solutions in the overall scenario concluded that Karachi (KHI) is the most suitable region to start installing optimal HES configurations, followed by Hyderabad (HYD) > Quetta (QTA) > Faisalabad (FSD) > Gujranwala (GRW) > Multan (MTN) > Peshawar (PEW) > Lahore (LHR) > Islamabad/Rawalpindi (ISL/RWP).

This study represents an initial step in developing a multi-stage optimisation-based decision-making framework that offers systematic approaches for HES system designing and scenario-based multi-regional optimal decision-making. The developed framework can assist policymakers in formulating clear policies that support investors insight into their financial standing. Implementing the Pareto optimal solutions identified in this study can significantly contribute to progress in achieving energy sustainability in the residential sector. However, it is noteworthy that the consideration of specific technical design variables for conceptualising HES scenarios was a primary limitation of this work, and the future work could expand the framework to include economic parameters. Additionally, the scenario-based optimisation of HES was conducted by using a limited number of objectives functions and focused on metropolitan regions in Pakistan. Extending the energy model and decision-making framework to include poly-generation systems and deriving optimal solutions would be an intriguing expansion of this study.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.sftr.2023.100122.

References

[1] OECD, 'Global Forum on Environment: new perspectives on the Water-Energy-Food-Nexus'. Published by Organization for Economic Co-operation and Development. available at: https://www.oecd.org/environment/nexus.htm.
[2] U.N., 'Sustainable development - department of economic and social affairs'. United Nations. available at: https://sdgs.un.org/.
[3] S. Radini, et al., Urban water-energy-food-climate nexus in integrated wastewater and reuse systems: cyber-physical framework and innovations, Appl. Energy 298 (2021), 117268.
[4] J.-L. Fan, X. Feng, Y. Dong, X. Zhang, A global comparison of carbon-water-food nexus based on dietary consumption, Glob. Environ. Chang. 73 (2022), 102489.
[5] F.Fuso Nerini, et al., Mapping synergies and trade-offs between energy and the sustainable development goals, Nat. Energy 3 (1) (2018) 10–15.
[6] M. Moner-Girona, G. Kakoulaki, G. Falchetta, D.J. Weiss, N. Taylor, Achieving universal electrification of rural healthcare facilities in sub-Saharan Africa with decentralized renewable energy technologies, Joule 5 (10) (2021) 2687–2714.
[7] H. Yazdani, M. Baneshi, Building energy comparison for dynamic cool roofs and green roofs under various climates, Sol. Energy 230 (2021) 764–778.
[8] H. Yazdani, M. Baneshi, M. Yaghoubi, Techno-economic and environmental design of hybrid energy systems using multi-objective optimization and multi-criteria decision making methods, Energy Convers. Manage. 282 (2023), 116873.
[9] E. Kabalci, Hybrid Renewable Energy Systems and Microgrids, Academic Press, 2020.
[10] S. Azizi, N. Nedaei, M. Yari, Proposal and evaluation of a solar-based polygeneration system: development, exergoeconomic analysis, and multi-objective optimization, Int. J. Energy Res. 46 (10) (2022) 13627–13656.
[11] R. Khezri, A. Mahmoudi, H. Aki, Optimal planning of solar photovoltaic and battery storage systems for grid-connected residential sector: review, challenges and new perspectives, Renew. Sustain. Energy Rev. 153 (2022), 111763.
[12] T. Mai, et al., Getting to 100%: six strategies for the challenging last 10%, Joule (2022).
[13] A. Mehmood, L. Zhang, J. Ren, T. Zayed, C.K. Lee, Multi-facet assessment and ranking of alternatives for conceptualizing sustainable hybrid energy infrastructure in Pakistan based on evidential reasoning driven probabilistic tool, J. Clean Prod. 378 (2022), 134566.
[14] H. Ritchie, M. Roser; and P. Rosado., 'Energy'. published at Our World in Data. available at: https://ourworldindata.org/energy.
[15] X. Liu, Q. Tan, Y. Niu, R. Babaei, Techno-economic analysis of solar tracker-based hybrid energy systems in a rural residential building: a case study in South Africa, Int. J. Green Energy 20 (2) (2023) 192–211.
[16] O.M. Babatunde, J.L. Munda, Y. Hamam, How can a low-income household procure small-scale hybrid renewable energy system? A techno-economic and acquisition analysis, Int. J. Energy Sect. Manage. (2019).
[17] Y. Li, W. Yang, P. He, C. Chen, X. Wang, Design and management of a distributed hybrid energy system through smart contract and blockchain, Appl. Energy 248 (2019) 390–405.
[18] G.A. Barzegkar-Ntovom, et al., Assessing the viability of battery energy storage systems coupled with photovoltaics under a pure self-consumption scheme, Renew. Energy 152 (2020) 1302–1309.
[19] B.K. Das, M.S.H. Tushar, R. Hassan, Techno-economic optimisation of stand-alone hybrid renewable energy systems for concurrently meeting electric and heating demand, Sustain. Cities Soc. 68 (2021), 102763.
[20] D. Kumar, T. Tewary, Techno-economic assessment and optimization of a standalone residential hybrid energy system for sustainable energy utilization, Int. J. Energy Res. 46 (8) (2022) 10020–10039.
[21] A. Aslam, N. Ahmed, S.A. Qureshi, M. Assadi, N. Ahmed, Advances in solar PV systems; a comprehensive review of PV performance, influencing factors, and mitigation techniques, Energies 15 (20) (2022) 7595.
[22] M. Thirunavukkarasu, Y. Sawle, H. Lala, A comprehensive review on optimization of hybrid renewable energy systems using various optimization techniques, Renew. Sustain. Energy Rev. 176 (2023), 113192.
[23] Ş. Okul, D. Aksu, Z. Orman, Investigation of artificial intelligence based optimization algorithm, İstanbul Sabahattin Zaim Üniversitesi Fen Bilimleri Enstitüsü Dergisi (İZÜFBED)/Journal of Istanbul Sabahattin Zaim University Natural Sciences Institute (JIZUNSI) (2019).
[24] D.H. Kim, 'Introduction to Systems Thinking'. available at: https://thesystemsthinker.com/introduction-to-systems-thinking/.
[25] Ecochallenge, 'A systems thinking model: the Iceberg'. available at: https://ecochallenge.org/iceberg-model/.
[26] Z. Said, A. Mehmood, A. Waqas, A.A. Hachicha, R. Loni, Central versus off-grid photovoltaic system, the optimum option for the domestic sector based on techno-economic-environmental assessment for United Arab Emirates, Sustain. Energy Technol. Assess. 43 (2021), 100944.
[27] A. Mehmood, J. Ren, L. Zhang, Achieving energy sustainability by using solar PV: system modelling and comprehensive techno-economic-environmental analysis, Energy Strategy Rev. 49 (2023) 101126.
[28] M. Siddique, N. Shahzad, S. Umar, A. Waqas, S. Shakir, A.K. Janjua, Performance assessment of Trombe wall and south façade as applications of building integrated photovoltaic systems, Sustain. Energy Technol. Assess. 57 (2023), 103141.
[29] M.P. Bakht, Z. Salam, A.R. Bhatti, U. Ullah Sheikh, N. Khan, W. Anjum, Techno-economic modelling of hybrid energy system to overcome the load shedding problem: a case study of Pakistan, PLoS One 17 (4) (2022) e0266660.
[30] Z. Said, A. Mehmood, Standalone photovoltaic system assessment for major cities of United Arab Emirates based on simulated results, J. Clean Prod. 142 (2017) 2722–2729.
[31] RETScreen, 'Clean energy project analysis: RETScreen engineering and cases textbook', 3rd edition. available at: https://msessd.ioe.edu.np/wp-content/uploads/2017/04/Textbook-clean-energy-project-analysis.pdf.
[32] J.A. Duffie, W.A. Beckman, N. Blair, Solar Engineering of Thermal processes, Photovoltaics and Wind, John Wiley & Sons, 2020.
[33] 'Conumser-end applicable tariff'. National Electric Power Regulatory Authority. available at: https://nepra.org.pk/consumer%20affairs/Electricity%20Bill.php.

