Computers & Industrial Engineering 201 (2025) 110901

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Energy storage and transmission line design for an island system with renewable power

Arya Sevgen Misic [a], Mumtaz Karatas [b,*], Abdullah Dasci [c]

[a] Department of Industrial Engineering, Izmir University of Economics, Izmir, 35330, Turkey
[b] Wright State University, Department of Biomedical, Industrial and Human Factors Engineering, College of Computer Science and Engineering, Dayton, OH, 45435, USA
[c] Sabanci Business School, Sabanci University, Istanbul, 34956, Turkey

ARTICLE INFO

Keywords:
Electricity storage systems
Renewable energy
Wind power
Solar PV
Island systems

ABSTRACT

This paper addresses an energy system design problem for an island system that relies on renewable sources such as wind or solar PV. Typically disconnected from main grids, island systems, i.e., small islands or remote areas, often resort to costly power generation sources such as diesel. The design problem considered here includes the capacity decisions of energy storage systems (ESSs) and transmission lines that minimize total annual operation and investment costs. To address this challenge, we first introduce a deterministic mixed-integer linear program that is immediately extended to consider the stochastic demand and renewable generation via sample average approximation method. We implement our model on a case partly based on El Hierro, a small island in the Canary Islands of Spain. Through our experimental analysis, we generate a number of managerial insights into system design decisions and operational outcomes under a variety of storage characteristics, renewable sources, and spatial considerations.

1. Introduction

Some geographical islands and rural areas cannot economically be connected to large national or regional electrical grids. Such remote areas, typically called "island systems", have traditionally relied on power generation using fossil fuels, predominantly diesel, which are not only expensive but are also among the major pollutants. According to International Energy Agency (IEA) data received in 2022, approximately 775 million people, predominantly living in such areas, have no access to a main electrical grid (IEA, 2022). Therefore, finding cost effective and environmentally friendly energy solutions for almost one tenth of the world's population is of paramount importance.

Island systems are particularly attractive markets for renewable energy systems (RESs) for several reasons: First of all, unlike conventional generation plants such as thermal, nuclear, or hydro, most RESs such as wind or solar are economical in much smaller scales, in addition to their other well-celebrated benefits. Secondly, as isolation already costing them much more as compared to those connected to the main grids, renewable power sources' high investment costs may be more justifiable for an island population. Thirdly, island systems are also attractive for technology improvements both in production as well as in energy storage and overall transmission system design as they present unique challenges as well as opportunities. Finally, although far from being straightforward to study, island systems are obviously much simpler than national or regional grids with their limited production options and demand characteristics. This simplicity allows a more precise economic analysis on renewable electricity supply, which would more likely be clouded by the complexities of large grids with a variety of power generation plants of various technologies and economies.

Arguably the biggest challenge before a wider adoption of major renewable sources such as wind or solar is their highly intermittent supply characteristics, which cannot be mitigated by building ample capacity alone. A major energy storage capability is almost a prerequisite to overcome that challenge, which further adds to the investment as well as operating costs. While they may be attractive venues for renewable power sources due to the reasons mentioned above, island systems may also face challenges of renewables more acutely, as they lack the geographically diverse populations and base-load power sources that can enable major grids to better mitigate those challenges. Island systems must rely on sources like diesel that is neither clean nor inexpensive for maintaining system stability and reliability as well as for load-balancing. Hence, when introducing RESs to island systems, it is currently impractical to completely eliminate those traditional sources (Mustayen, Rasul, Wang, Negnevitsky, & Hamilton, 2022). However abundant the renewable potential of an island system

* Corresponding author.
E-mail addresses: arya.sevgen@izmirekonomi.edu.tr (A.S. Misic), mumtaz.karatas@wright.edu (M. Karatas), abdullah.dasci@sabanciuniv.edu (A. Dasci).

https://doi.org/10.1016/j.cie.2025.110901
Received 10 December 2023; Received in revised form 20 November 2024; Accepted 19 January 2025
Available online 26 January 2025

may be, such an extreme approach would most likely be prohibitively expensive.

With this motivation, we present an electricity storage and transmission line design problem for an island system that has renewable energy, storage, transmission, and supplementary diesel generation components along with their related design and/or operational decisions. Illustrative instances of these systems include the famous Alcatraz Island, USA that has a hybrid solar/battery/diesel electricity system for its energy supply (U.S. Department of Energy, 2023); Bozcaada Island of Turkey where the entire electricity is generated from photovoltaic (PV) panels and wind turbines combined with hydrogen storage; or the tiny Isle of Eigg of Scotland (Tucker, 2023). While aforementioned cases are very small islands, there are also large islands like El Hierro, one of Spain's Canary Islands, Tilos Island of Greece, and non-interconnected areas of Corsica of France are some other prominent examples that showcase renewable integration through hybrid systems (FEDARENE, 2023; Notton et al., 2017; Tsagkari, 2020).

Here we develop a mathematical model to find the optimal transmission system design for an island system with a renewable source, incorporating investment decisions for storage systems and transmission line capacities to minimize total annual operating and investment costs. The island system we consider is a typical one with one demand site (a.k.a., load center) and one renewable power facility, which are at a distance from each other. Hypothetically, renewable and diesel together can provide the island with a stable and secure supply, but that would be quite expensive as well as highly polluting. Hence, some storage facility is indispensable to assist balancing renewable supply with load with less diesel generation as well as restraining the size of transmission lines.

Although we have started with a focus in wind power, which is the main renewable source of El Hierro Island that our case is loosely based on, we also consider the solar PV as a hypothetical alternative. These two are currently the two dominating RESs. As for the energy storage technologies, we consider two alternatives; the first one is a battery energy storage system (BESS), particularly Li-ion that holds a leading position among BESSs in various grid service operations (Choi et al., 2021). While they have become at the spotlight in popular discourse, due particularly to increasing popularity of electric cars, Li-ion batteries have also been at the center of renewable energy evolution with their minimal space requirements, portability, reliability, and low round-trip energy losses. Furthermore, in general BESSs have lower scale-economies, as they are just a stack of battery units and ability to co-locate at the RES site reduces the need for high-capacity and costly transmission lines (Ericson, Anderson, Engel-Cox, Jayaswal, & Arent, 2018) as well as reduces transmission losses and lowers the costs associated with permitting, planning, and construction (Gorman et al., 2020).

Despite all those benefits, however, BESSs are still prohibitively expensive to make them viable as a sole storage technology at the utility level. Therefore, main grids or even most island systems must rely on some inexpensive utility-level (a.k.a., bulk) energy storage system. As far as the latter is concerned, pumped hydro storage (PHS) is the single most dominant technology due mainly to its low operational expenses, quick response, large storage capacities, and low round-trip losses in their classes. However, technical feasibility as a well as economical viability of PHS are highly dependent on geography as it requires two water reservoirs at different altitudes, which can be built or refurbished economically only at select places. El Hierro has indeed one PHS built nearby the wind farm, but one cannot always expect attractive sites for RESs also to be endowed with such fortune. Although there are new developments in such mechanical bulk storage systems, it is far from guarantee of a feasibility of an on-site bulk storage system. Therefore, it may be necessary to consider a PHS or some other bulk storage system at some distance from the RES site. We will further revisit this issue in the next section where we review the academic literature and current developments.

Consequently, the island system that we study considers two storage technologies; one BESS at the RES site and one PHS at some predetermined location. The main decisions for the storage systems include a pair of capacity decisions; one is the total storage capacity that is commonly referred as the "energy rate" or storage size and the other is the rate at which it can charge or discharge electricity, which is usually called the "power rate". Our model can employ one or both of these storage systems at some capacity levels. In addition to storage systems, our hypothetical island system also needs a transmission system that may consist of two line segments; one from the RES site to the PHS site and the second part is from PHS to the load center. In cases where a PHS is not employed or employed at the RES or the load site, two segments essentially becomes just one long line. Finally, if the demand cannot be satisfied from the RES or storage systems via transmission lines, the shortage is supplied from diesel generators that assumed to be located at the load center.

Considering all design decisions of the problem as well as the integrated planning decisions at hourly intervals, we first develop a mixed-integer program under deterministic demand and power generation assumptions. This formulation is immediately extended to a stochastic model that includes uncertainty related to generation and load via sample average approximation (SAA) method. The resulting stochastic mixed integer program (SMIP) can be solved by a commercial optimizer provided the number of scenarios are moderate. We implement our model to a system inspired from the small island of El Hierro in the Canary Islands, Spain. For this case study, we utilize available time series data to generate synthetic hourly demand and generation scenarios to serve as inputs for our SMIP model. We then carry out an extensive set of what-if analyses to evaluate the impact different problem settings, parameters, and the number of scenarios.

The remainder of the paper is structured as follows: Section 2 provides the literature review on past work incorporating energy storage decisions within island/remote or microgrid systems along with contemporary developments to motivate our work. Section 3 presents the detailed problem description, assumptions, and the proposed mathematical formulation of our model. The case study for El Hierro Island is outlined in Section 4, where we present electricity demand and generation data and describe the methods and results of synthetic data generation. Section 5 presents the details of the experimental settings, reports on the numerical results, and discusses main managerial insights. Finally, Section 6 concludes the paper with our final remarks.

2. Literature review

The literature on energy storage systems (ESSs) involves a myriad of issues that include a vast variety and blend of design, planning, operational, and real-time control decisions, all of which have been the subject of intense level of investigation. Of this voluminous literature, most prominently due to increasing RES employment worldwide, the context of island systems arguably forms the greater portion, due in part, to their simplicity and in part to their attractive features as mentioned earlier. There are many other terms used for islands systems in the literature; for example, more commonly as remote, isolated, micro-grid, off-grid and less commonly as insular, stand-alone, autonomous, or non-interconnected. Such variety of terminology adds to the difficulty of the review of relevant literature as do their liberal usages for some grid-connected entities as well.

As it will also soon to be clear to the reader, our aim can only be a modest one consisting of a glimpse on this literature, which is not only vast in its volume but also fast-expanding. Even the number of recent review or survey papers that contain some relevance to our problem easily exceeds dozens. With the full awareness of missing many others, we can mention *literally* a couple of dozens such as, for general reviews of electricity systems (Parker, Tan, & Kazan, 2019) and RES (Weschenfelder et al., 2020); reviews of works on storage system design issues in electricity grids (Haas et al., 2017; Hannan et al., 2020;

Table 1
A synthesis of the related literature (refer to Table 2 for abbreviations).

