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Research article

COVID-19 impact on wind and solar energy sector and cost of energy prediction based on machine learning

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ABSTRACT

This study examines the impact of the COVID-19 pandemic on renewable energy sectors across seven countries through techno-economic analysis and machine learning (ML). In China, the renewable fraction decreased in grid-connected systems due to 14.6 % higher diesel fuel prices. They reduced grid electricity prices, with Cost of Energy (COE) reductions driven by a 2.8 % inflation decrease and a 3 % discount rate cut. The increase in renewable energy adoption in the USA during the pandemic was driven by decreased initial and operational costs of renewable components, a significant rise in diesel fuel prices, and government policy changes, despite a reduction in renewable energy sell-back prices and rising capital and annual costs due to expanded renewable capacity. Canada noted a shift to standalone systems with 50 % lower PV sell-back prices, 2 % lower WT prices, and a 48 % fuel cost rise, reducing COE except in grid/WT scenarios. Germany managed rising electricity and fuel costs, decreasing COE despite inflation. India expanded standalone HRESs driven by a sevenfold PV capacity increase, lowering COE. Japan saw stable COE with minimal variation. Iran faced economic challenges with a 104 % inflation increase, impacting COE despite a grid-connected COE decrease. Machine learning forecasts suggest that COVID-19 may cause an increase in COE in China and India due to pandemic effects.

1. Introduction

In December 2019, a novel virus was discovered in Wuhan, China [1,2]. This virus rapidly spread worldwide and evolved into a pandemic. Consequently, on January 30, 2020, the World Health Organization (WHO[1]) officially declared COVID-19 a global pandemic and public health emergency of international concern [3]. In a short period, COVID-19 caused widespread closure of public places, quarantine [4], and numerous fatalities [5]. According to WHO data, as of July 2022, more than 775 million cases of COVID-19 have been reported worldwide, with over 7 million fatalities [6].

The advent of the COVID-19 pandemic has profoundly impacted human life and government policies across various domains,

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[1] Nomenclature table, including Abbreviations and Greek Symbols, can be found in Appendix A1.

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particularly in the energy sector. Implementing quarantine measures and closing businesses and industries led to an abrupt decrease in energy consumption in numerous countries. Statistical data reveals that the United States of America (USA) experienced its most significant decline in energy consumption since World War II due to the COVID-19 pandemic [7]. The swift spread of the COVID-19 epidemic and its substantial influence on the energy sector have highlighted the criticality of sustainability within this domain [8]. A comparison of energy consumption in China between 2019 and 2020 demonstrates an 8 % reduction during January and February [9]. However, another study analyzing long-term data on energy consumption during the pandemic in China reveals a decline of almost 25 % compared to the scenario without the pandemic [10]. Meanwhile, Germany experienced a notable decrease in energy usage within the energy sector, coupled with an increased share of renewable energy, reaching 41 % [9]. In contrast, residential energy consumption in the USA witnessed a 20 % rise, whereas electricity sales to industries dropped by 4.2 % in 2020 [9]. It is estimated that energy consumption during the lockdown in India decreased by 20–40 % [11]. A study conducted solely in the Ontario province of Canada revealed a 14 % decline in energy usage within the electricity sector [12]. Additionally, Japan experienced a 7.8 % decrease in electricity demand in 2020 [13]. In countries like Iran, where fossil fuels meet primary electricity demands, the yearly energy consumption remained unchanged. A comparison of electricity production in Iran between 2019 and 2020 shows a modest increase of 0.93 % [14], as depicted in Fig. 1(a), which illustrates electricity production during the COVID-19 lockdown in 2019 and 2020 for selected industrialized countries and Iran [14]. Although China witnessed a decline in power usage during January and February, overall electricity production increased by 3.8 %.

The sudden fluctuations in energy consumption have also impacted the renewable energy market. Several reports indicate that the reduction in energy usage has led to a 7 % increase in the share of renewable energy consumption in 2020 [14], setting new records in countries such as Germany and the USA [15]. Fig. 1(b) depicts the production of renewable electricity in various countries [14]. According to the figure, China experienced a 9.7 % rise in renewable electricity production during the COVID-19 lockdown. However, India's change in this regard was negligible. In contrast, Japan and Canada witnessed 6.5 % and 2.3 % increases in renewable electricity production, respectively. Mainly, Iran achieved an 88 % surge in renewable electricity production during the lockdown by implementing substantial capacity expansions in hydroelectric plants.

However, the COVID-19 lockdown adversely affected renewable energy investment [16], and the redirection of government incentives towards COVID-19 treatment priorities and supply chain disruptions exacerbated the negative impacts on the renewable energy sector [17]. These challenges raised concerns among investors, governments, and advocates for renewable energy and environmental preservation. The repercussions of the COVID-19 pandemic and subsequent lockdown measures resulted in the reduction of production or temporary closure of numerous solar panel and wind turbine (WT) manufacturing companies [18]. Consequently, many companies had to lay off or temporarily furlough their employees [19].

Considering these issues, evidence from the renewable energy market shows that the global renewable energy sector, encompassing

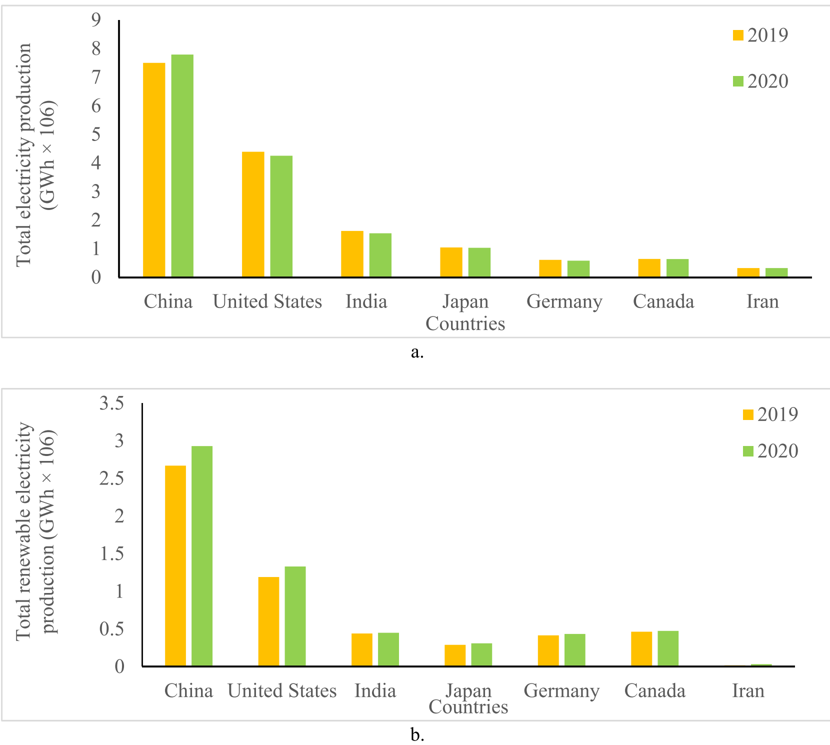


Fig. 1. Total electricity production (a) and total renewable electricity production (b) in some industrial and oil exporting countries (based on the data from Ref. [14]).

wind and solar energy, experienced growth in 2020 [20]. However, the pandemic-induced lockdowns resulted in fluctuations in the renewable stock markets [21], company closures, workforce reductions, price fluctuations of renewable technologies, and limitations on the importation of renewable technology from source countries [22]. These developments have raised concerns among governments and investors regarding the long-term effects of the pandemic on the renewable sector [23]. In preparation for future pandemics, the renewable energy industry must strategize and adapt to mitigate such challenges effectively.

One practical approach to addressing these questions is to analyze the financial outcomes of projects and case studies, including metrics such as the Cost of Energy (COE), Net Present Cost (NPC), and initial investment cost [24]. Valuable insights can be gained by comparing these results before and after the COVID-19 lockdown. Assessing these essential financial parameters can help attract or deter potential investors.

2. Literature review

In recent decades, numerous people have worked on several renewable systems consisting of solar energy devices, WT, etc., with various intentions such as optimizing the devices [25], energy saving [26], and economic analysis of the systems [24]. Also, Since the onset of the COVID-19 pandemic, numerous studies have been published examining the economic aspects of renewable energy systems. For instance, Micheli et al. (2021) investigated the short-term impact of the COVID-19 lockdown on the (COE), specifically focusing on the proportion of photovoltaics (PV) in Spain. Their findings indicated a 0.09 €/MWh reduction in COE for every GWh decrease in total electricity demand. Likewise, the share of PV achieved a record high of 9 % in July 2020 [27].

Another investigation by Vaziri Rad et al. (2022) explored a stand-alone hybrid renewable energy system (HRES) comprising PV, Diesel Generator (DG), and Battery (Bat) to meet the electricity needs of a rural health clinic during the lockdown. Their results demonstrated that the COE of a dependable HRES, with a renewable fraction of 50 %, amounted to 0.141 $/kWh [28]·

Beitelmal et al. (2022) examined three types of HRES to supply electrical demand in a remote area of Libya during the COVID-19 pandemic. They concluded that an HRES employing PV/Bat was the optimal and most cost-effective for the case study [29]·

Furthermore, Zahid et al. (2022) investigated the financial and technical parameters of proposed microgrids and virtual power plants based on PV and wind energy. The aim was to increase the share of renewable energy in the Pakistani electricity grid from 4.6 to 4.7 %. The study encompassed PV and wind power plants in various provinces, yielding COE values ranging from 0.0172 to 0.0197 $/kWh for PV and 0.019 to 0.036 $/kWh for wind energy [30]·

Samy et al. (2020) designed a cost-effective, grid-connected HRES using WT, PV, and batteries for a small hamlet in northern Egypt. Optimized via a multi-objective particle swarm optimization technique, their study considered grid availability from 100 % to 70 %. They found the lowest system surplus energy rate at 85 % grid availability and the highest at 70 %. The optimal system for a system surplus energy rate of 0.33 % included 12 PV panels, one wind turbine, and 1420 batteries, achieving a COE of 0.145 $/kWh [31].

Considering climate diversity and energy efficiency, Mokhtara et al. (2021) optimized a DG/PV/WT/battery HRES for rural Algerian residential buildings. Using ArcGIS for renewable energy mapping and particle swarm optimization, they aimed to minimize the COE and maximize system reliability and renewable fraction. For low-efficiency buildings, PV/WT/DG/battery was optimal for Adrar and Tindouf towns, while PV/DG/battery suited other areas. High-performance buildings in Biskra and Tamenrast achieved a 100 % renewable PV/battery configuration with a COE of 0.21 $/kWh [32].