[34] S. Kumar, et al., Multi-objective optimization for stormwater management by green-roofs and infiltration trenches to reduce urban flooding in central Delhi, J. Hydrol. (Amst) 606 (2022), 127455.

[35] J. Jemai, M. Zekri, K. Mellouli, An NSGA-II algorithm for the green vehicle routing problem, in: Evolutionary Computation in Combinatorial Optimization: 12th European Conference, EvoCOP 2012, Springer, Málaga, Spain, 2012, pp. 37–48. *April 11-13, 2012. Proceedings 12*.

[36] A. Kamjoo, A. Maheri, A.M. Dizqah, G.A. Putrus, Multi-objective design under uncertainties of hybrid renewable energy system using NSGA-II and chance constrained programming, Int. J. Electr. Power Energy Syst. 74 (2016) 187–194.

[37] H.G. Rodriguez, J. Popp, C. Maringanti, I. Chaubey, Selection and placement of best management practices used to reduce water quality degradation in Lincoln Lake watershed, Water Resour. Res. 47 (1) (2011).

[38] A. Preis, A. Ostfeld, Multiobjective contaminant sensor network design for water distribution systems, J. Water Resour. Plann. Manage. 134 (4) (2008) 366–377.

[39] H. Ren, Y. Lu, Q. Wu, X. Yang, A. Zhou, Multi-objective optimization of a hybrid distributed energy system using NSGA-II algorithm, Front. Energy 12 (2018) 518–528.

[40] H. Tansar, H.-F. Duan, O. Mark, A multi-objective decision-making framework for implementing green-grey infrastructures to enhance urban drainage system resilience, J. Hydrol. (Amst) 620 (2023), 129381.

[41] A.E. Torkayesh, E.B. Tirkolaee, A. Bahrini, D. Pamucar, A. Khakbaz, A systematic literature review of mabac method and applications: an outlook for sustainability and circularity, Informatica. (2023) 1–34.

[42] K. Maniya, M.G. Bhatt, A selection of material using a novel type decision-making method: preference selection index method, Mater. Des. 31 (4) (2010) 1785–1789.

[43] Population Census, Pakistan bureau of statics- govt. of Pakistan. http://www.pbs.gov.pk/population-tables, 2017.

[44] SCMP, 'Rich getting richer: Pakistan's packed tim hortons reveals growing disparity as crisis brews', published by South China Morning Post. 15-Feb-2023. available at: https://www.scmp.com/news/asia/south-asia/article/3210190/rich-getting-richer-pakistans-packed-tim-hortons-reveals-growing-disparity-crisis-brews?module=perpetual_scroll_0&pgtype=article&campaign=3210190.

[45] S. Mishra, 'Pakistan's Economic crisis', Michigan News, University of Michigan, 2023 available at: https://news.umich.edu/pakistans-economic-crisis/.

[46] A. Mehmood, M.S. Shaheen, H. Ghaffar, H.E. Gelani, Data preservation and energy theft control in smart meterS, J. Electric. Eng. 13 (4) (2013), 6-6.