Study	Decisions				Grid components			Modeling features and solution approaches				
	Size	Type	TL	RES	RES	XPow	ESS	UC	Model	Method	Objective Function	
Korpaas, Holen, and Hildrum (2003)					W	G	∗		DP	DRA [H]	max	Rev - O&M
Zhou, Scheller-Wolf, Secomandi, and Smith (2016)					∗	G	∗	+	MDP	BI [E]	max [D]	Cash flow
Hassler (2017)					∗	G	∗	+	MDP	DRA [H]	max	Cash flow
Heredia, Cuadrado, and Corchero (2018)					W	G	B	+	MILP	Solver	max	Cash flow
Yang, Guo, Liu, Li, and Chu (2018)					W, CSP	G	T		MILP	Solver	max	Rev - IC
Zhou, Scheller-Wolf, Secomandi, and Smith (2019)					∗	G	∗	+	MDP	DRA [H]	max [D]	Cash flow
Marino and Marufuzzaman (2020)					∗	C, G	∗	+	MINLP-SAA	Solver	min	O&M
Gutierrez, Abdul-Jalbar, Sicilia, and San-Jose (2022)				+	PV	G	B		MINLP	SE [E]	min	RES+O&M
Karakoyun, Avci, Kocaman, and Nadar (2023)					W	G	B	+	MDP	BI [E]	max	Cash flow
Chen, Gooi, and Wang (2011)	+				PV	F, G	B		MINLP	GA [H]	max [D]	Rev - ESS - O&M
Johnston, Díaz-González, Gomis-Bellmunt, Corchero-García, and Cruz-Zambrano (2015)	+				W	G	B		LP	Solver	max	Rev - ESS - O&M
Anagnostopoulos and Papantonis (2007)	+			+	W	G	P	+	MINLP	EA [H]	max min	ROI proxy IR
Castronuovo et al. (2014)					W	G	P	+	LP-CC	Solver	max min	Rev - O&M IC
Papaefthymiou and Papathanassiou (2014)	+			+	W	F	P		NLP	GA [H]	max min [D]	RES penetration RES+ESS+O&M
Bueno and Carta (2005a, 2005b)	+			+	W	F	P		Sim	SE [H]	min [D]	RES+ESS+O&M
Caralis and Zervos (2007)	+				W	F	P		Sim	SE [H]	min [D]	ESS+O&M
Brown, Lopes, and Matos (2008)	+				W	C	∗	+	LP	Solver	min	ESS+O&M
Abbey and Joós (2008)	+				W	C	∗	+	MILP	Solver	min	ESS+O&M
Kaldellis, Kapsali, and Kavadias (2010)	+				W	C	P		Sim	SE [H]	min	RES loss
Vrettos and Papathanassiou (2011)	+				W, PV	C	B		NLP	GA [H]	min [D]	RES+ESS+O&M
Katsaprakakis et al. (2012)	+			+	W	C	P	+	Sim	SE [H]	min [D]	ESS+O&M
Ru, Kleissl, and Martinez (2012)	+				PV	G	B		DP	LP [H]	min	ESS+O&M
Bortolini, Gamberi, and Graziani (2014)	+			+	PV	G	B		Sim	SE [H]	min [D]	RES+ESS+O&M
Harsha and Dahleh (2014)	+				∗	G	∗	+	MDP	DRA [H]	min [D]	ESS+O&M
Malheiro, Castro, Lima, and Estanqueiro (2015)	+			+	W, PV	F	B		MILP	Solver	min [D]	RES+ESS+O&M
Miranda, Silva, and Leite (2015)	+				W	C, P	B		MILP	TD [H]	min	non-RES costs
Ahadi, Kang, and Lee (2016)	+			+	W, PV	–	B		Sim	SE [H]	min [D]	RES+ESS+O&M
Billionnet, Costa, and Poirion (2016)	+				W, PV	F	B	+	MILP-RO	Solver	min	RES+ESS+O&M
Shang, Srinivasan, and Reindl (2016)	+			+	W, PV	C	B		NLP	PSO [H]	min [D]	RES+ESS+O&M
Alharbi and Bhattacharya (2017)	+				W, PV	C	B		MINLP	TD [E, H]	min [D]	ESS+O&M
Merzifonluoglu and Uzgoren (2018)	+			+	PV	G	B		MILP-SAA	Solver	min [D]	RES+ESS+O&M
Nguyen-Hong, Nguyen-Duc, and Nakanishi (2018)	+				W	C	B	+	MILP	Solver	min	ESS+O&M
Psarros, Karamanou, and Papathanassiou (2018)	+			+	W, PV	C, P	B		MILP	TD [H]	min [D]	RES+ESS+O&M
Psarros, Kokkolios, and Papathanassiou (2018)	+				W, PV	C, P	B		MILP	TD [H]	min	non-RES costs
Moretti et al. (2019)	+			+	PV	C	B		MILP	Solver	min [D]	RES+ESS+O&M
Viteri, Henao, Cherni, and Dyner (2019)	+				W, PV	C, F	B	+	MILP	Solver	min [D]	RES+ESS+O&M
Benalcazar, Suski, and Kamiński (2020)	+			+	W, PV	F	B		LP	Solver	min [D]	RES+ESS+O&M
Fiorentzis, Katsigiannis, and Karapidakis (2020)	+			+	W, PV	F, G	B		Sim	SE [H]	min [D]	RES+ESS+O&M
Lopes, Castro, and Silva (2020)	+				W, G	F	P		NLP	PSO [H]	min [D]	ESS+O&M
Iliadis et al. (2021)	+				W, CSP	C	B	+	Sim	SE [H]	min [D]	ESS+O&M
Arnaoutakis, Kefala, Dakanali, and Katsaprakakis (2022)	+			+	W, PV	C	P	+	Sim	SE [H]	min	RES+ESS+O&M
Pombo, Martinez-Rico, and Marczinkowski (2022)	+	+		+	W, PV	C	B		MILP	Solver	min [D]	RES+ESS+O&M
Yang and Nehorai (2014)	+	+		+	∗	C	∗	+	NLP-CC	TD [H]	min	RES+ESS+O&M
Dong, Li, and Xiang (2016)	+	+		+	W, PV	–	B, H	+	MINLP-CC	ACO [H]	min [D]	RES+ESS+O&M
Katsaprakakis (2016)	+	+			W, PV	F	B, P	+	Sim	SE [H]	min	ESS+O&M
Moshi, Bovo, Berizzi, and Taccari (2016)	+	+		+	W, PV	C	B	+	MILP-RO	Solver	min [D]	RES+ESS+O&M
Gioutsos, Blok, van Velzen, and Moorman (2018)	+	+		+	∗	F	B, P		NLP	Solver	min [D]	RES+ESS+O&M
Javed et al. (2021)	+	+		+	W, PV	–	B, P		NLP	PSO [H]	min [D]	RES+ESS+O&M
Crozier and Baker (2021)	+	+			∗	–	∗		Sim	SE [H]	min [D]	ESS+O&M
Psarros, Dratsas, and Papathanassiou (2021)	+	+		+	W, PV	C, P	B, P		MILP	TD [H]	min [D]	RES+ESS+O&M
Berna-Escriche, Vargas-Salgado, Alfonso-Solar, and Escrivá-Castells (2022)	+	+		+	W, PV	F	B, P		Sim	SE [H]	min [D]	RES+ESS+O&M
Pombo, Martinez-Rico, Spataru, Bindner, and Sørensen (2023)	+	+		+	W, PV	C	B, P		MILP	Solver	min [D]	RES+ESS+O&M
Marocco, Novo, Lanzini, Mattiazzo, and Santarelli (2023)	+	+		+	W, PV	F	B, H		MILP	Solver	min [D]	RES+ESS+O&M
Kuznia, Zeng, Centeno, and Miao (2013)	+		+	+	W	C, G	∗	+	MILP	BD [H]	min	ESS+TL+O&M
Xie, Wei, Ge, Wu, and Mei (2022)	+		+		PV	–	∗	+	LP-RO	Solver	min	ESS+TL
Our work	+	+	+		∗	F	B, P	+	MILP-SAA	Solver	min	ESS+TL+O&M

He & Wang, 2018; Javed, Ma, Jurasz, & Amin, 2020; Saboori, Hemmati, Ghiasi, & Dehghan, 2017; Sarbu & Sebarchievici, 2018; Shaqsi, Sopian, & Al-Hinai, 2020; Tahir, 2024; Toufani, Karakoyun, Nadar, Fosso, & Kocaman, 2023; Weitzel & Glock, 2018; Zidar, Georgilakis, Hatziargyriou, Capuder, & Škrlec, 2016); reviews of works on energy and electricity management issues solely for island systems (Anderson & Suryanarayanan, 2019; Erdinç, Paterakis, & Catalão, 2015; Mathew, Hossain, Saha, Mondal, & Haque, 2022; Mustayen et al., 2022); and finally, reviews of works on storage related issues solely for island systems (Arani, Gharehpetian, & Abedi, 2019; Choudhury, 2022; Faisal et al., 2018; Georgious, Refaat, Garcia, & Daoud, 2021; Hajiaghasi, Salemnia, & Hamzeh, 2019; Hannan et al., 2020; McIlwaine, Foley, Best, Morrow, & Al Kez, 2023; Psarros, Dratsas, & Papathanassiou, 2024; Salman, Al-Ismail, & Khalid, 2020; Symeonidou & Papadopoulos, 2022).

In what follows, we review or at least mention some of the most pertinent past work in suitably defined clusters, but at the outset we must remark that despite the plethora of research in energy storage

Table 2
Abbreviations used in Table 1.

Decisions
Size: Whether ESS Size(s) is explicitly considered
Type: Whether simultaneous employment of multiple ESS types considered
TL: Whether transmission line capacity decision(s) is explicitly considered
Res: Whether RES capacity decisions are explicitly considered
Grid components
∗: General, unspecified
(RES) W: Wind, PV: Solar photovoltaic, CSP: Concentrated solar power, G: Geothermal
(XPow: Supplementary power source) G: Grid, C: Conventional, F: Flexible, P: Penalty
(ESS) B: Battery, P: Pumped Hydro, H: Hydrogen, T: Thermal
Modeling features and solution approaches
UC: Whether uncertainty is explicitly considered
(Model) DP: Dynamic program, MDP: Markov Decision Process, LP: Linear program
NLP: Nonlinear program, MI: Mixed integer, Sim: Simulation
CC: Chance constrained, RO: Robust optimization, SAA: Sample average approximation
(Method) [H]: Heuristic, [E]:Exact
DRA: Decision rule approximation, BI: Backward induction, SE: Scenario evaluation
Solver: Commercial or open-source general-purpose solver
GA/EA/PSO/ACO: Genetic/Evolutionary/Particle-swarm/Ant-colony metaheuristics
BD: Benders decomposition, TD: Temporal decomposition
(Objective Function) [D]: Discounted, Rev: Revenue, ROI: Return-on-investment
RES/ESS: Renewable and storage investment costs, TL: Transmission line costs
O&M: Relevant operations and maintenance costs
IC: Imbalance cost, IR: Imbalance ratio, RES loss: Dumped or curtailed RES generation

systems, it appears that integrated grid design problems with spatial issues, such as transmission line design or storage location considerations, have attracted a surprisingly a low level investigation for island systems. At the end of this review, we will relate to the reasons and motivate our work with observations on the current state and future outlook of island RES-ESS system design research and practice.

The guiding framework of our review of this vast literature is presented in Table 1. It contains over 50 works that are identified along some important attributes in three main sets as (*i*) type of design decisions are made, (*ii*) relevant components of the island system, and (*iii*) important modeling features and solution approaches employed by them. Despite looking scrambled, the works are listed chronologically in a few clusters that will be explained shortly.

The top quarter portion of the table is devoted to works that mostly deal with some profit measure or dual objectives of different kinds. Although majority of these works do not consider any design decisions, all of them can be utilized to evaluate some design scenarios even though their authors might not have explicitly stated or undertaken it. Almost all of these works consider isolated systems in the more liberal sense mentioned above, because their main emphasis is on the management of pricing dynamics of the grid they are connected (Castronuovo et al., 2014; Hassler, 2017; Korpaas et al., 2003; Zhou et al., 2016, 2019). We have however come to appreciate such works portrayal of island systems, particularly in relation to distributed generation. Electricity merchandisers of different kinds (Liu, Bo, Wang, & Chen, 2021), peer-to-peer trading using batteries (Khodoomi & Sahebi, 2023; Liu, Dai, Bo, Meng, & Ou, 2023) or even electrical vehicles (Sharifi, Banerjee, & Feizollahi, 2020) are important developments, which can loosely be considered as island systems.