Tazay et al. (2020) conducted a feasibility analysis of an HRES for an autonomous college building at Baha University in Saudi Arabia. The HRES integrates PV, WT, fuel cells, and batteries. The study assessed the system's technical and economic viability using actual data on monthly load consumption, climate, and available installation space. Sensitivity analysis revealed that incorporating hydrogen energy reduces economic and ecological support compared to other resources. The PV system significantly impacts the NPC and COE [33].

Numerous papers published during the COVID-19 lockdown have examined the techno-economic aspects of renewable energy systems. Table 1 provides an overview of these studies.

In addition to traditional calculations and analysis of various parameters, such as the impact of the COVID-19 pandemic, the

Table 1
Summary of some techno-economic studies on renewable energy systems during the COVID-19 lockdown.

Study	System	Location	Year	COE ($/kWh)
[34]	Hydro Turbine/Wind/PV/Bat	Rwanda	2020	0.1715
[35]	PV/Bat	Sweden	2021	0.31
[36]	PV	Uganda	2021	0.257
[37]	Fuel Cell/Electrolyzer	–	2021	0.3–0.45
[38]	PV/DG/Bat	Nigeria	2019	0.396
[39]	PV/Wind/Fuel Cell/Bat	Egypt	2020	0.15
[40]	PV/Wind/Bat	Hong Kong	2020	0.223
[41]	Biomass/PV	Egypt	2019	0.462
[42]	PV/Wind/Biogas Generator/Bat	Bangladesh	2021	0.101
[43]	PV/Wind/Bat	Australia	2021	0.255
[44]	PV/Wind/DG/Bat	India	2021	0.179
[45]	PV/Wind/Bat	Pakistan	2020	0.0895
[46]	PV/Biogas Generator/Pumped Hydro Storage	India	2021	0.24
[47]	PV/Bat	India	2020	0.09402

employment of ML and artificial intelligence (AI) has gained prominence in recent years in investigating the renewable energy market [48]. ML is capable of handling extensive datasets, expediting computations [49], avoiding complex formulas for modeling complicated problems [50], and revealing complex relationships between input features and outputs based on past data [51].

One notable example of ML applications in the energy sector is the study by Olubusoye et al. (2021), wherein the correlation between multiple socioeconomic factors and the COE during the COVID-19 pandemic in 2020 and 2021 was explored [52]. Another investigation by Arya and Vijaya Chandrakala (2021) employed ML to analyze and predict electricity prices in the USA electricity market, considering the volatile fluctuations in demand [53]. Furthermore, Ben Jabeur et al. (2021) examined various ML algorithms for predicting oil prices, considering clean energy resources, environmental indices, and the stock market [54].

These examples underscore the growing adoption of ML and AI methodologies to address challenges within renewable energy and allied domains.

While numerous studies have scrutinized the impact of COVID-19 on the energy sector, the majority have concentrated on broad policy implications, often overlooking the pandemic's direct technical and economic effects on specific renewable technologies. This study fills this research gap by investigating the exact consequences of COVID-19 on the wind and solar energy sectors in seven diverse countries: China, the USA, India, Japan, Iran, Germany, and Canada. These countries offer various industrialized and developing nations, each with unique economies, some of which are heavily oil-dependent. The COVID-19 pandemic has had significant repercussions in these nations.

This study aims to shed light on the influence of each sub-parameter on the renewable industry by examining the effects of COVID-19 on the renewable energy sector in these selected countries. It also scrutinizes the results of the management policies implemented in these nations. The following sections discuss several unique aspects and innovations of this study.

- Diverse country focus: This study provides an inclusive global perspective by investigating the impact of COVID-19 on renewable energy sectors across countries with varying economic conditions and grid infrastructures.
- Integration of techno-economic analysis and ML: This study uniquely blends a thorough techno-economic approach with advanced ML techniques. It uses historical data specifically collected for this research to predict and explore the long-term impacts of COVID-19 on the COE.
- Detailed design of HRES: The study designs grid-connected and stand-alone HRES, comprising PV and WT technologies, based on each country's economic factors and prices pre-COVID-19 and post-COVID-19.
- Comparative techno-economic analysis: The study compares the effects of COVID-19 on the renewable energy sector in each system for pre-COVID-19 and post-COVID-19 periods. This comparison underscores the outcomes of management policies in the countries and identifies which countries suffered the most damage in the renewable sector.
- Historical COE trend analysis: The study concludes the COE trend over the past decade using a unique database compiled from published techno-economic papers, providing a robust foundation for analysis.
- Long-term impact predictions using ML: The study employs ML techniques and the collected database to predict and examine the long-term impacts of COVID-19 on renewable COE, considering both with-COVID-19 and without-COVID-19 scenarios in the selected countries.

For the prediction part of the study, due to data limitations, the focus is narrowed down to three countries: India (a developing country), Iran (a less developed country with an oil-dependent economy and power system), and China (a country that is more developed compared to the other two with a high GDP). This selection still offers a diverse perspective on the impacts of COVID-19 on the renewable energy sector.

The structure of this paper is organized as follows. Section 3 provides a detailed introduction and discussion of the materials and methods employed in this study, including the system description, utilized methodologies, initial data sources, and information about the selected study areas. Subsequently, in section 4, the findings of this study are presented and thoroughly analyzed. Finally, section 5 presents the conclusions derived from this research endeavor.

3. Materials and methods

The methodology employed in this study integrates two novel approaches to assess the impact of COVID-19 on renewable energy technologies. The first component involves conducting a techno-economic analysis for both pre-COVID-19 and post-COVID-19 periods. This analysis aims to quantify the pandemic's effects on the COE in the renewable energy sector, providing a detailed understanding of economic viability amidst global disruptions. To define pre-COVID-19 and post-COVID-19 periods better.

- Pre-COVID-19 Period: This period uses financial inputs from 2019 in each country. It reflects a stable economic and operational environment for renewable energy technologies, characterized by consistent supply chains, predictable costs for components and maintenance, stable electricity prices, and unaltered market demands.
- Post-COVID-19 Period: This period is defined using financial inputs from 2021. It captures the significant disruptions caused by the pandemic, including supply chain interruptions, increased costs for components and maintenance, fluctuating electricity prices, labor shortages, and changes in market demands. These factors collectively impact renewable energy projects' economic feasibility and operational efficiency.

The second component introduces a unique approach by utilizing two widespread datasets for the three selected countries: one containing data including the COVID-19 period and another containing data excluding the COVID-19 period. These datasets are curated from recent literature, capturing real-world impacts and responses to the pandemic. ML applied to these datasets to forecast COE trends specifically for the future years, considering with and without COVID-19 scenarios. By comparing these forecasts with historical data, the study elucidates the direct and indirect impacts of COVID-19 on the COE of solar and wind energy technologies. To define better the terms with and without the COVID-19 scenario.

- Without-COVID-19 Scenario: This scenario uses data exclusively from years before the COVID-19 pandemic (up to and including 2019). It represents a stable economic and operational period in the renewable energy sector, with predictable costs, supply chains, and market demands.
- With-COVID-19 Scenario: This scenario uses data from the same sources and the same manner as the Without-COVID-19 Scenario but includes additional data from 2020 to 2021. This inclusion allows the analysis to account for the changes and disruptions caused by the pandemic, providing an inclusive view of its impact on the renewable energy sector.

For a detailed illustration of the methodology, please refer to Fig. 2.

Furthermore, additional information regarding the case studies and resources, such as the selection of countries, socio-economic data about these countries, and information related to their renewable resources, can be found in Appendix A2.

3.1. System description

This study investigates four types of HRES. The first system under consideration is a grid-connected system comprising PV panels and a converter to supply an Alternating Current (AC) load. The second system is a stand-alone system consisting of PV panels, a Bat, and a converter. To enhance the system's reliability, it is connected to a DG. The third system is a grid-connected system featuring a WT. Lastly, the fourth system is a stand-alone system, where the DG serves as a substitute to ensure system reliability. In this system,

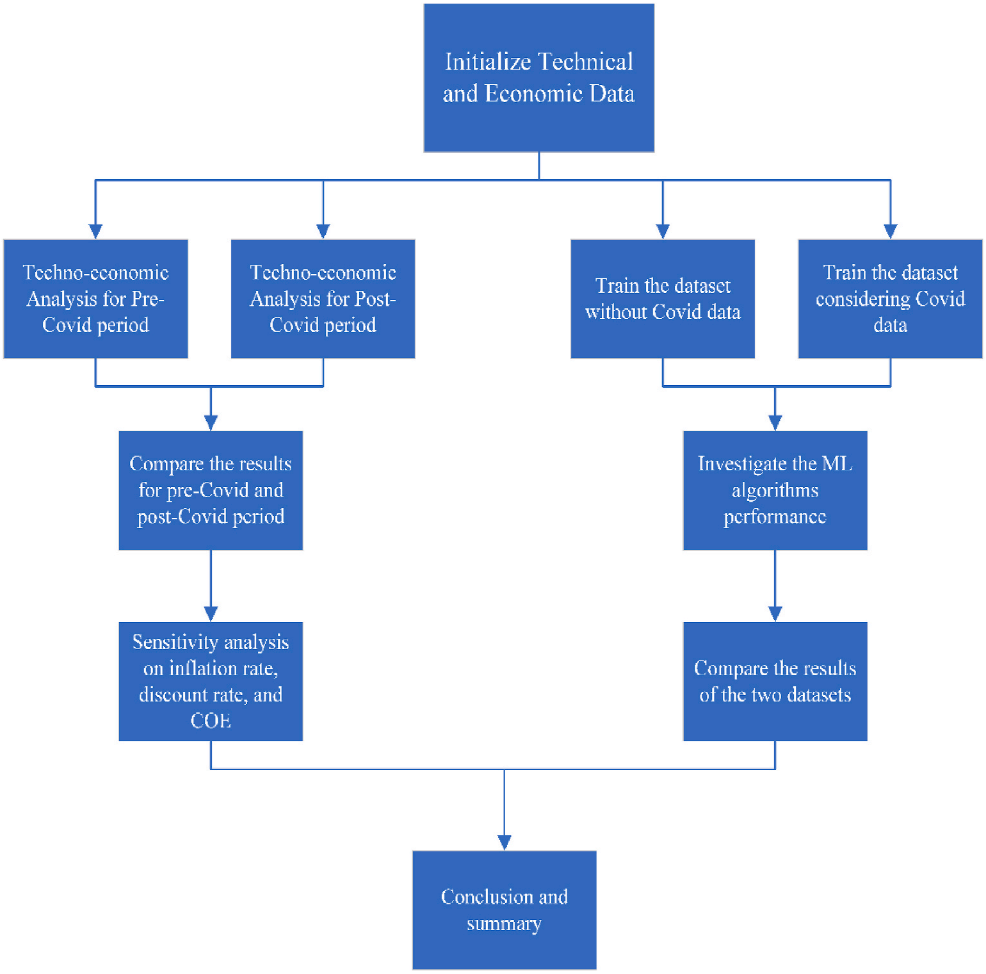


Fig. 2. The methodology of the study.

including storage is imperative to mitigate potential reliability issues. A visual representation of the HRES systems studied can be observed in Fig. 3.

This research specifically focuses on examining the impacts of COVID-19 on solar and wind energy, thereby deeming the authors' consideration of electrical load fluctuations and variations in consumption patterns in countries as non-essential. Consequently, the electrical load remains consistent across all seven countries and four HRES considered in this study. This AC load is standardized and set at a scale of 7.55 kWh/day, with a maximum load power of 1.62 kW. Given that all chosen countries are in the northern hemisphere, the load is expected to increase during summer due to elevated temperatures and the urgent demand for cooling systems. Table 2 depicts the monthly electrical load in this study, highlighting the maximum load as the highest value, the average load as the middle value, and the minimum load as the lowest value for each respective month.

The financial inputs of the study, which encompass component capital, maintenance, and replacement costs, as well as electricity

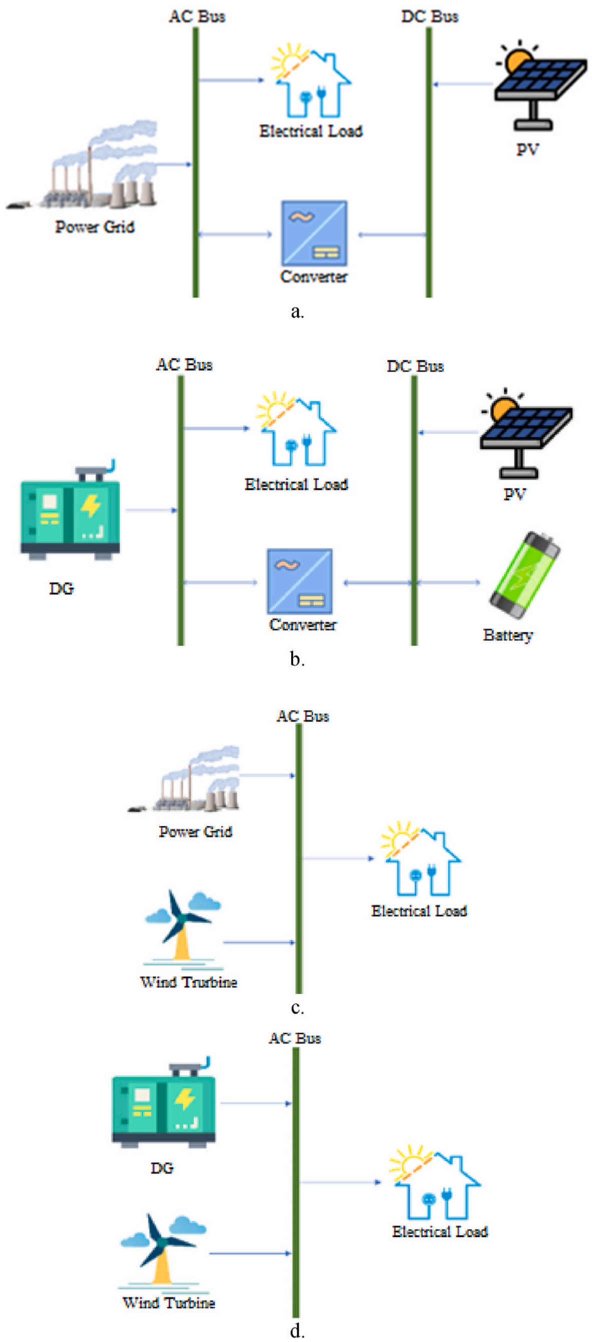


Fig. 3. Schematic of considered HRES for this study (a. PV/Grid, b. PV/Bat/DG, c. Wind/grid, d. Wind/DG).

Table 2
The monthly electrical load.

Months Loads	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Minimum Load	0.02	0.02	0.03	0.03	0.02	0.04	0.04	0.04	0.03	0.03	0.01	0.03
Average Load	0.25	0.25	0.29	0.32	0.34	0.37	0.37	0.38	0.35	0.31	0.28	0.26
Maximum Load	1.04	0.95	1.16	1.31	1.3	1.29	1.62	1.47	1.39	1.21	1.27	0.98

and fuel prices, can be found in Appendix A3. To account for the impact of COVID-19, these costs and prices are provided for both pre-COVID-19 and post-COVID-19 periods.

Furthermore, the equations utilized to compute the financial and technical parameters, along with information regarding inflation and discount rates in the selected countries during the post-COVID-19 and pre-COVID-19 periods, can be found in Appendix A4. These equations encompass economic equations geared towards calculating the COE and NPC and technical equations designed to determine the output power of each component.

3.2. Machine learning

Primarily, this section will outline the process of data collection. Subsequently, the collected data will be described. Finally, the ML algorithms utilized in this study will be presented and supported by relevant references, and a concise explanation of these algorithms will be provided.

3.2.1. Data collection and description

This study employs a techno-economic dataset specifically compiled for China, Iran, and India. These countries were selected based on their unique economic characteristics: India as a developing country, Iran as a less developed country with an oil-dependent economy and power system, and China as a more developed country with a high GDP. Given the wealth of techno-economic case studies available for these countries, the authors assembled this dataset from ninety-eight high-quality papers. The complete references for this database can be found in Appendix A5. This dataset exhibits high dimensionality, considering multiple input features, including PV capacity, Wind Capacity, Bat connectivity, Grid connectivity, DG capacity, year, and NPC of the system. The COE serves as the sole output variable in this analysis. Fig. 4 represents all the dataset features with their lowest, average, and highest values.

Following the adopted methodology, the first step involves training the system without incorporating data from the COVID-19 period, thereby enabling the prediction of COE based on the trained system. In the subsequent step, the system is trained using data from the COVID-19 period. A comparison of the predicted COE values can illuminate the influence of the COVID-19 pandemic on the future of the renewable sector. For each step, the database is allocated as follows: 60 % for training, 20 % for cross-validation, and 20 % for testing.

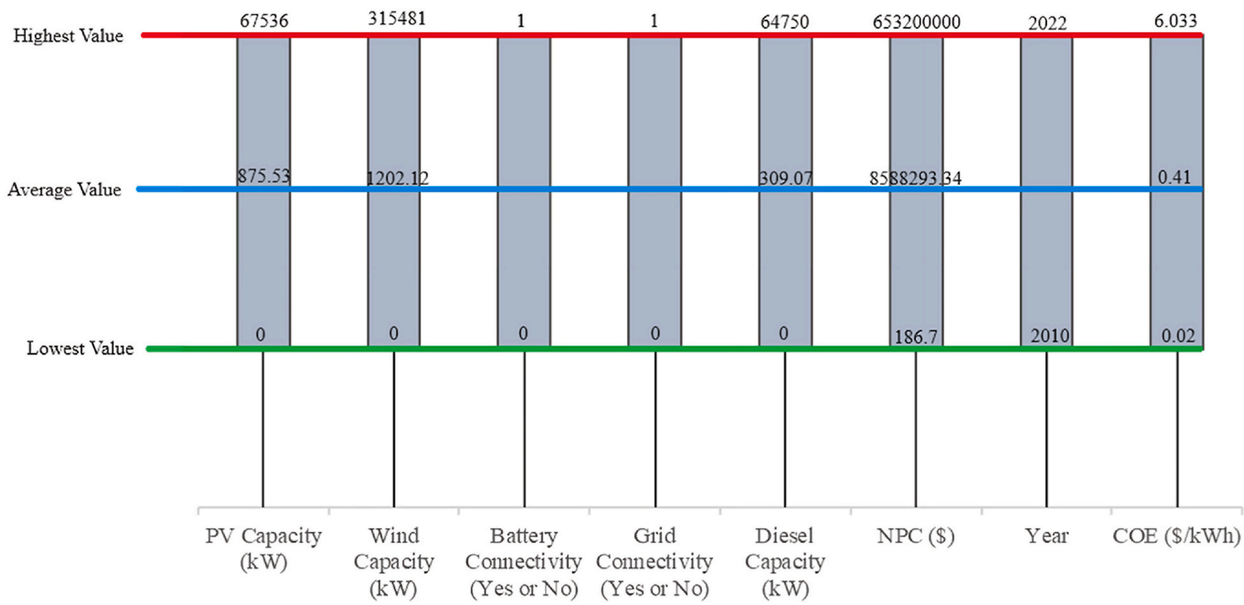


Fig. 4. Characteristics of used data for this study.

3.2.2. ML algorithms

This study employed the Artificial Neural Network (ANN) algorithm to predict the COE. This algorithm was chosen for its high accuracy and ability to address complex engineering problems. Furthermore, its wide usage in various ML problems served as an additional justification for its selection. This algorithm has been extensively utilized and referenced in numerous papers and books, so this study will not provide the associated equations. Interested readers can refer to reference [55] for detailed information on the equations related to this algorithm.

The dataset will be trained, and the output of the ANN for each scenario will be examined to provide insights into its accuracy and performance. The ANN model will employ two hidden layers. The first hidden layer will comprise sixteen nodes, while the second layer will have eight nodes.

The input features, as mentioned in Section 3.1.1, will include technical and economic parameters such as component capacity, the year of the study, and NPC. At the same time, the output will be the predicted COE.

The ANN will be trained using the stochastic gradient descent optimization algorithm with an initial learning rate 0.1. The training will continue for 300 epochs, with early stopping implemented to prevent overfitting. The dataset will be split into training, cross-validation, and test sets with a 60-20-20 % ratio to evaluate model performance. The model will use the default ReLU activation function for its hidden layers.