The middle-half of the table, from Bueno and Carta (2005a, 2005b) to Arnaoutakis et al. (2022) and a few of the earlier lines, contain works that consider some form of storage sizing decisions alone or jointly with RES sizing decisions. Whatever their differences may be, one overarching feature is the consideration of a single storage technology that is co-located with the RES. That does not imply, however, that these works cannot be utilized to evaluate different storage technologies (in fact, many of them do), but they do not consider different ESS technologies *simultaneously* or storage technologies that are viable away from RES sites. These are not superficial concerns; the fact that investment costs of ESSs depends on their energy and power rates as well as varying O&M costs due to differing characteristics, lifetimes, and real-time operational decisions, etc., a suitable portfolio of storage technologies may arise as a better solution than a single technology alone, even when locational concerns are set aside. Despite the sizeable number of works we have displayed in the first three quarters of the table, our list is necessarily only sample from the great multitude. In the last quarter of the table, where we list the most relevant works, we have done our utmost to present a complete list to the best of our knowledge. These are the works that consider simultaneous sizing decisions of different ESS technologies or jointly with transmission line decisions.

Having laid out the review framework and the synthesis table, we now move on to some pertinent observations on the past works. The first column of the grid component set is what type(s) of RES source is considered by the works. Except a very few, Iliadis et al. (2021), Lopes et al. (2020), Yang et al. (2018), all of them consider either wind and/or solar PV, which is not surprising given their present predominance in the market. However, there are several more works (denoted with "∗") and even some of those that specify wind or PV technology are actually independent of RES type or can easily be adapted to other technologies. We also consider wind or PV, but like those we have just mentioned, all we need is the generation data and therefore, our setting is independent of the type of RES.

The second grid component (XPow) indicates the available course(s) of action, when the island RES-ESS system faces a shortage and sometimes, also a surplus. Only a handful of works *seem* to have neglected this issue, but they either enforce 100% load provision (Ahadi et al., 2016; Javed et al., 2021) or impose some pre-specified service level (Dong et al., 2016; Xie et al., 2022). The rest of the works have one or more types of recourse with some financial consequences. The grid-connected islands usually have a two-way trade; in fact, as mentioned earlier, some of those models are specifically directed for energy merchandising or peer-to-peer trades. However, some island systems have more limited relationship to the grid; for example, they can only purchase from Harsha and Dahleh (2014), Kuznia et al. (2013) or only sell to the grid (Castronuovo et al., 2014; Johnston et al., 2015) or trades are limited due to transmission line capacities (Chen, Duan, Cai, Liu, & Hu, 2011; Karakoyun et al., 2023; Korpaas et al., 2003; Marino & Marufuzzaman, 2020; Zhou et al., 2019). For many grid-connected islands, the main issue is the management of trade and the nature of price process is also a major point of differentiation. For example, some assume prices as known and constant (Fiorentzis et al., 2020; Kuznia et al., 2013; Ru et al., 2012) or varying in time or in markets such as day-ahead, secondary-market, etc. Bortolini et al.

(2014), Castronuovo et al. (2014), Chen, Gooi, and Wang (2011), Gutierrez et al. (2022), Harsha and Dahleh (2014), Johnston et al. (2015), Korpaas et al. (2003), Marino and Marufuzzaman (2020). There are also works with stochastic and exogenous price processes (Hassler, 2017; Karakoyun et al., 2023; Zhou et al., 2016, 2019) and those with bid-price decisions (Heredia et al., 2018).

In the true island systems and as well as in some grid-connected ones, there is usually a supplementary power source or some imputed penalties. Among the power sources, diesel generation is arguably the most commonly cited source, but few works also consider other sources such as heavy fuel oil, gas, and hydro. Regardless of the mentioned generation technology, however, we have found it more informative to classify them according to the assumed operating characteristics as "flexible" and "conventional". Because two works that may cite the same type of generation source may assume a substantially different set of operating conditions. Hence, in our classification, a flexible source implies that any amount of shortage can be satisfied at a known unit cost. Nearly half the works assume flexible source, if we also include (Harsha & Dahleh, 2014; Kuznia et al., 2013), whose grid relationship is technically identical to a flexible source and Miranda et al. (2015), Psarros, Karamanou, and Papathanassiou (2018), Psarros, Kokkolios, and Papathanassiou (2018) who actually use conventional generation, but also impose penalty for shortage, which again technically is no different than the flexible option.

About the same number of works consider some form of conventional generation with varying details of operating restrictions. The only universally shared assumption is that when a conventional unit is operational, power generation must be within a minimum threshold and maximum capacity. Beyond this commonality, they seem to be a disorderly multitude, which can only be meaningfully clustered by the detail of operating restrictions. Among the less detailed, Viteri et al. (2019) assume that a conventional generator is always operational, while (Abbey & Joós, 2008; Marino & Marufuzzaman, 2020; Nguyen-Hong et al., 2018) allow shut-down and start-up at any time. Then, there are a number of works that consider more involved restrictions on shut-down and start-up actions and duration as well as ramp-up/down constraints (Miranda et al., 2015; Psarros et al., 2021; Psarros, Karamanou, & Papathanassiou, 2018; Psarros, Kokkolios, & Papathanassiou, 2018; Shang et al., 2016). All of these works assume that the supplementary generation consist of a single unit, but there are also works that consider multiple independent units potentially with varying fuels, costs, and operating characteristics. These works may again include simple start-up/show-down decisions for each unit (Arnaoutakis et al., 2022; Brown et al., 2008; Iliadis et al., 2021; Kaldellis et al., 2010; Katsaprakakis et al., 2012; Moretti et al., 2019; Yang & Nehorai, 2014) or more involved restrictions as well as constraints on ramp-up/down on them (Alharbi & Bhattacharya, 2017; Moshi et al., 2016; Pombo et al., 2022, 2023). Finally, among the works that consider conventional generation, two other works, in addition to the two mentioned above, also impose penalties; Miranda et al. (2015) on dumped or curtailed energy and Psarros et al. (2021) on likewise but also for the shortage.

The last major grid component we like to relate is the type(s) of ESS assumed in the model. Except for those grid-only works, only a handful of the other works consider a non-battery technology as the sole storage option (those represented by "*ast*" in the relevant column refer to generic storage modeling of which are well-suited to batteries). The great majority consider battery alone or as part of alternatives. The next common technology is PHS, treatment of which also vary among the works. Some consider them generically (Castronuovo et al., 2014; Papaefthymiou & Papathanassiou, 2014; Psarros et al., 2021), but more of them usually consider somewhat more detailed design aspects such as reservoir volumes, penstock size, turbines, etc. Finally, we also see one work on thermal storage (Yang et al., 2018) and two on hydrogen storage (Dong et al., 2016; Marocco et al., 2023), although (Berna-Escriche et al., 2022) report that they approximate their PHS system via hydrogen storage (apparently, the generic platform they utilize do not have an explicit PHS modeling capability). However, we must be somewhat cautious here as we focus on storage technologies for electricity provision, and therefore, storage technologies for other energy purposes are naturally thinly represented here.

Having discussed important structural aspects of the past work, we now move on with some summary observations about the modeling and solution approaches. We were somewhat surprised to find out that far less than half (23 out of 56) of the works have considered uncertainty in their models. The ratio falls a bit further down among the works that consider some strategic decision (18 out of 47) and strikingly much further down among the works that consider RES-ESS design decisions simultaneously (only six out of 26), which presumably should be even more uncertain given the absence of past generation data. Clearly, despite the widely-acknowledged renewable generation intermittency, dealing with uncertainty even in island systems has obviously been challenging. Among those that consider uncertainty, there is a cluster of works (at the top of the table) that do not deal with structural decisions and therefore, some type of decision scenario generation and evaluation is still needed. Among the remainder we see a few simulation models and about half a dozen mathematical models that consider a chance-constrained or robust optimization structure and altogether only a about another half dozen mathematical models that explicitly consider some type of scenario-based approach.

The majority of works that develop static formulations (e.g., LP, MILP, NLP, etc.), employ a commercial or open-source optimizer, such as Gurobi, CPLEX, or MATLAB. Few adopt metaheuristics or heuristic algorithms that are based on solving operational sub-problem in shorter time intervals and integrated with the main solution algorithm (noted in the table with the imperfect term of TD,"time-decomposition"). Those that develop dynamic programs (DPs and MDPs) usually adopt a method that starts with decision rule approximation, followed by a subsequent method such as value function approximation or policy iteration or linear programming. A couple of works that adopt the exact approach of backward induction are naturally limited by the size of the problem they can handle. Finally, about a fifth of the works develop simulation models that are employed to evaluate some pre-specified set of design decisions. Each of these simulation models entail some algorithm to find the operational decisions, either heuristically or, in some deterministic cases, exactly, which are then integrated with the simulation model.

Finally, the last two columns of the table summarize the objective functions of the models. As mentioned earlier, a great majority is about financial indicators, although there are also few non-financial ones that are related to the RES usage. The greater majority of the works adopt a cost minimization objective either of discounted-type for long term planning (indicated with "[D]") or shorter periods, e.g., yearly or monthly, with commensurate investment costs, if relevant. Despite their uniform appearances, almost no two objective functions are exactly the same. They vary greatly according to how and what parts of O&M costs are accounted for, particulars of RES and ESS system design investments, or if the total cost, discounted cost, or some measure of unit cost is considered.

As we have indicated earlier, we have done our utmost to identify past work that consider simultaneous employment of multiple storage technologies or some spatial aspects. As one can glean from the table, our efforts were more fruitful for the former, as we have identified about a dozen of such works. The spatial aspects are almost entirely neglected; even those with the connection to the main grid, transmission capacity is altogether neglected except for the handful already mentioned above (Chen, Duan, et al., 2011; Karakoyun et al., 2023; Korpaas et al., 2003; Marino & Marufuzzaman, 2020; Zhou et al., 2019). We were able to identify only two works that consider transmission line capacity as a decision: In their comprehensive island system design problem, Kuznia et al. (2013) formulated a stochastic optimization model, where they explicitly consider the capacity decisions to supplement the power shortage from the main grid. The second such related work is presented by Xie et al. (2022) who consider connecting a RES to the main grid with an objective to minimize ESS and transmission line capacity investment costs, while maintaining a minimum level of curtailed or dumped energy, which is handled in a distributionally robust optimization framework. Their experiments show that the proposed method effectively determines energy storage and transmission line capacities and investigate the supplementary and complementary relationships between the transmission and storage capacities with respect to their relative costs and uncertainty in the renewable generation.