Furthermore, to assess and compare the performance of the algorithms, two evaluation metrics, namely mean absolute error (MAE) and mean squared error (MSE), will be utilized. The MAE is described in Equation (1) [56], while Equation (2) [57] outlines the calculation of MSE. Within these equations, 'n' represents the row number of the data, COE(n) denotes the actual COE value in the nth row, and COE'(n) represents the predicted COE value for the nth row in the dataset. Comparative analysis utilizing the MAE and MSE will facilitate the determination of the superior algorithm, which will then be employed for COE estimation.

$$MAE = \frac{1}{N}\sum_{n=1}^{N}\left|COE(n) - COE'(n)\right| \tag{1}$$

$$MSE = \frac{1}{N}\sum_{n=1}^{N}\left(COE(n) - COE'(n)\right)^2 \tag{2}$$

4. Results and discussion

This section presents the techno-economic findings of the proposed HRES, emphasizing novel methodologies to assess the unprecedented impact of COVID-19 on renewable energy sectors across multiple countries. The study details optimal system configurations and economic outcomes tailored to each country's specific technology, fuel prices, and financial parameters over twenty years. A significant aspect of this research is the sensitivity analysis conducted to evaluate HRES resilience to economic fluctuations during the pandemic-induced lockdown period, highlighting the novelty of exploring the robustness of renewable energy investments under varying economic conditions. Additionally, the study integrates ML techniques to forecast post-lockdown trends in the COE, offering forward-looking assessments of COVID-19's long-term impacts on renewable energy economics. By innovatively combining these methodologies and findings, this research contributes to a deeper understanding of how global disruptions influence the economic feasibility and strategic planning of renewable energy investments.

4.1. Techno-economic results

- *China*

Comparing the scenarios during the lockdown reveals a decrease in the renewable fraction of grid-connected HRES. This outcome can be primarily attributed to decreased electricity prices from the grid, as demonstrated earlier. Conversely, diesel fuel prices increased by approximately 14.6 % during the pandemic. Consequently, in off-grid scenarios, an increase in the capacity of PV and WT systems is observed. For detailed results regarding the sizing of the considered HRESs, please refer to Table 3.

The comparison of NPC and COE between the pre-COVID-19 and post-COVID-19 periods reveals a slight variation. Across all HRESs, there was a decrease in COE, with the most significant reduction observed in the grid/WT system. This decrement primarily stems from a decrease in total annual costs, encompassing both purchase and operational expenditures, while the electrical load

Table 3
The results of the sizing for scenarios in China.

HRES	Pre-COVID-19					Post-COVID-19				
	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)
Grid/PV	1.17	–	–	–	0.619	0.931	–	–	–	0.487
Grid/WT	–	1	–	–	–	–	1	–	–	–
DG/PV/Bat	3.63	–	2	1.8	1.08	4.43	–	2	1.8	1.29
DG/WT/Bat	–	2	2	1.8	0.961	–	3	3	1.8	1.2

remains constant between the two periods. The contribution of this decrement can be attributed to the reduction in inflation rates and discount rates of 2.8 % and 3 %, respectively, during the pandemic. These factors, alongside a sharp decline in annual costs, resulted in a decrease in NPC, which is particularly noticeable in on-grid scenarios. Furthermore, grid-connected scenarios demonstrated lower NPC and COE values. Conversely, the DG/WT/Bat system exhibited the highest COE and NPC figures due to the excessive costs associated with fuel and Bat components. The variations in COE and NPC in China are visualized in Fig. 5.

- *USA*

The comparison of the optimal system before and after the pandemic reveals an increase in the proportion of renewable energy sources (HRESs). Markedly, despite the constant grid electricity, the prices for selling back renewable energy experienced a slight reduction during the pandemic. However, the primary factor contributing to the higher share of renewables is the reduction in initial capital and yearly operating costs of renewable components. This shift toward greater reliance on renewable energy sources can also be attributed to significant changes in the American fuel market. Data indicates that between 2019 and 2021, diesel fuel prices increased by an alarming 54 %. Under these circumstances, renewable technologies become more economically viable. The results of the optimal sizing for the selected HRESs in the USA are presented in Table 4.

In the pre-COVID-19 years, the renewable COE was a global decline. Financial findings indicate a further COE reduction during the USA pandemic. Comparing the COE figures between China and the USA reveals that the impact of the pandemic on the renewable energy market in the USA is modest, and the downward trend in COE continues at a steeper rate compared to China. Nevertheless, the government attempted to regulate the market by implementing a discount rate reduction exceeding 4 % between 2019 and 2021, increasing NPC across all scenarios. While the prices of renewable components decreased during the pandemic, the significant enlargement of PV size by threefold in grid/PV HRES, or the expansion of converter and Bat capacity in off-grid HRES, contributes to the notable rise in capital and annual costs, thereby affecting the NPC. Fig. 6 depicts the NPC and COE during the pandemic in the USA.

- *Canada*

In Canada, the renewable fraction in grid-connected scenarios experienced a decrease during the pandemic, whereas in stand-alone systems, the proportion of renewable energy increased. Initial data reveals a significant reduction in grid electricity prices between 2019 and 2021. Concurrently, the sell-back prices for PV and WT electricity decreased by 50 % and 2 %, respectively. Additionally, fuel prices increased 48 % during the same period. These observations suggest that in grid-connected HRESs, it is economically advantageous to procure electricity from the grid. Conversely, renewable energy utilization becomes more economically justifiable in stand-alone HRESs, where fuel prices are higher, and the renewables' initial and operational and maintenance (O&M) costs decrease. The optimal design of HRESs for Canada is presented in Table 5.

As depicted in Fig. 7, the COE exhibits a declining trend across all HRESs. Furthermore, the COE is remarkably lower in grid-connected HRESs, primarily due to lower grid electricity prices and a higher share of renewable energy. Remarkably, the increased inflation rate by a factor of two, alongside the government's efforts to mitigate the economic impacts of the pandemic by reducing discounts, has led to an overall increase in the NPC for most HRES scenarios, except for Grid/WT HRES. A comparison between the Grid/PV scenarios before and after the COVID-19 period reveals the utilization of three WT units in both cases, with identical WT output power. However, owing to a significant decrease in grid prices and WT O&M costs, the total annual fee has been reduced more substantially in this scenario compared to other HRES configurations, resulting in a decrement in the NPC.

- *Germany*

Table 6 highlights the optimal HRES design for Germany. In 2019, Germany exhibited the highest electricity and fuel prices compared to the other selected countries, and these prices continued to rise during the pandemic. These price fluctuations have resulted in exciting outcomes for the country. The optimal system designs indicate a threefold increase in PV capacity and a twofold

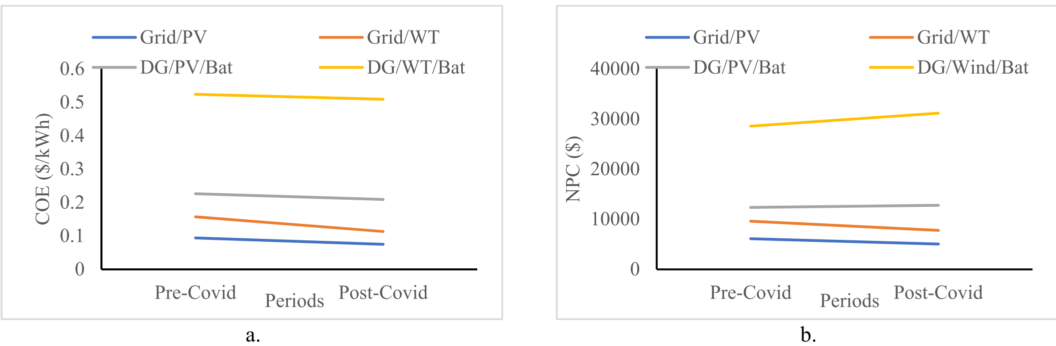
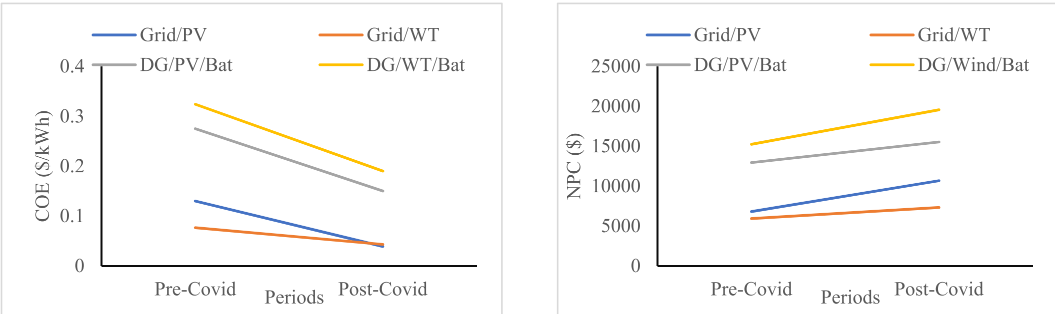


Fig. 5. COE (a) and NPC (b) for pre-COVID-19 and post-COVID-19 periods in China.

Table 4
The results of the sizing for scenarios in the USA.

HRES	Pre-COVID-19					Post-COVID-19				
	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)
Grid/PV	1.16	–	–	–	0.544	5.36	–	–	–	2.63
Grid/WT	–	1	–	–	–	–	1	–	–	–
DG/PV/Bat	3.55	–	2	1.8	1.06	5.36	–	3	1.8	1.42
DG/WT/Bat	–	1	1	1.8	0.731	–	2	2	1.8	1.07

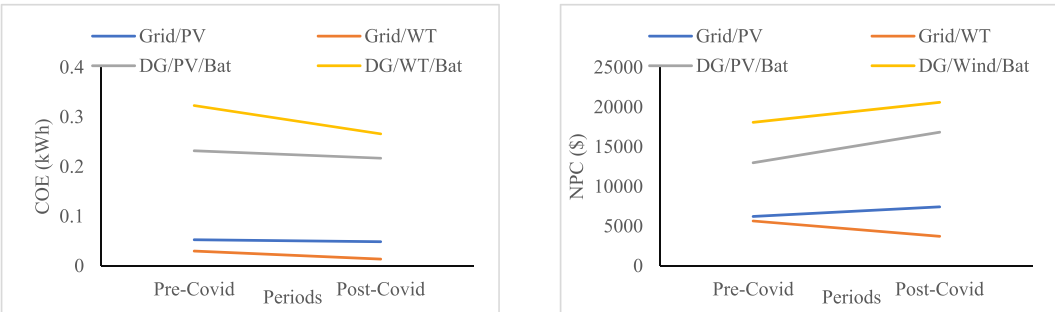


a. b.

Fig. 6. COE (a) and NPC (b) for pre-COVID-19 and post-COVID-19 periods in the USA.

Table 5
The results of the sizing for scenarios in Canada.

HRES	Pre-COVID-19					Post-COVID-19				
	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)
Grid/PV	4.02	–	–	–	2.05	3.75	–	–	–	1.78
Grid/WT	–	3	–	–	–	–	3	–	–	–
DG/PV/Bat	4.71	–	2	1.8	1.24	5.61	–	3	1.8	1.42
DG/WT/Bat	–	2	2	1.8	0.92	–	2	2	1.8	1.06



a. b.

Fig. 7. COE (a) and NPC (b) for pre-COVID-19 and post-COVID-19 periods in Canada.

increase in WT capacity in grid-connected HRESs, as they heavily rely on grid electricity prices. Furthermore, the renewable fraction has increased in DG/PV/Bat HRESs, although this increment is smaller than that observed in on-grid HRESs. The increase in grid electricity prices is approximately 10 % higher than the change in fuel prices between 2019 and 2021, which can explain the more significant impact of these price fluctuations on grid-connected HRESs.

The results depicted in Fig. 8 indicate a consistent decrease in the COE across all hybrid HRESs. In on-grid HRESs, this reduction in COE can be attributed to higher utilization of renewable components, resulting in lower annual costs and reduced reliance on grid electricity. However, when analyzing the NPC variation, a different trend becomes apparent. HRESs incorporating PV components exhibit an increase in NPC, whereas those incorporating WT components show a decreasing trend. According to the optimal design table, the grid/PV HRES witnessed a threefold increase in both PV and converter capacity, leading to a substantial rise in annual O&M

Table 6
The results of the sizing for scenarios in Germany.

HRES	Pre-COVID-19					Post-COVID-19				
	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)
Grid/PV	4.92	–	–	–	2.19	13.8	–	–	–	5.95
Grid/WT	–	1	–	–	–	–	2	–	–	–
DG/PV/Bat	5.64	–	4	1.8	1.28	6.94	–	4	1.8	1.41
DG/WT/Bat	–	2	2	1.8	0.987	–	2	2	1.8	1.16

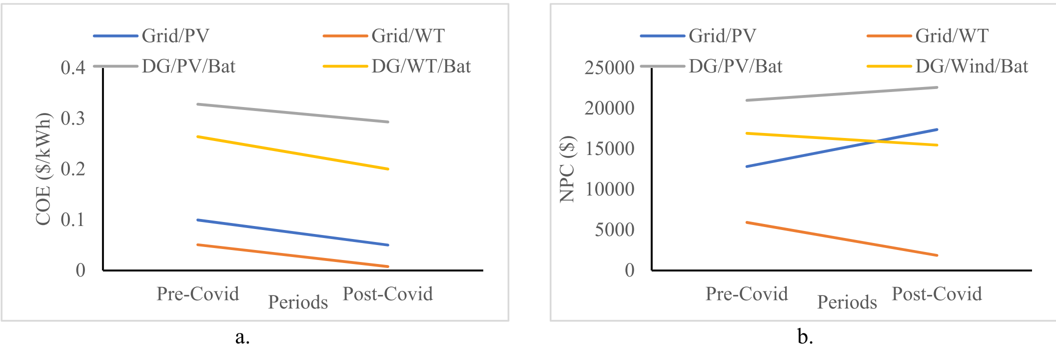


Fig. 8. COE (a) and NPC (b) for pre-COVID-19 and post-COVID-19 periods in Germany.

costs. Conversely, the renewable capacity increment in DG/PV/Bat HRES was lower than in grid/PV HRES, resulting in a smaller NPC increment. Additionally, the upward trend in inflation between 2019 and 2021 contributed to the NPC increase in these scenarios. In the two other HRES configurations, the changes in renewable capacity were minimal. Therefore, it appears that the impact of O&M cost reduction, decreased consumption of purchased grid electricity, and fuel usage outweighed the effects of changes in the inflation rate, causing the NPC to decline from 2019 to 2021.

- *India*

In India, there has been a significant increase in the renewable fraction within stand-alone HRESs. A comparison between fuel prices and renewable component prices reveals that the rise in fuel prices, coupled with the decline in capital and O&M costs of renewable components, has incentivized the adoption of more renewable components in these scenarios. During the lockdown period, the electricity price in India experienced a decrease. A comparable situation occurred in Canada, leading to a reduction in the renewable fraction within grid-connected scenarios. The primary distinction between Canada and India lies in their solar and wind resources. India boasts the highest solar irradiance and clearance among the countries with the lowest average wind speed. These resource disparities remarkably influence the renewable fraction within grid-connected HRESs. Table 7 reveals that the PV capacity has increased sevenfold due to the decreased capital and O&M costs associated with PV components. However, considering the increased capital and O&M costs for WTs during the pandemic, the capacity of WTs has remained unchanged.

Fig. 9 demonstrates a consistent decrease in the COE across all HRESs during the pandemic. In grid-connected scenarios, the combination of lower capital and O&M costs and reduced grid electricity prices has decreased annual costs and, consequently, a lower COE. Likewise, in off-grid scenarios, the higher renewable fraction, driven by increased fuel and reduced component costs, has decreased COE. Furthermore, the results indicate that the NPC remains constant for grid-connected scenarios. The simultaneous impact of inflationary trends and lower annual costs has resulted in a stable NPC. Conversely, in off-grid HRESs, the NPC exhibits an increasing trend, particularly prominent in the DG/WT/Bat scenario. Comparing the renewable fraction of the HRESs between the pre-COVID-19 and post-COVID-19 periods reveals a threefold increase during the pandemic. This substantial rise imposes a significant financial burden on the system, leading to a sharp increase in the NPC.

Table 7
The results of the sizing for scenarios in India.

HRES	Pre-COVID-19					Post-COVID-19				
	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)
Grid/PV	1.18	–	–	–	0.590	8	–	–	–	4.17
Grid/WT	–	1	–	–	–	–	1	–	–	–
DG/PV/Bat	2.97	–	2	1.8	1.06	5.08	–	2	1.8	1.42
DG/WT/Bat	–	1	1	1.8	0.414	–	3	3	1.8	1.32

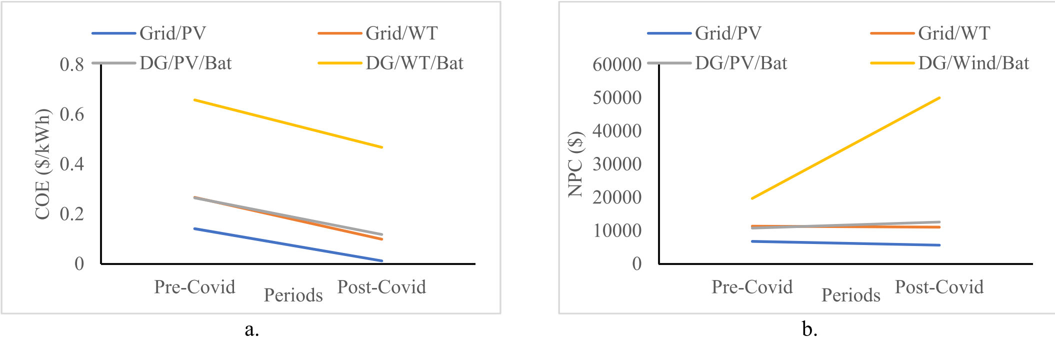


Fig. 9. COE (a) and NPC (b) for pre-COVID-19 and post-COVID-19 periods in India.

- *Japan*

Table 8 and Fig. 10 present Japan's optimal HRES design and financial outcomes during the COVID-19 pandemic. These results demonstrate minimal variations in the renewable fraction, COE, and NPC compared to the other selected countries. Among these countries, China exhibits the closest financial output variation to Japan during the lockdown. Despite keeping the discount rate unchanged, Japan experienced a decreased inflation rate during the pandemic. Additionally, there were slight adjustments in the prices of grid electricity and diesel fuel, with a change of 0.03 ($/kWh) and 0.006 ($/L), respectively. The outcomes of these policies exhibited effective management in terms of NPC and COE. When comparing Japan with other countries, it becomes evident that the financial outputs in other nations displayed significant fluctuations, particularly concerning NPC. In contrast, Japan's renewable energy sector remained unaffected during the pandemic.

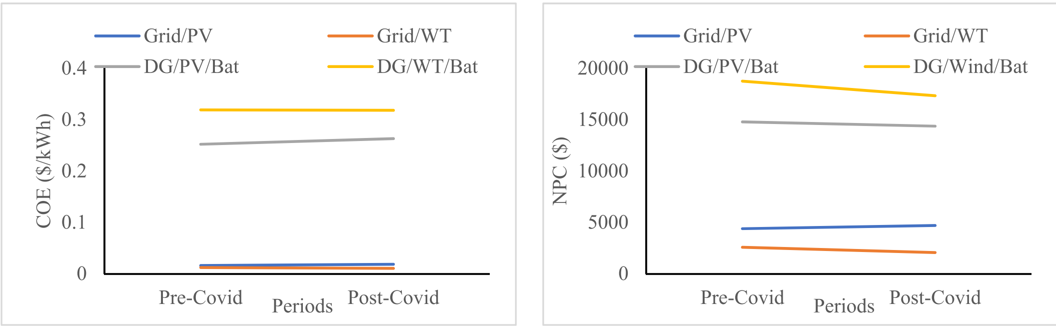
- *Iran*

The situation in Iran diverges from that of other countries, as its economy suffered considerable damage during the COVID-19 pandemic. Industrial and commercial sectors endured prolonged closures, exacerbating the challenges faced by the nation. Despite the pandemic, Iran opted to keep the discount rate unchanged while experiencing a substantial increase in the inflation rate by 104 %. Furthermore, Iran is one of the world's major oil-producing countries, and it has a fossil fuel-based electricity sector. Consequently, the country has one of the lowest electricity prices globally, which decreased during COVID-19. This highly affordable electricity translated into unfavorable conditions for the optimal HRES design, resulting in a low renewable fraction before the pandemic. Despite the decrease in renewable component prices in 2021 compared to 2018 and 2019, the renewable fraction continued to decline due to the persistently low grid electricity prices. However, the renewable fraction increased in off-grid scenarios, which were less impacted by grid electricity prices. This upward trend can be attributed to the rise in fuel prices during the COVID-19 pandemic and the resilience of off-grid systems. Table 9 presents the optimal HRES design for Iran, reflecting the unique circumstances faced by the country.