We like to conclude this section with a commentary for the lack of interest of the spatial concerns in island systems and how it can potentially have a more promise in the future. Let us first begin with some solemn observations: Transmission systems are usually separate organizations and therefore it is up to the RES ownership to assess a need for storage and assume costs and confines of its site. Hence, in most cases, the storage and transmission decisions naturally made by separate entities that pursue separate objectives. It is only a policymaker that can provide incentives or regulations for integration, which is arguably a more manageable and perhaps a natural task in isolated systems. Secondly, utility-level storage applications such as PHS have been viable in national or regional grids or large islands. Hence, it is no surprise that almost all PHS installations are in large grids (see for example, Nikolaos, Marios, and Dimitris (2023) and the online and up-to-date Hydropower Pumped Storage tracking tool by the International Hydropower Association (IHA) at https://www.hydropower.org/hydropower-pumped-storage-tool). If an island or a remote system has endowed with a storage facility, it is mostly of the smaller grade such as batteries or flywheels. In their Europe-wide research, Fotopoulou et al. (2024) identify 15 island systems that have existing storage facilities with only three employing PHS and they further report that out of the seven Greek islands with storage facility plans, only one of them is for a PHS and the rest for battery systems.

However discouraging these observations may seem, they are overtaken by many brighter notes: As far as energy storage or even the RESs are considered, the energy transformation in the world is still in its infancy. For example, even though it has been in use over a hundred years, many parts of the world still do not possess any utility grade electricity storage, including five among the G20 countries (Brasil, Indonesia, Mexico, Saudi Arabia, and Turkey) according to the IHA website. Yet, International Energy Agency (IEA) predicts a tremendous growth of PHS installations particularly with the growing concentrated solar power usage (IEA, 2021) and both IHA and IEA recounts many PHS projects currently under construction, planned, or announced. We also witness a much increased activity on recent surveys or feasibility studies of PHSs in different parts of the world. For example, in their comprehensive study, Stocks, Stocks, Lu, Cheng, and Blakers (2021) identify well-over 600,000 potentially viable PHS locations in the world and these are only the so-called closed-systems (i.e., non-river connected). In another comprehensive study, Hunt et al. (2023) carry out a survey of 5600 potential PHS locations in Brazil. There are several more studies for different parts of the world, which are compiled by Görtz, Aouad, Wieprecht, and Terheiden (2022) who also conduct survey of PHS potentials along two rivers in Chile.

The great potential of even the traditional PHS has yet to be materialized not only on large scale but also particularly in smaller scale. There is a growing number of studies that survey and study viability of small-scale or mini PHSs (see for example, Crettenand, 2012; Pacot, Martignoni, Smati, Denis, & Münch-Alligné, 2022 for case studies in Switzerland, Morabito & Hendrick, 2019 in Belgium, and Licheri, Petrollese, Cocco, & Cambuli, 2023 in Southern Italy) and comparisons to battery systems (Onbaşılı, Williams, & Dhundhara, 2020). Furthermore, there are novel PHS inspired developments such as utilizing coastal freshwater and underground reservoirs, deep-sea mechanical systems (Nikolaos et al., 2023), and high-density hydro (e.g., using fluids denser than water) developed by U.K. based startup company, RheEnergise (www.rheenergise.com). All these new developments and progress point out to growing potential PHS or similar mechanical systems in any scale, which eventually make the spatial considerations more prominent because such systems' viability continue to depend on the suitability of the topology.

Finally, one should not confine the integration of RESs with the electricity storage only. In fact, there are already mature and common bulk-storage systems for "non-electricity" energy storage purposes. For example, molten salt for thermal storage, other heating and ventilation applications, CAES for air-pressure, hydrogen fuel cells that may need to be transported to wherever is demanded. Furthermore, other energy intensive applications such as methane production or water desalination can also be utilized as a way to "store" peak generation on such vital commodities. Most of these applications more likely amplify the impact of geography rather than abate it.

In summary, especially given the rise of RESs, there is a rich body of literature on ESSs in island contexts, with a particular focus on design, operational, and management issues. Although considerable work has been done on ESS sizing and integration with RES, there is still a noticeable gap in addressing spatial concerns, such as transmission line design and the strategic location of storage facilities. Moreover, only a small subset of works deals with uncertainty in island system design, despite the inherent variability in RES generation. Our review of literature highlights the importance of considering a wider range of storage technologies and incorporating spatial and transmission concerns into future research.

3. Problem description and mathematical formulation

3.1. Problem description

As we have observed from the literature, perhaps the single most commonly neglected issue is related to the spatial aspects. However, many bulk energy storage systems or alternative outlets does have some locational implications, neglect of which may have undue negative consequences towards adoption and usage of RESs. In an electricity grid context, spatial considerations necessarily entail transmission network design decisions, such as the route and capacity of the lines. While ownership of transmission systems are generally separate from generation or distribution organizations, it may be more possible to have joint ownership structure in isolated systems. In any case, joint considerations of transmission and storage can inform policymakers towards developing certain regulations or incentives to achieve an overall better grid system design.

This paper may be considered the first of such study that explicitly consider transmission line design decisions within in an island system. We hope this work leads to an increased appreciation of the importance of the subject and stimulate further research in this field. To be clear, there *are* joint storage and transmission design problems that have been studied in the literature. But the general focus on those works are towards developing effective solution algorithms in larger grid systems. In such models, one really cannot see trade-offs related to system design components and spatial aspects in any clarity. Hence, our work may also be considered as a step back to investigate design decisions with spatial concerns in a more simplified setting.

The island system we consider may be considered too simple even for an island, but it should suffice for the purposes just stated above. In our system, we have one RES site and one major demand center (i.e., the load site) that are distant from each other and therefore, there must be a transmission system that must be constructed from RES to the load site. Assumption of a single RES site is perhaps not a very strong one: for an isolated system, probably only a single RES site may be possible or desirable due to technological and economical reasons. The assumption of a single demand center appears to be a stronger one that needs further clarification: If the island had originally relied on a central generation facility for some of its load, there must have already been some sub-transmission and distribution system in place. Hence, a single load center here does not necessarily imply a single population center but rather the point of connection to the island's existing sub-transmission and distribution system.

Given the highly intermittent nature of RESs, a storage system is almost obligatory for any isolated system that aspires to make renewables meaningful portion of its energy supply. In our model, we consider a storage system that consists of two separate and independent units: The first one is battery system (BESS) that is assumed to be co-located with the RES and the second one, presumably a bulk storage system like PHS, that can be set up at a fixed location somewhere between the RES and load site. Although a BESS can technically be located anywhere in the geography, it is not necessary to consider any location other than the RES site, simply because the degree of RES intermittency is far greater than that of demand uncertainty. Therefore, any location away from the RES site would only increase the transmission cost without any benefits, and one does not even need to consider other complexities and costs associated with separate locations. As we have mentioned above, a bulk storage system like PHS can be economically built only at select places. In our mathematical model, we consider one fixed location somewhere between the RES site and load center. Although our model can easily be extended to multiple locations, we find it unnecessary to consider more, as alternatives can be evaluated one at a time.

The operation of this integrated RES-ESS system is as follows: Whatever generated by the RES are used immediately to satisfy the load and if any remains they may be used to charge one or both storage systems, all the while transmission and storage restrictions are observed. If there is still some excess with no possible use, it is simply grounded (a.k.a., "dumped") with no penalty. On the other hand, if RES generation falls short of load at a moment, one or both of the storage systems can be discharged to supplement, again within the technical restrictions of transmission and storage. If there is still some shortage, a flexible power generation at the load center assumed to cover the remaining shortage at a unit cost. This could be a centrally managed generation or privately owned stand-by generators at the buildings or localities, or simply be considered as an imputed penalty cost.

Our problem, which may be named as transmission and storage design problem, consists of capacity decisions of the transmission line(s) and storage systems. The capacity of transmission line(s) is simply expressed as the maximum rate of energy that can be transmitted at any instant, but the capacity of the storage units actually consists of two main quantities: the size or "energy rate" that quantifies the maximum energy the system can store and the "power rate" that indicates the maximum rate at which the unit can charge or discharge the energy. Depending on where the PHS is available or whether it is employed, there could be two transmission lines; first from RES-BESS site to the PHS site and the second from the PHS to the load site. If a PHS is not employed or employed at the RES or load sites, then these two essentially become a single segment.

In the design problem, one also need to consider operational decisions of the system, i.e., at a moment, how the generation is to be used, if the storage systems are charged or discharged and how much supplementary source to be used, etc. We consider hourly time segments to approximate what is essentially a real-time control problem. For a design problem, consideration of operational issues at hourly intervals is the most detailed we observe across the past studies, which is also dictated by the publicly available data. There are some losses during the charge and discharge of storage systems. They actually depend on many factors, such as their age, rate at which they perform, the current storage level, among other things. However, we consider some baseline technology-specific average loss ratios, which is also commonly assumed by the majority of works. There are also self-discharges or losses over transmission lines, which we ignore in the interest of clarity, but they can easily be taken into account within the framework of our model.

The objective of the problem is to minimize the overall cost over a year, which includes the installation costs of the transmission and storage systems, operation and maintenance of costs of storage systems, and penalty costs incurred due to the use of supplementary power source. All costs are assumed to be commensurate; that is, investment costs represent the annualized portion of the entire ownership costs, including investment costs as well as major refurbishing and replacement expenses. As far as the system operations are considered, there are essentially three clusters of technical constraints. One cluster is related to maintaining flow balances at the nodes of the system including at the storage systems and the other cluster is related to size restrictions of flow rates over transmission and storage charge/discharges and the storage levels. Finally, the third is about the maximum possible energy and power rates for the storage systems. In what follows, we present our mathematical model under deterministic load and generation assumption, which will subsequently be extended to stochastic programming formulation using the sample average approximation (SAA) technique.

Below we list the important features of the problem:

- Our problem addresses a commonly neglected issue in studies on RES adoption: the importance of spatial aspects, particularly the locational implications of bulk energy storage systems and transmission network design.
- We assume a simplified island system with a single RES and one major demand center, separated by a transmission line. This setup allows for a focus on design decisions with spatial considerations.
- The storage system consists of two separate units—a BESS at the RES site and a bulk storage system at a fixed location between the RES and load site.
- The main design problem involves capacity decisions for both transmission lines and storage units. Transmission capacity refers to the maximum rate of energy transmission, while storage capacity includes energy rate and power rate.
- The problem involves operational decisions related to real-time control, including how RES generation is allocated (to load or storage), when storage systems are charged or discharged, and how supplementary power sources are used. These decisions are modeled at an hourly time resolution.
- The model also accounts for losses during charging and discharging of storage systems, considering technology-specific average loss ratios, but neglects self-discharge or transmission line losses for simplicity.
- The objective is to minimize the overall annual cost, which includes installation, operation, and maintenance of transmission and storage systems, as well as penalty costs for using supplementary power sources.
- The system is subject to constraints related to flow balances, size restrictions on transmission and storage flows, and storage system capacity limits for energy and power rates.
- While we initially assume deterministic load and generation, we later extend to a stochastic programming formulation using SAA to handle uncertainties in generation and demand.

3.2. Deterministic problem formulation

Building upon the outlined problem framework and underlying assumptions, we now present our deterministic formulation. We first introduce the notation for sets, parameters, and decision variables, and then proceed to the problem formulation and its explanation.