According to Fig. 11, which illustrates the variations in the COE and NPC in Iran, there was a significant decrease in COE during the pandemic. In grid-connected scenarios, this reduction can be attributed to changes in grid electricity prices. Conversely, in off-grid HRESs, the decline in COE is primarily influenced by a higher renewable fraction and reduced fuel consumption. The NPC decrement observed in grid-connected scenarios is driven mainly by the low electricity prices offered by the grid, leading to substantial reductions in annual costs. This highlights the more significant impact of grid electricity prices on NPC compared to changes in the inflation rate in grid-connected contexts. In the DG/PV/Bat HRES, there is a higher increase in the renewable fraction compared to the DG/WT/Bat HRES. Because of this increment, fuel usage decreases, resulting in a rapid reduction in annual costs. Consequently, the lower annual costs associated with the DG/PV/Bat HRES contribute to a decrease in NPC despite the inflation rate in the post-COVID-19 period. However, in the DG/WT/Bat HRES, the marginal increase in the renewable fraction fails to offset the significant impacts of the inflation rate, leading to a rapid rise in NPC. Among the proposed HRESs, the DG/PV/Bat configuration emerges as the only one that successfully mitigates the economic impacts of the COVID-19 pandemic in Iran.

Table 8
The results of the sizing for scenarios in Japan.

HRES	Pre-COVID-19					Post-COVID-19				
	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)
Grid/PV	10	–	–	–	5.67	10	–	–	–	5.58
Grid/WT	–	3	–	–	–	–	3	–	–	–
DG/PV/Bat	4.16	–	3	1.8	1.21	5.05	–	2	1.8	1.15
DG/WT/Bat	–	2	2	1.8	0.914	–	2	2	1.8	0.913

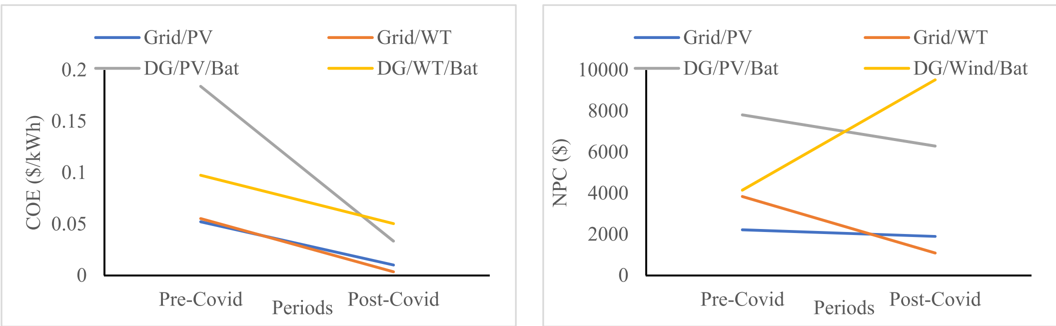


a. b.

Fig. 10. COE (a) and NPC (b) for pre-COVID-19 and post-COVID-19 periods in Japan.

Table 9
The results of the sizing for scenarios in Iran.

HRES	Pre-COVID-19					Post-COVID-19				
	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)	PV (kW)	WT (unit)	Bat (unit)	DG (kW)	Converter (kW)
Grid/PV	0.0104	–	–	–	0.00391	0.0013	–	–	–	0.00391
Grid/WT	–	1	–	–	–	–	1	–	–	–
DG/PV/Bat	1.69	–	1	1.8	0.591	3.06	–	3	1.8	1.24
DG/WT/Bat	–	2	1	1.8	0.581	–	2	2	1.8	1.07



a. b.

Fig. 11. COE (a) and NPC (b) for pre-COVID-19 and post-COVID-19 periods in Iran.

4.2. Sensitivity analysis

A sensitivity analysis was conducted for the selected countries to examine the effects of inflation and discount rate variations on scenarios and COE. The outcomes of the sensitivity analysis indicate that as the inflation rate increases, the optimal scenarios tend to recommend utilizing both the grid and DG. Under such circumstances, the COE begins to decrease. Furthermore, as the discount rate increases, the proportion of renewables in the energy mix rises, leading to a corresponding increase in COE. A complete presentation of the results from this sensitivity analysis can be found in Appendix A6.

4.3. Comparison of cases

A comparative analysis of the results obtained for the selected countries reveals that the COE did not undergo any significant increase during the pandemic period. Across all countries, the COE demonstrates an upward trend with an increase in the discount rate, decreasing as the inflation rate rises. In most comparative methodologies, the NPC assumes paramount importance and can be a valuable parameter for classifying and comparing the results. In line with this study, the NPC outcomes exhibit greater diversity and serve to classify and compare the various countries.

Based on the findings, Japan exhibits consistent NPC values with minimal variation. The lowest NPC variation is observed in Japan, where economic policies have contributed to maintaining a constant state of the COE and financial parameters. Consequently, Japan has experienced the slightest fluctuation in NPC. Following Japan, China has achieved similar control over its energy sector, resulting in a stable NPC.

The USA and Canada share comparable conditions, albeit with more pronounced NPC variations. A closer examination of the results reveals a slight increase in NPC for both countries. In Canada and the USA, the optimal HRES designs recommend the utilization of both PV and WTs.

In the case of Germany and India, the changes in NPC are highly contingent upon the specific type of HRES employed. A more detailed investigation reveals that solar irradiance and wind speed play essential roles in NPC variations. For instance, Germany exhibits the lowest solar irradiance and clearance index among the selected countries. Furthermore, Germany's higher grid electricity prices increase the share of renewable energy resources. The combination of a higher renewable fraction and limited availability of low-density resources leads to an increased reliance on PV technologies, consequently resulting in higher NPC values. In contrast, India displays the lowest wind speeds among the selected countries, and during the pandemic years, the NPC experienced a notable surge. Additionally, the recommended HRES configurations in Germany and India prioritize using WT and PV, respectively.

In contrast, Iran cannot be easily classified alongside any other countries. Before the COVID-19 pandemic, Iran had one of the lowest grid electricity and diesel fuel prices. However, during the pandemic, due to reduced energy consumption, there was a decline in oil exports, leading to a further decrease in oil prices. Furthermore, implementing lockdown measures and the ensuing economic crisis contributed to a sharp increase in inflation. These factors culminated in a reduced renewable fraction within Iran, with an increased reliance on the grid and DG. In this context, although the COE decreases, it is not contingent on the prices of renewable technologies; instead, it is highly influenced by fluctuations in fossil fuel prices within the country.

Since COVID-19 had varied impacts on different countries' renewable energy sections, analyzing key factors such as price sensitivity, economic stability, infrastructure investment, grid integration, and tailored approaches may help better understand these impacts.

Price sensitivity is one of those essential factors in the adoption of energy systems. In China, the increment in grid electricity prices increased the renewable fractions of grid-connected systems. The increment in diesel fuel prices during the pandemic caused an increase in the capacity of PV and WT. Similarly, low grid electricity prices and decreased sellback prices for PV and WT made grid-connected systems less attractive in Canada. In the meantime, high diesel fuel prices incentivized PV and WT in standalone systems. In Iran, meager electricity prices due to the fossil fuel-based energy system discouraged renewable adoption in grid-connected systems despite the rise in fuel prices during the pandemic. These examples represent the need for stable and predictable pricing mechanisms to increase the competitiveness of PV and WT.

Stability in inflation and discount rates, which are the most essential things in economic stability, affect energy systems and renewable energy systems investment. During the pandemic, China and Japan experienced fewer variations in renewable fractions and economic outputs due to stable economic policies. Conversely, Iran faced severe economic challenges, such as a 104 % increase in inflation rate, which hindered renewable energy adoption. In other cases, the USA and Canada implemented discount rate reductions and supported renewable investments despite economic fluctuations. Stable economic policies and controlled inflation rates are essential for creating a favorable investment climate for renewable energy.

Another essential factor in expanding and supporting renewable energy systems is investment. A threefold increase in PV capacity and a twofold increase in WT capacity in Germany during the pandemic represent significant infrastructure investment due to high electricity prices. Also, in India, a sevenfold increase in PV capacity was observed due to declining capital and O&M costs, which shows the impact of investment in renewable technologies. The USA also experienced an increment in PV, battery, and converter capacities, and all these cases show the effects of an adequate financing mechanism and incentives to support large-scale investments in renewable infrastructure.

The other essential factor is an efficient and smart grid to increase renewable integration and maximize their potential. For instance, in Canada, lower grid electricity prices decrease renewable fractions in grid-connected systems, while in Germany, higher utilization of renewables in grid-connected systems caused a constant decrease in COE. These samples show that the policymakers must focus on developing grid infrastructure that can accommodate high shares of renewable energy to reduce the reliance on fossil fuels, reduce renewable COE, and enhance reliability.

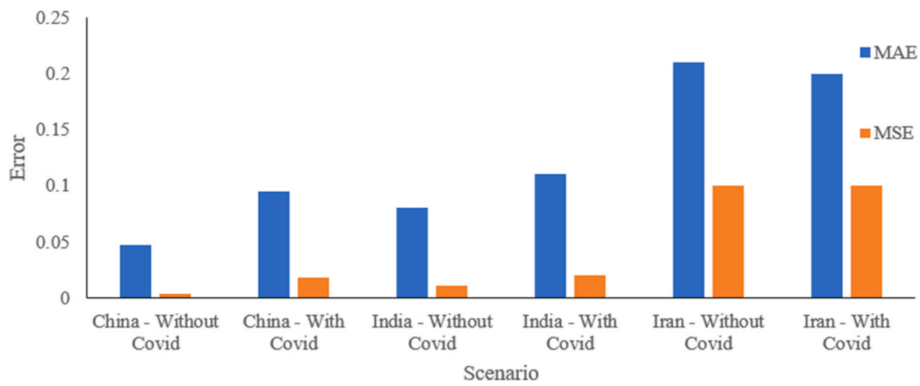


Fig. 12. MAE and MSE results for all scenarios.