Sets

$i \in I$	:	Set of storage types (i = 1: Battery Energy Storage System, i = 2 PHS)
$t \in T$	:	Set of time slots
$k \in K$	:	Set of transmission lines (k = 1: line from wind farm and battery storage to PHS, k = 2: line from PHS to the load center)

Parameters

F_i	:	Fixed costs of storage type i
C_i^e	:	Energy related investment cost of ith storage
C_i^p	:	Power related investment cost of ith storage
C_i^{OM}	:	Operation cost of ith storage
C_k^{TR}	:	Unit transmission cost of building kth line
G_t	:	Generation at time t
D_t	:	Demand at time t
π_t	:	Penalty at time t
η_i^c	:	Charging efficiency of ith storage
η_i^d	:	Discharging efficiency of ith storage
E_i^{max}	:	Maximum technically installable energy rate for each storage i

Decision Variables

x_i	:	1, if ith storage type is constructed and 0 otherwise
s_{it}	:	ith storage level at time t
s_{it}^{ch}	:	Charging rate of ith storage at time t
s_{it}^{dis}	:	Discharging rate of ith storage at time t
E_i	:	Energy rate for ith storage
P_i	:	Power rate for ith storage
f_{kt}	:	Flow at line k at time t
tr_k^{max}	:	max. capacity of kth transmission line
L_{kt}	:	Dump load at kth line at time t
U_t	:	Generation from diesel at time t

$$\mathbf{P(1)}: \quad \min \sum_{i\in I} F_i x_i + \sum_{i\in I}(C_i^e E_i + C_i^p P_i) + \sum_{k\in K} C_k^{TR} tr_k^{max} + \sum_{i\in I}\sum_{t\in T} C_i^{OM} s_{it}^{dis} + \sum_{t\in T}\pi_t U_t \tag{1a}$$

s.t.

$$f_{1t} = G_t - s_{1t}^{ch} + s_{1t}^{dis} - L_{1t}, \quad t \in T \tag{1b}$$

$$f_{2t} = f_{1t} - s_{2t}^{ch} + s_{2t}^{dis} - L_{2t}, \quad t \in T \tag{1c}$$

$$f_{2t} = D_t - U_t, \quad t \in T \tag{1d}$$

$$f_{kt} \le tr_k^{max}, \quad k \in K, t \in T \tag{1e}$$

$$s_{it} \le E_i, \quad i \in I, t \in T \tag{1f}$$

$$s_{it} \le E_i^{max} x_i, \quad i \in I, t \in T \tag{1g}$$

$$s_{i1} = 0 \quad i \in I \tag{1h}$$

$$s_{it} = s_{i(t-1)} + s_{it}^{ch}\eta_i^c - s_{it}^{dis}/\eta_i^d, \quad i \in I, t \in \{2,3,\dots|T|\}, \tag{1i}$$

$$s_{it}^{ch}\eta_i^c \le P_i, \quad i \in I, t \in T \tag{1j}$$

$$s_{it}^{dis}/\eta_i^d \le P_i, \quad i \in I, t \in T \tag{1k}$$

$$E_i, P_i \ge 0, \quad i \in I \tag{1l}$$

$$s_{it}, s_{it}^{ch}, s_{it}^{dis} \ge 0, \quad i \in I, t \in T \tag{1m}$$

$$f_{kt}, L_{kt} \ge 0, \quad k \in K, t \in T \tag{1n}$$

$$tr_k^{max} \ge 0, \quad k \in K \tag{1o}$$

$$U_t \ge 0, \quad t \in T \tag{1p}$$

$$x_i \in \{0,1\}, \quad i \in I \tag{1q}$$

The objective function (1a) comprises five components. The first term represents the total fixed costs incurred by installing storage units. The second term consists of two parts: the first one represents the fixed cost per installed energy rate, and the second depends on the installed power rate of the storage. The third term accounts for the costs of the transmission lines. The fourth element includes operational and maintenance expenses for the storage, which depend on discharge rates. The fifth and final component represents the total penalty cost associated with diesel usage across all time periods.

Constraint (1b) is the balance constraint that guarantees the flow rate from the generation side matches that of the bulk storage. Similarly, Constraint (1c) balances the flow rate from the bulk storage to the load center. Constraint (1d) ensures that the diesel generators are used if demand cannot be satisfied by the generators or the batteries. A shortage could occur when the transmission lines lack sufficient capacity to transmit the entire available energy. In such cases, the diesel generators provide the required electricity. Naturally, the model may opt for diesel generators instead of batteries or even renewable energy sources. However, using diesel generators is more expensive than using batteries and renewable generators. Therefore, they are typically employed when the system cannot generate enough energy to meet the demand.

Constraint (1e) represents the transmission capacity. Constraint (1f) ensures that the storage level does not exceed the energy rate for any given period, i.e., each storage type can be filled up to its capacity at most. The maximum physical energy rate capacity is defined in Constraint (1g). Storage levels are updated for all periods, dependent on the previous level and the charge or discharge units in the current period in (1h) and (1i). Constraints (1j) and (1k) set the power rate capacities for all periods. Variable domains are defined in Constraints (1l)–(1q).

3.3. Scenario representation

Electricity generation from renewable sources is highly dependent on uncertain weather conditions. Furthermore, the electricity demand is random and is affected by external factors such as weather patterns, seasonal fluctuations, and other unpredictable circumstances. Hence, it is necessary to integrate uncertainty into the model for a more accurate representation. One approach to achieve this involves incorporating various scenarios by simulating generation and demand time series. In our modeling approach, we represent these scenarios as datasets on an hourly basis spanning 365 days, encompassing data on wind generation and electricity load.

Representing the problem with a tree scenario is not practicable due to the potentially enormous tree size. Therefore, we have opted for the SAA method, a widely employed approach for addressing stochastic optimization problems, embraced by numerous authors across various domains. This technique entails solving the stochastic optimization problem as a discrete optimization model by integrating random samples into the model. Subsequently, the objective function value is estimated through the sample average function.

We begin by introducing a set of scenarios into the primal model. These scenarios comprise randomly generated datasets, each associated with a specific probability. The primary decisions pertain to the energy and power rates of two storage types, determining whether they are installed or not, and setting the capacity of the transmission lines. These decisions are independent of the scenarios, while operational decisions depend on the specific scenario. We formulate the problem as SMIP as follows:

Additional Set

$s \in S$: Set of scenarios

Additional Parameters

G_{ts} : Generation at time t for scenario s
D_{ts} : Demand at time t for scenario s
π_t : Penalty at time t for scenario s
P_s : Probability of scenario s

Additional Decision Variables

s_{its} : ith storage level at time t for scenario s
s^{ch}_{its} : Charging rate of ith storage at time t for scenario s
s^{dis}_{its} : Discharging rate of ith storage at time t for scenario s
X_{kts} : Flow at line k at time t for scenario s
L_{kts} : Dump load at kth line at time t for scenario s
U_{ts} : Slack variable at time t for scenario s

$$\mathbf{P(2)}: \quad \min \sum_{i\in I} F_i x_i + \sum_{i\in I}(C^e_i E_i + C^p_i P_i) + \sum_{k\in K} C^{TR}_k tr^{max}_k$$

$$+ \sum_{s\in S} P_s \left[\sum_{i\in I}\sum_{t\in T} C^{OM}_i s^{dis}_{its} + \sum_{t\in T} \pi_t U_{ts} \right] \tag{2a}$$

s.t.

$$x_{1ts} = G_{ts} - s^{ch}_{1ts} + s^{dis}_{1ts} - L_{1ts}, \quad t \in T, s \in S \tag{2b}$$

$$x_{2ts} = x_{1ts} - s^{ch}_{2ts} + s^{dis}_{2ts} - L_{2ts}, \quad t \in T, s \in S \tag{2c}$$

$$x_{2ts} = D_{ts} - U_{ts}, \quad t \in T, s \in S \tag{2d}$$

$$x_{kts} \le tr^{max}_k, \quad lt \in T, s \in S \tag{2e}$$

$$s_{its} \le E_i, \quad i \in I, t \in T, s \in S \tag{2f}$$

$$s_{its} \le E_{max} x_i, \quad i \in I, t \in T, s \in S \tag{2g}$$

$$s_{i1s} = 0 \quad i \in I, s \in S \tag{2h}$$

$$s_{its} = s_{i(t-1)s} + s^{ch}_{its}\eta^c_i - s^{dis}_{its}/\eta^d_i, \quad i \in I, t \in \{2,3,\dots,|T|\}, s \in S \tag{2i}$$

$$s^{ch}_{its}\eta^c_i \le P_i, \quad i \in I, t \in T, s \in S \tag{2j}$$

$$s^{dis}_{ist}/\eta^d_i \le P_i, \quad i \in I, t \in T, s \in S \tag{2k}$$

$$E_i, P_i \ge 0, \quad i \in I \tag{2l}$$

$$s_{its}, s^{ch}_{its}, s^{dis}_{its} \ge 0, \quad i \in I, t \in T, s \in S \tag{2m}$$

$$X_{kts}, L_{kts} \ge 0, \quad k \in K, t \in T, s \in S \tag{2n}$$

$$tr^{max}_k \ge 0, \quad k \in K \tag{2o}$$

$$U_{ts} \ge 0, \quad t \in T, s \in S \tag{2p}$$

$$x_i \in \{0,1\}, \quad i \in I \tag{2q}$$

The objective function (2a) is formulated to minimize both investment and operational costs. The first two terms of the objective function represent scenario-independent investment decisions and fulfill the same role as in the deterministic model. The final term takes scenarios into account, calculating the expected operational costs of ESSs and the costs associated with failing to meet demand. Constraints (2b)–(2k) correspond to constraints (1b)–(1k) in the deterministic model. This set of constraints are simply specified for each time slot and scenario. Variable domains are defined in Constraints (2l)–(2q).

Fig. 1 illustrates the flowchart of the solution approach and experiments conducted in this study. The proposed approach and SMIP model P(2) are implemented to data from the island of Sardinia. Input data for the model, including load, wind, and solar data, are synthetically generated based on realistic data to create different scenarios, as elaborated in the subsequent section. Model parameters, such as costs and other variables, are sourced from the literature. Once the inputs are established, the model is solved for various instances. Renewable energy sources, wind and solar, are investigated independently. Furthermore, instances for each renewable energy type are analyzed with both BESS+PHS and BESS-only configurations, achieved by adjusting parameters such as PHS location, load profile, and cost parameters. Subsequently, the results are individually analyzed for all cases, and the influence of renewable energy type on model outputs is investigated.

4. The case: El Hierro Island

As an implementation of our model, we have chosen the small island of El Hierro of the Canary Islands. Along with the others of the archipelago, it has been a major focus of renewable energy generation since a 11.5 MW wind farm and PHS became operational in 2015. The wind power was intended to supply electricity needs of residents as well as three desalinization facilities (Frayer, 2014) and by 2018 it has alone satisfied over 56% of the island's electricity demand Andrews (2019).

In this section, we describe the electricity demand and generation data for the island. We have obtained real demand and wind generation data from the website of Red Eléctrica de España for the year 2018 that consists of 8760 hourly data points. This website provides data on electricity demand and generation for mainland Spain and various islands at 5-minute intervals (website is given in de España, 2024). Since the island does not have a major solar PV generation installment, we have estimated it using solar radiation data in a three-year period of 2018–2020 obtained from the European Union Photovoltaic Geographical Information System (PVGIS) website. This website contains a publicly available database for solar PV radiation at a sufficient geographical and temporal detail (Suri, Huld, Cebecauer, & Dunlop, 2008).

This section is devoted to description of these data and their utilization in synthetically produce hourly demand and generation data scenarios used in the SMIP model. As will be seen shortly, generation of each of demand, wind, and solar PV scenarios poses different challenges that require separate treatments. Other aspects of our experimental design parameters, along with the results of the optimization model and discussion will be carried out in the next section.