Besides, each country's unique context requires tailored approaches to renewable energy policy. In the USA, capital and O&M cost decrement for renewable components and significant fuel price increment drove high renewable adoption. Also, it leveraged its high solar resources to increase the PV capacity due to lower wind resources. Iran's reliance on low-cost fossil fuel-based electricity highlighted the need for strategies that address local energy dynamics. Also, Japan's stable economic policies and minimal price adjustments helped steady renewable adoption.

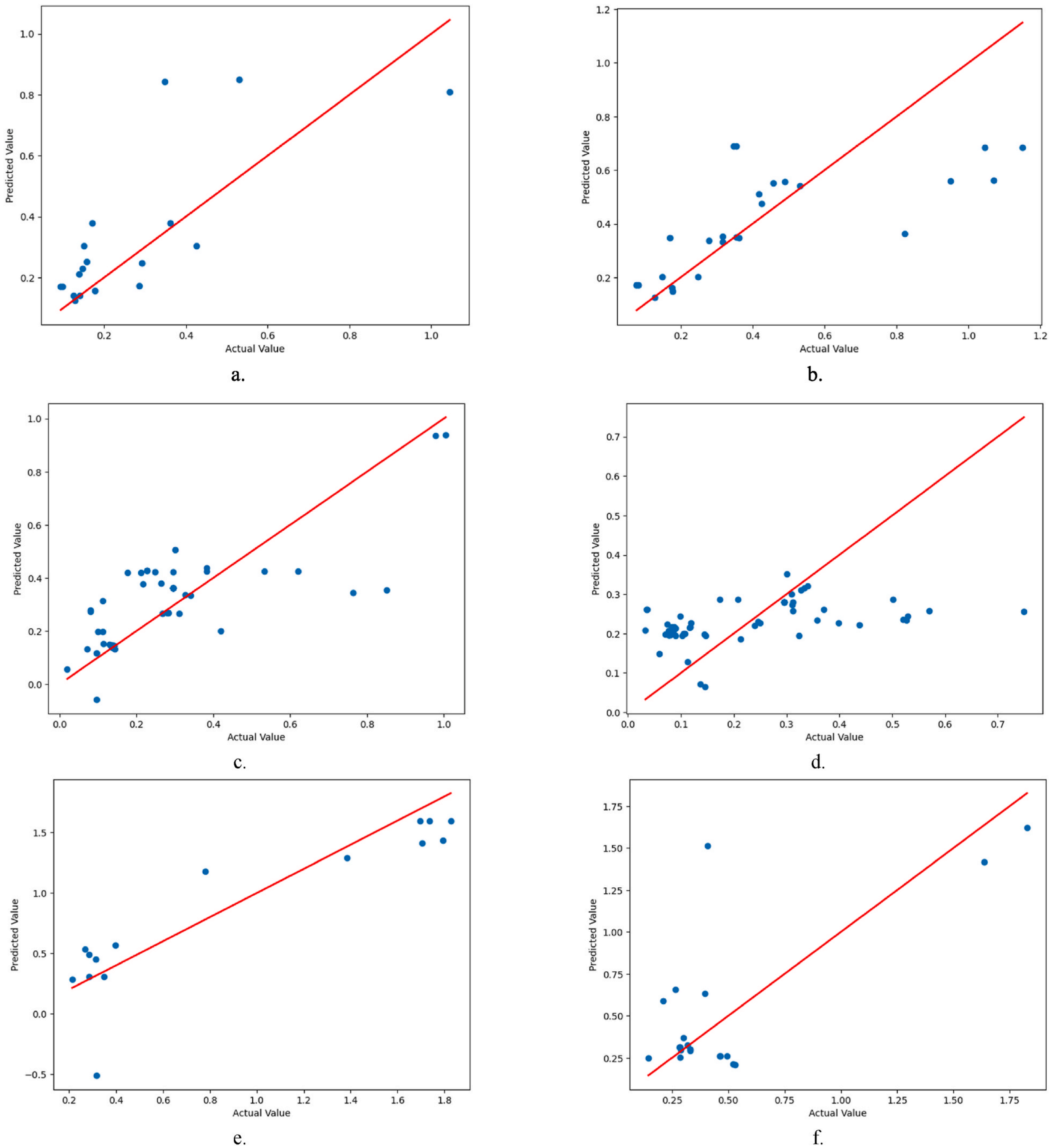


Fig. 13. Comparison of predicted and actual values for ANN (a. China – Without COVID-19, b. China – With COVID-19, c. India – Without COVID-19, d. India – With COVID-19, e. Iran – Without COVID-19, f. Iran – With COVID-19).

4.4. COE prediction

Upon training the dataset and examining the output of the ANN for each scenario, the MAE and MSE results provide insights into its accuracy and performance. ANN models were employed with two hidden layers. The first hidden layer comprised sixteen nodes, while the second had eight. A depiction of the MAE and MSE results for all scenarios can be found in Fig. 12.

Based on the findings illustrated in Fig. 12, it is evident that the errors in China and India are low, while they increase in Iran. However, the maximum MAE of 0.21 is still acceptable. This demonstrates the ANN's reliable performance in most scenarios and its high accuracy in predicting the COE. Mainly, errors in India, Iran, and China were negligible. To provide a visual representation of this, Fig. 13 highlights the disparity between the predicted and actual values of the test dataset.

Fig. 13(a) and (b) show that the predicted COE is close to the actual value in most cases and for both scenarios in China. Also, these figures show that the difference between actual and predicted values in higher COEs is higher. In the without-COVID-19 scenario, the error for the prediction of COEs higher than 0.4 $/kWh increases, while in the with-COVID-19 scenario, the error for the prediction of COEs higher than 0.7 $/kWh increases.

Additionally, based on Fig. 13(c) and (d), the predicted COE is close to the actual value in most cases and for both scenarios in India. In the without-COVID-19 scenario, the error for predicting COEs is slightly higher between 0.5 and 0.8 $/kWh. In the with-COVID-19 scenario, the error for predicting COEs increases for values higher than 0.4 $/kWh.

In the case of Iran, based on Fig. 13(e) and (f), the predicted COE is close to the actual value in most instances for both scenarios. However, there is one test case in each scenario where the predicted values significantly differ from the actual values.

The increased error in higher COEs is due to the limited number of records with such high COE values in the dataset. Despite this, in all scenarios, the prediction errors fall within acceptable ranges, indicating the reliability of the predictive model.

In the last step, the COE between 2023 and 2026 will be predicted for all locations using the trained dataset with the ANN. The predicted COE will then be compared for with-COVID-19 and without-COVID-19 scenarios. The COE values between 2023 and 2026 are presented in Table 10 and Fig. 14. These results indicate that COVID-19 has a long-term impact on renewable COE in the selected countries. It is worth noting that since the dataset used for this analysis was obtained from real projects and papers, the results may differ from techno-economic outcomes primarily based on fuel and technology prices during the COVID-19 lockdown.

Fig. 14 and Table 10 broadly analyze the predicted COE from 2023 to 2026 for China, India, and Iran under two scenarios using ANN. These predictions highlight the significant impact of COVID-19 on electricity costs across these countries. The With-COVID-19 scenario shows higher COE values in China and India, indicating that the pandemic has introduced additional economic and operational challenges expected to increase renewable electricity costs over the forecast period.

Fig. 14(a) represents China, with a marked increase in COE over the four years. In the Without-COVID-19 scenario, the COE values start at 0.075 $/kWh in 2023 and increase slightly to 0.088 $/kWh by 2026. However, in the with-COVID-19 scenario, the COE starts at 0.074 $/kWh in 2023 and rises significantly to 0.134 $/kWh by 2026. This trend highlights the substantial impact of COVID-19 on China's energy sector, likely due to disruptions in supply chains, increased operational costs, and shifts in energy demand patterns. The steeper rise in the With-Covid-19 scenario underscores the broader implications of the pandemic on renewable energy costs in China.

Fig. 14(b), which pertains to India, shows a similar trend, though the numerical values differ, reflecting India's unique economic and renewable energy sector. In the Without-COVID-19 scenario, the COE values start at 0.28 $/kWh in 2023 and increase to 0.38 $/kWh by 2026. In the with-COVID-19 scenario, the COE starts at 0.27 $/kWh in 2023 and rises to 0.46 $/kWh by 2026, 21 % more than the without-COVID-19 scenario. The increase in COE under the With-COVID-19 scenario underscores the broader implications of the pandemic on renewable energy costs in India. Like China, factors such as disruptions in supply chains, increased operational costs, and shifts in energy demand patterns likely contribute to this trend.

Fig. 14(c), focusing on Iran, presents a slightly different pattern. In the Without-COVID-19 scenario, the COE values start at 0.49 $/kWh in 2023 and increase to 0.59 $/kWh by 2026. In the With-COVID-19 scenario, the COE starts at 0.47 $/kWh in 2023 and rises to 0.51 $/kWh by 2026. The impact of COVID-19 on Iran's COE is less pronounced than in China and India. The closer proximity of the predicted numbers in Iran's case may reflect Iran's specific economic conditions or resilience factors that mitigate the pandemic's impact on electricity costs. This could be due to the availability of cheap diesel fuel, a lower fraction of renewable energy sources, and a high reliance on grid and DG systems. Overall, these figures underscore the critical role of COVID-19 in shaping future energy costs and highlight the importance of incorporating such factors into energy planning and policymaking.

The predictions highlight the significant impact of the COVID-19 pandemic on the COE in various countries, with notable differences in the extent of this impact across different regions. In China and India, COVID-19 has increased COE, suggesting that the pandemic has disrupted progress in the renewable energy sector. This disruption could be attributed to several factors, such as supply chain interruptions, delayed projects, and reallocation of financial resources towards immediate pandemic response rather than long-term renewable energy investments. The stark contrast in the COE trends with and without COVID-19 in these countries underscores

Table 10
COE predictions for Without-COVID-19 and With-COVID-19 scenarios using ANN.

Country	Without COVID-19 ($/kWh)				With COVID-19 ($/kWh)			
	2023	2024	2025	2026	2023	2024	2025	2026
China	0.075	0.079	0.079	0.088	0.074	0.074	0.091	0.134
India	0.28	0.31	0.34	0.38	0.27	0.31	0.35	0.46
Iran	0.49	0.53	0.56	0.59	0.47	0.49	0.5	0.51

Fig. 14. The predicted COE between 2023 and 2026 using ANN (a. China-b. India-c. Iran).

the vulnerability of their renewable energy sectors to global disruptions.

Policymakers and stakeholders need to consider these findings to reinforce the resilience of renewable energy sectors against such global disruptions and ensure sustained progress toward sustainable energy futures. Future studies could go further into country-specific factors contributing to these trends and explore strategies to mitigate the adverse impacts of such unprecedented events on the renewable energy sector.

4.5. Results validation

This study aims to validate the calculated and predicted results by comparing them with findings from other research papers. The techno-economic analysis computed the COE for the post-COVID-19 period (specifically 2021), considering both With-COVID-19 and Without-COVID-19 scenarios. To facilitate the comparison of techno-economic outcomes, Fig. 15 presents data from other papers spanning 2019 to 2022, focusing on selected countries.

Based on the data from published papers spanning 2019 to 2022, the COE for various HRESs incorporating PV, WT, Bat, and DG technologies ranges from 0.032 to 0.854 $/kWh. It should be noted that Fig. 15 represents only a tiny fraction of the techno-economic studies conducted during the period. Upon comparing the calculated data from the techno-economic analysis with the predicted data from the ML analysis, it is observed that all the results obtained in this study fall within the range of previously published studies.

In countries like China and India, there is an increasing difference between the predicted results in the with-COVID-19 scenario and the without-COVID-19 scenario, indicating the negative impact of the COVID-19 pandemic on the renewable sector in these countries. However, it is essential to note that the predicted results in all scenarios and countries remain within the normal range depicted in Fig. 15.

5. Conclusion and policy implications

This study innovatively employed a techno-economic analysis to rigorously assess the impact of the COVID-19 lockdown on renewable energy systems across seven specific countries. By calculating COE values for both pre-COVID-19 and post-COVID-19 periods, incorporating economic data specific to each country and global renewable technology prices, the research provides a wide-ranging understanding of how the pandemic has influenced renewable energy economics. A key novelty of this study lies in utilizing a widespread dataset sourced from recently published papers and official websites. This dataset was decisive in forecasting COE trends from 2023 to 2026, enabling a detailed investigation into the direct and indirect effects of COVID-19 on renewable COE dynamics within each country. This innovative approach contributes to the existing literature and offers valuable insights for

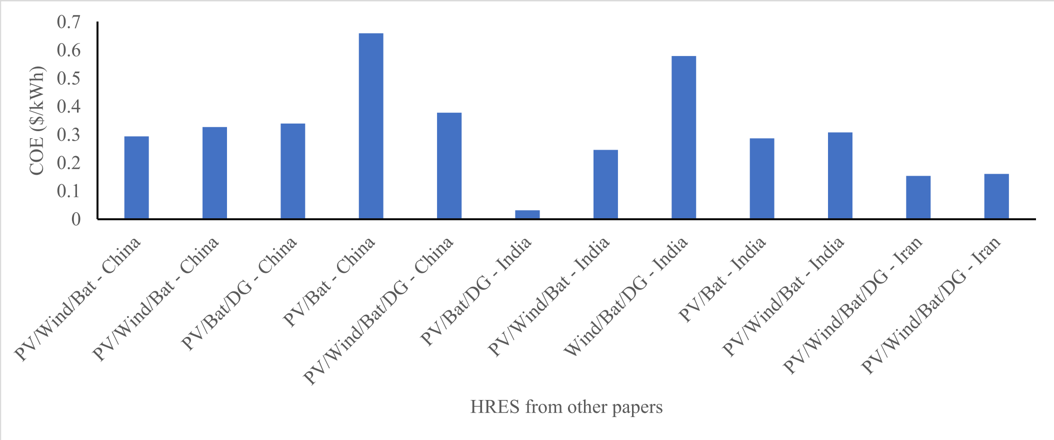
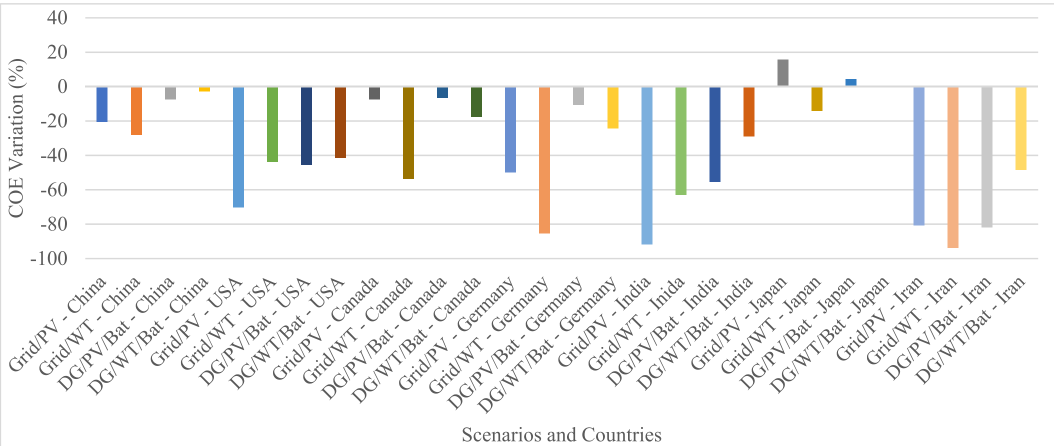
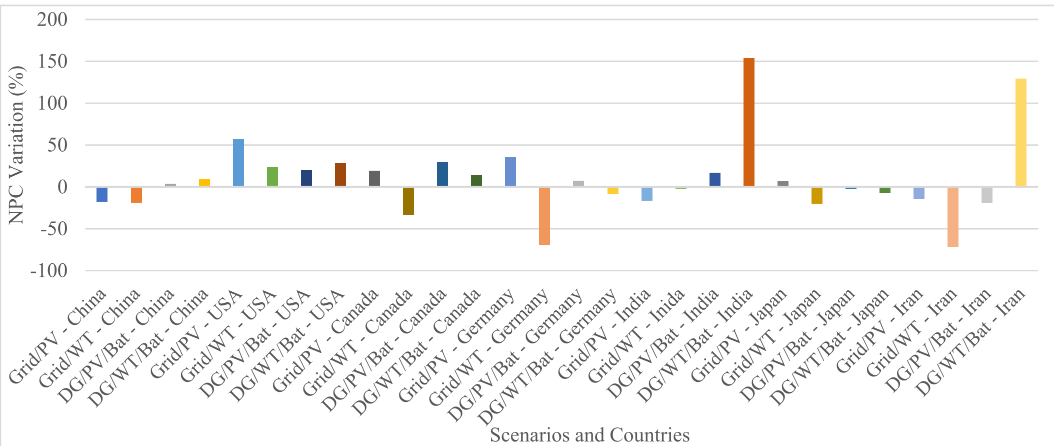


Fig. 15. Calculated COE in other papers during 2019–2022 [44,58–65].



a.



b.

Fig. 16. COE (a) and NPC (b) variations in selected countries for all scenarios.

policymakers and stakeholders directing global disruptions in the renewable energy sector. The primary findings of this study can be summarized as follows.

- The variations in inflation and discount rates significantly impact economic outputs, where countries with higher inflation and discount rates experience more significant fluctuations in the COE and NPC. The results indicate that an increase in the discount rate leads to a higher COE, while an increase in the inflation rate results in a lower COE. Furthermore, an increase in the inflation rate leads to a higher share of grid and DG, whereas a decrease in the inflation rate increases the share of renewable energy sources.
- In the case of China and Japan, the variation in NPC was negligible, suggesting a lower short-term impact of the COVID-19 pandemic on the renewable energy sector in these countries.
- Based on the techno-economic analysis, the USA and Canada experienced increased NPC during the pandemic. However, it is worth noting that despite the economic effects of the lockdown measures, all optimal scenarios for HRES recommended the utilization of PV and WT technologies.
- In Germany and India, the techno-economic results were highly influenced by natural resources and grid electricity prices. For example, Germany's lower solar irradiance and higher electricity prices increased PV capacity and NPC. Conversely, despite lower wind speeds in India, an increase in WTs contributed to the rise in NPC.
- Iran, due to lower electricity and fuel prices and increased inflation, experienced a unique situation compared to other countries. These factors decreased renewable energy fraction during the pandemic, reducing COE. In conclusion, Fig. 16 widely represents the variations in NPC and COE across all countries and scenarios. This figure was derived from the results presented in Figs. 5–11, illustrating the changes in COE and NPC in the post-COVID-19 period compared to the pre-COVID-19 period.

- Based on the ML outcomes, China and India are expected to experience more intensive long-term impacts. The prediction results showed that COVID-19 could increase the renewable COE in these countries in the long term.
- Iran's COE values exhibit a less significant impact from COVID-19 compared to China and India, likely due to cheap diesel fuel, a lower reliance on renewable energy sources, and a strong dependence on grid and DG systems.

This study considered technical and economic analyses, including assessing cost implications, renewable market trends, and economic variables fluctuations. However, its scope is still limited. Future research should emphasize a broader range of aspects, including further economic analyses, investment impacts, policy implications, and social dimensions, to obtain more detailed insights into the impact of COVID-19 on the renewable energy sector. Although the results of the COE prediction suggest that COVID-19 has slowed down the progress of renewable extension, it is essential to note that COVID-19 is not the sole influential factor. Other parameters, such as government policies, energy consumption patterns, and changes in economic variables, can contribute to these results and may change them. Therefore, more broad investigations considering these additional parameters will yield more reliable and robust outcomes. Additionally, utilizing more extensive databases and exploring alternative ML algorithms would enhance the predictive capabilities of COE in similar lockdown scenarios.

This study's findings and methodology can be applied to other sites and locations by considering several essential parameters. While the technical specifications of the HRES remain consistent, the economic parameters, such as inflation rates, discount rates, fuel prices, electricity prices, and components'' prices, must be adjusted to reflect the local economic conditions. For the ML models, replacing the dataset with relevant information from the new location ensures accurate predictions tailored to the specific context. The diverse selection of countries in this study, encompassing developed and developing nations and fossil fuel-based economies, provides a robust basis for generalizing the findings. Consequently, it is anticipated that the results for new cases will be like those observed in this study, supporting the broader applicability of our methodology.

CRediT authorship contribution statement

Saheb Ghanbari Motlagh: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Fatemeh Razi Astaraei:** Writing – review & editing, Supervision, Resources, Project administration. **Mohammad Montazeri:** Writing – review & editing. **Mohsen Bayat:** Software, Methodology, Formal analysis, Data curation.

Declaration of generative AI and AI-assisted technologies in the writing process

While preparing this work, the authors used AI-assisted technologies like ChatGPT and Grammarly to check grammar and improve language quality.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e36662.

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