4.1. Scenario generation for load

The demand (a.k.a., load) fluctuates hourly over the course of a day to meet the needs of residential, commercial, industrial, and transportation customers. Residential customers constitute the majority on this relatively small island, as the industrial sector is not widespread, except the desalinization facilities. Electricity consumption for residential customers follows a general trend, influenced by human-specific daily routines. On the island, the pattern is consistent, with peak demand typically occurring around 10 p.m. in the evening, as depicted in Fig. 2. Although the hourly load pattern remains relatively consistent across all months, the consumption levels for specific time slots vary based on the current month. Fig. 5(b) illustrates the average 24-h load for twelve months. Peak consumption occurs in August, while the lowest consumption is observed in December.

Let $h \in H$, $d \in D$, and $m \in M$ represent the set of hours, days, and months, respectively. For each $h \in H$ we first compute the average demand as $\overline{D}_h = \frac{1}{365}\sum_{m\in M}\sum_{d\in D} D_{mdh}$ where D_{mdh} represents the actual demand data for hour h of day d in month m in our dataset. Similarly, we compute the hourly average demand value for each hour $h \in H$ of month $m \in M$ as $\overline{D}_{hm} = \frac{1}{30}\sum_{d\in D} D_{mdh}$.

After calculating both the hourly averages and the monthly-based hourly averages, we compute the differences between $\overline{D}_h$ and $\overline{D}_{hm}$ for each hour $h \in H$ and month $m \in M$, denoted as Δ_{hm}. As the initial prediction equation, we employ $\chi_{mdh} = \overline{D}_h - \Delta_{hm}, \forall m \in M, d \in D, h \in H$. Next, we define ϵ_{mdh} as the error between the actual demand and the

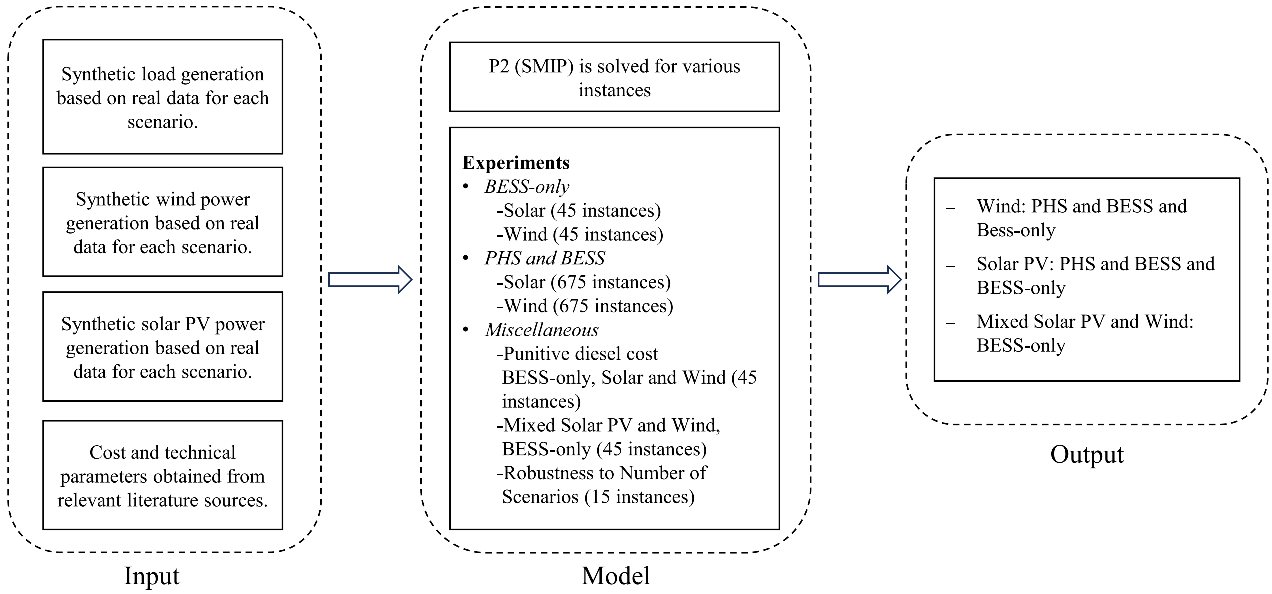

Fig. 1. Flowchart of the solution approach.

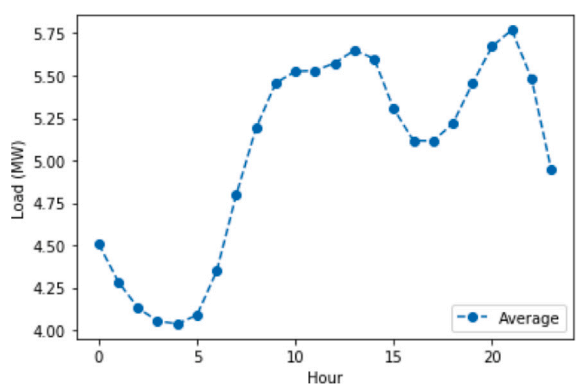

Fig. 2. Average hourly load for 365 days.

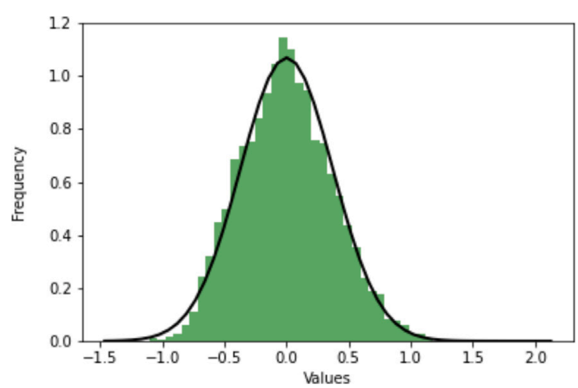

Fig. 3. Histogram and PDF of error data.

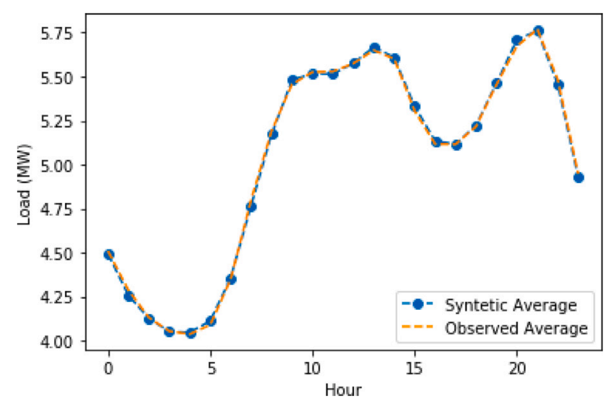

Fig. 4. Average hourly load, real vs. synthetic.

predicted demand for all time slots and compute it as $\varepsilon_{mdh} = \chi_{mdh} - D_{mdh}, \forall m \in M, d \in D, h \in H$.

Lastly, the prediction equation is used to estimate the demand for any specific hour of a day in any month. Any time slots can be generated numerous times due to the fitted error probability distribution. For this data set, the prediction error is fitted to a normal distribution. According to Kim (2013), using formal normality tests for the relatively larger data sets (e.g., $n > 300$), may provide unreliable results. The author proposes to consider skewness and kurtosis with the histogram of data set in order to decide whether data is distributed normal. They suggest ranges for absolute values of skewness and kurtosis (skewness > 2 and kurtosis > 7) for determining substantial non-normality. Thus, normality check is done by histogram, normal probability plot and checking the skewness and kurtosis values of the error data. This data are positively skewed with the value of 0.24 and the kurtosis is 0.11. We see the histogram of the error data in Fig. 3. Even though it is positively skewed, this figure seems to be normally distributed. The resulting errors are fitted to a probability distribution and incorporated into our prediction equation. Subsequently, the prediction equation is defined as follows:

$$Y_{mdh} = \chi_{mdh} + \tilde{\varepsilon}, \qquad m \in M, d \in D, h \in H \tag{3}$$

In Eq. (3) Y_{mdh} represents the predicted demand for month m, day d and hour h. We compare the generated hourly load time series with the historical data. In Fig. 4, the average hourly load is shown for both datasets. We observe that the generated series closely mimics the real data. Similarly, the monthly average data created by month are presented in Fig. 5(d). The generated data replicates the real data patterns for all months. Consequently, this approach produces data points that closely align with the observed series.

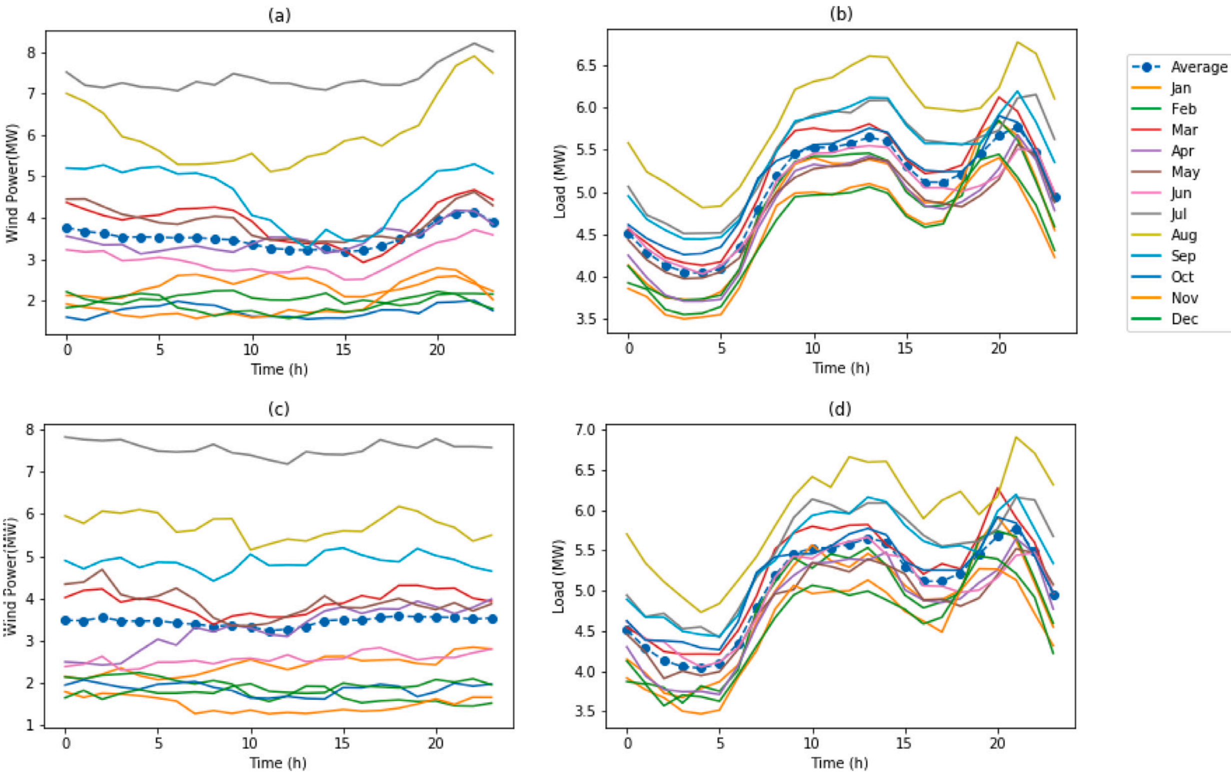

Fig. 5. Average hourly time series by months (a) Observed wind power, (b) Observed load, (c) Synthetic wind power, (d) Synthetic load.

4.2. Scenario generation for wind power

The wind power hourly averages by month are illustrated in Fig. 5(a), which shows that the amount of wind energy produced varies from month to month, depending on climate conditions. Production amounts may even reach up to 10 MW per hour (of 11.5 MW installed capacity) in July and may decrease significantly during the winter months. Although, in comparison to the demand profile, it may seem the variability are comparable in load and wind generation, we like to point out the vertical axis scales and positions.

The topic of synthetic data generation for wind speed and wind power have been well-studied in the literature. One widely accepted method is the use of Markov chain processes to generate time-series data for wind power. While many studies focus on wind speed time series, generating wind power data directly from observed data leads to more accurate results. Converting wind speed into wind power production can introduce errors, as it involves predicting power using a power curve function, potentially resulting in errors of up to 9% according to Chen, Pedersen, Bak-Jensen, and Chen (2009). Additionally, unpredictable production issues such as failures cannot be accounted for in wind speed data alone. On the contrary, wind power data inherently include these problems, making it a more comprehensive and reliable source of information.

A Markov chain analysis design include definitions of states, which are essentially, the binning of the relevant data to form a reasonably accurate discrete state space and the degree of dependency of in the transition matrix, which is called the order of the Markov chain. For example, a first-order Markov chain (FOMC) model considers only the previous state in estimating transition probabilities to the next stage, whereas a second-order Markov chain (SOMC) can use the two most recent states to compute those probabilities. FOMCs were implemented, for example, by Sahin and Sen (2001) and Nfaoui, Essiarab, and Sayigh (2004) to predict the hourly wind speed. Sahin and Sen (2001) determined states using the mean and standard deviation of the data SOMC could produce better results. Similarly, Shamshad, Bawadi, Hussin, Majid, and Sanusi (2005) utilized first and second-order Markov models to create synthetic hourly wind speed time series based on 7-year observed data. They found that the second-order Markov model outperformed the first-order model in statistical properties such as mean, standard deviation, and autocorrelation functions. Both first and second-order Markov chains were also employed by Carpinone, Giorgio, Langella, and Testa (2015) using wind power data to predict power for a very short-term horizon. In another study (Hocaoglu, Gerek, & Kurban, 2008) discussed the impact of the state size of a Markov chains. They constructed probability matrices with 13 and 26 states for comparison and concluded that increased state size led to greater model accuracy. Tang, Brouste, and Tsui (2015) proposed two new improvement methods. The first involved a new state characterization utilizing empirical distributions of wind speed. The second method suggested using empirical distributions for states with a large number of elements instead of a common distribution. This approach aimed to prevent the assignment of inappropriate distributions to states. Brokish and Kirtley (2009), on the other hand, discussed the potentially risky aspects of employing a Markov-based model to generate wind speed or power time series. They emphasize that using time steps shorter than 15 to 40 min could result in inappropriate outcomes. In the end, the predictive quality of the model very much depends not only on the complexity of the model, but also the availability of data compute the related model parameters with satisfying level of accuracy.

We experimented with various orders and numbers of states in the Markov chain models, training the entire dataset to construct synthetic series using both first and second-order Markov chains with different state sizes. Although it showed similarities to the probability distribution of the observed series, the model failed to replicate specific aspects of the actual data. Firstly, it failed to capture the expected monthly seasonality, posing challenges in accurately sizing energy storage technologies. Secondly, when the entire dataset was used, the autocorrelation function of the generated data showed a rapid decline. Autocorrelation, a crucial statistical characteristic, was not effectively replicated. To address these issues, we analyzed the data on a monthly basis. However, constructing monthly models led to a reduction in the length of the time series from 8760 to an average of 740 h. At this point, the FOMC proved more accurate, as the SOMC suffered from a lack of data. It is worth noting that higher-order Markov chain models typically yield superior results if a sufficient amount of observed data is available. Another critical consideration was the choice of the time step. Although we had access to 10-minute wind power data, we opted for hourly data as suggested by Brokish and Kirtley (2009) and again dictated by the availability of data to get robust enough results.

Hence, we generate synthetic wind power data using Markov chains through four primary steps as follows:

Step 1 - Categorize the states: In the first step, all continuous data values are assigned to specific states, which are uniformly discretized. The original time series ranges from a minimum wind power of 0 kW to a maximum of 10.3 kW. Therefore, we constructed 21 states with an increment scale of 0.5, ranging from 0 to 10.5 kW.

Step 2 - Construct the transition matrix: After assigning values to states, we generate a 21 × 21 transition matrix for each month. Let $p_{ij} \in [0,1]$ represent the transition probability from the ith state at time t to the jth state at time $t+1$ and the sum of each row equals 1. The transition probabilities can be estimated as $p_{ij} = \frac{m_{ij}}{\sum_j m_{ij}}$, where m_{ij} represents the observed frequencies that state i is followed by state j.

Step 3 - Simulation: In this step, synthetic values are generated. Before determining the exact values, it is necessary to establish the states for these values. In order to assign values to the states, a cumulative probability matrix is required. Let P_{ik} denote the transition probability of the kth state in the ith row. Then the cumulative probability of P_{ik} can be calculated as $P_{ik} = \sum_{j=1}^{k} p_{ij}, \forall i, k = \{1, 2, \dots, 21\}$.

Transition probability matrices for all twelve months are converted to cumulative matrices to assign new states using random numbers. For instance, let us consider being at time t in the kth state. At $t+1$, the new state is determined by utilizing the cumulative probabilities from the row i. Using a random uniform number between 0 to 1, the new state can be assigned using the cumulative probabilities of that particular row. The next state assignment is determined based on the state established at $t+1$. This process continues until all 8760 states are determined. The initial state is determined by randomly selecting a state, considering the probabilities of state occurrences from the real data.

Step 4 - Conversation of the states into values: In this step, the states created in Step 3 are converted into corresponding wind power values. Upon investigating the states, we observed that uniform distribution closely approximates the elements within the states. However, as proposed by Nfaoui et al. (2004), it should be noted that other distributions might represent certain intervals more accurately, especially for states with fewer members. To ensure the suitability of the Markov chain approach for the specific dataset, we performed the Augmented Dickey–Fuller Test to confirm the stationarity of the series. The test results indicate that the historical time series is stationary, validating the use of a Markov chain-based model.

Autocorrelation functions for both observed and generated wind time series are computed with 50 lags, checking for correlations between the first data point and the 50th data point, as illustrated in Fig. 6. While the initial lags exhibit similarities, the autocorrelation in the generated time series is relatively weaker. However, the generated monthly series outperform both the FOMC and SOMC models created using the entire dataset.

To compare the averages of real and synthetic time series we have selected a particular scenario. As demonstrated in Fig. 5(c) synthetic time series is capable of mimicking the monthly variability in wind power. It should also be noted that the average values might vary slightly for other scenarios due to the random assignment of initial values. Fig. 7 demonstrates that the synthetic time series generally follows the same distribution. However, we note that this observation is specific to a particular scenario and can vary for others to some extent.

4.3. Scenario generation for solar PV

As mentioned earlier, since El Hierro does not have PV installation data, we have obtained PVGIS data for the nearby island of Tenerife, also of the Canaries. The data consists of three year hourly solar radiation and power production under optimized conditions. This dataset will form the basis of estimation of a hypothetical solar PV generation data for El Hierro.

Unlike wind power, solar PV power has a much more predictable pattern, at least within a 24-h period. For example, there is no generation between around sunset to sunrise and there are peaks during high noon, albeit with predictable seasonal differences. The Canary Islands are about 2000 miles north of the Equator and therefore, display Northern Hemisphere characteristics to some extent. For example, as observed from Fig. 8(a) summer and most spring seasons (represented with warmer colors) clearly have more production on average as opposed to winter and fall months (represented with colder colors), but the range of productive hours across the seasons does not show as much variation, which probably would not be case in parts of the Northern Hemisphere that is much further from the Equator.

While the issue of autocorrelation for solar PV is not as pronounced as it is for wind, it entails a very intricate and high level of heteroscedasticity, which can be observed in Fig. 8(b). While high seasons display little variability during the peak productions hours, those of the low seasons' have the highest variability in the entire year. Although less pronounced, the situation is almost exactly the opposite among the seasons during off-peak productive hours. Therefore, we have opted for a standardization procedure for the residuals. Although, we have given all the data monthly fashion in Fig. 8, in our implementation we have estimated the standard deviations of the residuals on a 15-day rolling horizon basis and perform the residual standardization based on those values. This scheme had the advantage of having sufficient data for more stable variability estimation for each hour of the year and avoid the impact significant of changes of production levels within a month.

Fig. 8(d) depicts the smoothed depiction of the frequency of the standardized residuals based on over 13,000 hourly observations that have some power generation. The time-stamps where there is no production in any of the three years are excluded from the data. The standardized residuals are somewhat skewed to the left with a coefficient of −0.52 and excess kurtosis of 2.38. Despite these modest values, Jarque–Bera test for normality has rejected the null hypothesis at a very high level of significance. Our initial attempts to fit a distribution from the beta family have been unsatisfactory. Therefore, we have decided to use the empirical error frequency distribution, since we have such a large number of observations. Fig. 8(c) is the average of the values that we have synthetically generated by this estimation method, to be compared to the actual data already given right above (a).

4.4. Descriptive results

Before move to our results of our optimization model, we like to briefly describe the load and generation balance statistics for the synthetically generated scenarios. Had the intermittency of renewable power production closely matched the variation of the daily demand, there would be no real concern or motivation for energy storage. This is obviously not the case and in what follows we will first describe how well, or indeed how badly, solar PV or wind generation matches with the variations in demand during a day. The particular results we present in this section, are only those of the "base" case, that is where aggregate yearly generation is equal to the total demand. Under the cases with systemic deficits of surpluses, which we will also investigate, the levels of balances change, but the results on variation of the balances continue to hold.

Arguably, one would expect more variation in the supply/demand imbalance for the cases of solar PV as compared to wind power. Solar power has obvious seasonal daily patterns, whereas wind's behavior

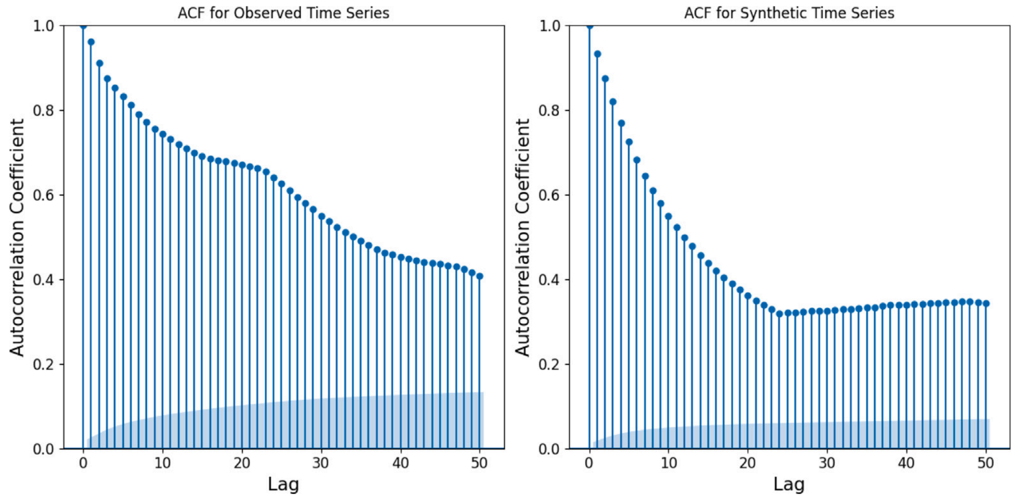

Fig. 6. Autocorrelation function with 50 lags for (left) synthetic and (right) observed time series.

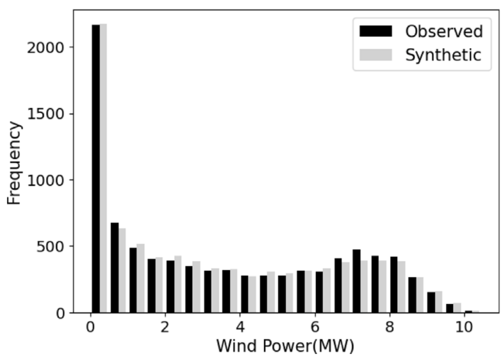

Fig. 7. Observed vs synthetic data.

is not all so clearly anticipated. Hour-by-hour balance statistics of our data confirms this expectation as depicted with box-plots of the hourly differences between the generation and the demand in Fig. 9. The large portion of the figure in the middle are 24 box-plots of the balances solar PV and demand for each hour. Each of these box plots summarizes 3600 data points for each hour on average (i.e., 12 months; 30 days; and 10 scenarios). The balance almost mimics the solar PV production profile, perhaps with less pronounced highs due to deduction of the load.

Unsurprisingly, except for the eight or nine hours of large surpluses during daytime, the balances are negative for the rest of the day albeit with very little variability. On the other hand, most productive hours are also marked with a significant level of variation not only on the surplus side but also on the deficit side. The same figure contains, two box plots related to the wind and load balance and represented at the extreme ends of the graph. We choose to consolidate wind data in 12 hour-segments; because there is barely any noticeable difference among hours and what we have shown is quite representative for any hour. That does not suggest, wind is necessarily a more stable source, because as can be seen from the figure, although Tukey fences are rather modestly apart and there appears to be no outliers, their interquartile ranges (IQR) are wider than solar at all hours.

Above observations are not sufficient to give a qualified prescription on the effectiveness of the either source, especially when combined with storage options. On the one hand, solar PV seems to have a more predictable daily pattern that might allow storing energy during peak production hours to be used during off-peak hours. However, those peak hours are also marked with the highest levels of unreliability. Although wind has a higher level of variation throughout, the variation seems to be uniform and predictable throughout. However, wind power is also marked with high autocorrelation and hence, potentially extended periods of drought that cannot be adequately observed from such hourly balance statistics.

Regardless of above considerations, neither solar nor wind can be viable without the aid of base load provision from conventional sources or energy storage. The former is also usually not viable for island systems and therefore, the storage remains the only viable alternative along with diesel for managing imbalances. Hence, provided that some storage infrastructure is considered, above balances may be more informing viewed from a more aggregated time. Bulk storage facilities, of which PHS is the single most commonly used for electricity storage, are designated to provide around 12–18 h of service at their top power rates. For the more expensive battery systems, the current technology allows for about one third of bulk storage, i.e. four to six hours at the top power rate. Of course, these service times can extend if energy supply from storage systems are required at more modest rates.

We like to conclude this section with the reporting of two more supply/demand balances, They are aggregate daily and 3-daily balances, which are depicted in Figs. 10 and 11, respectively (we still report balances per hour, for ease of comparison across the box-plots). Among these two figures, the former is perhaps more informative than the latter. When one glances over 3-daily balances (given per quarter, due to limited data points), both solar PV and wind balances seem similar, i.e. for two of four the quarters solar balance is slightly higher on average, and wind is higher for the other two quarters, altogether with overall comparable variations.

Perhaps, daily balances as depicted in Fig. 10 may be considered the most revealing for the difference between the nature of intermittency of these two renewable sources. Solar, for four consecutive months, has considerable surpluses with relatively less variation, while for three consecutive months with considerable expected deficits, albeit with some higher variation. The expected surpluses or deficits also show a pattern, but at a more alternating way and, more importantly, at a much less pronounced way. Winds' variability is also somewhat constant across the months, although higher than solar PV's during summer months, but quite comparable in the rest of the year. These early descriptive statistics probably suggest that wind will probably to be shown to be a more effective source for the island system in consideration. The next section aimed to test these expectations along with a more qualified and detailed results in usage of storage systems, as well as the impacts of systemically low and high renewable generation installations under a variety of cost and technical considerations.

Hence, it is probably very difficult to draw any plausible prescription as to the storage problem based on these results. Both, solar and

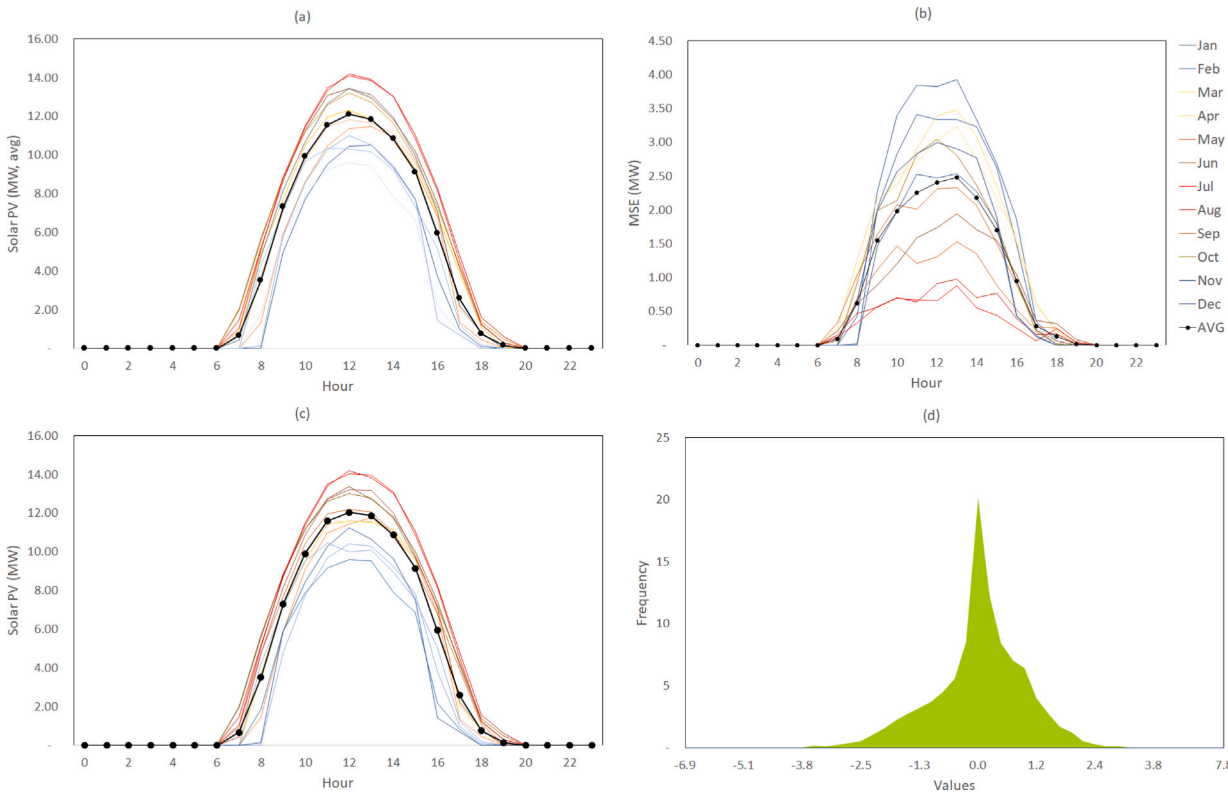

Fig. 8. Hourly solar PV time series by months (a) Average power, (b) Mean squared errors, (c) Average of synthetic solar PV power, (d) Frequency diagram of standardized residuals (includes only regular productive hours).

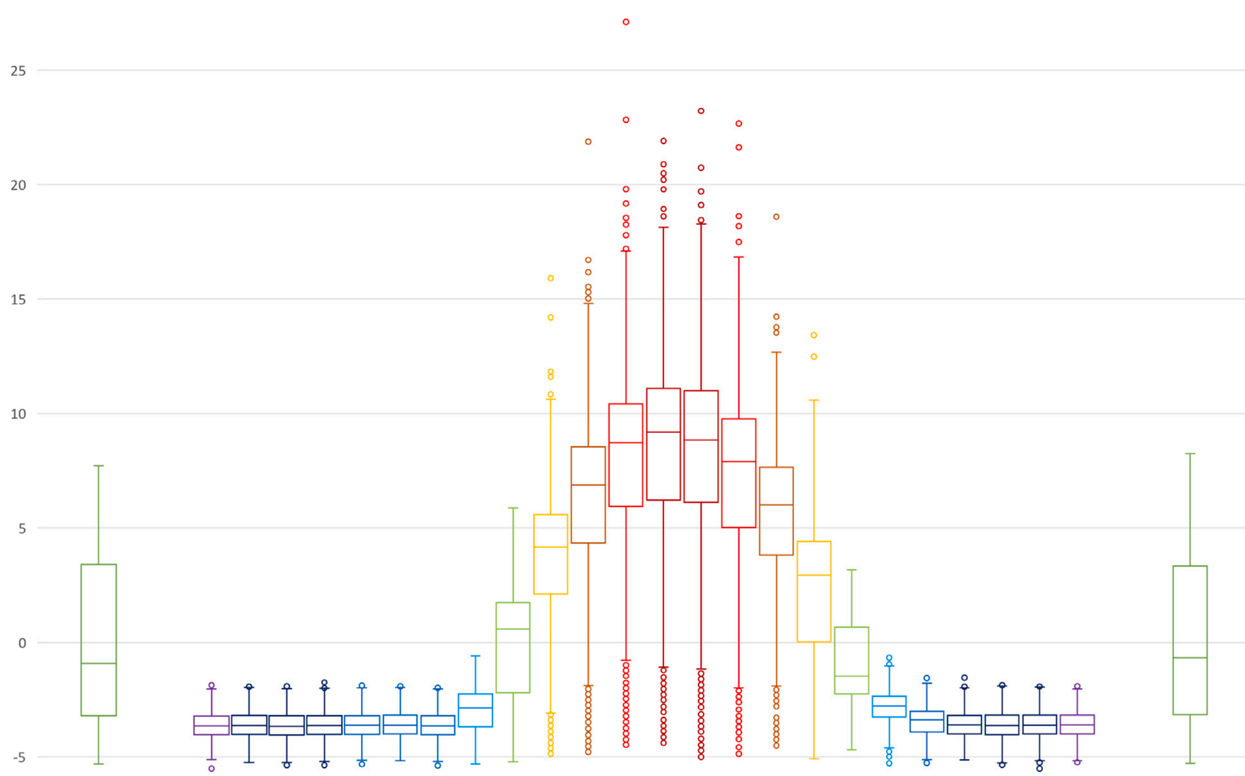

Fig. 9. Hourly Supply/load balances (MW): The box plots in the middle are those of Solar PV over 24 h from 00:00 to 23:59; the two at the far left and right at the edges are those of wind, consolidated over 12 h each.

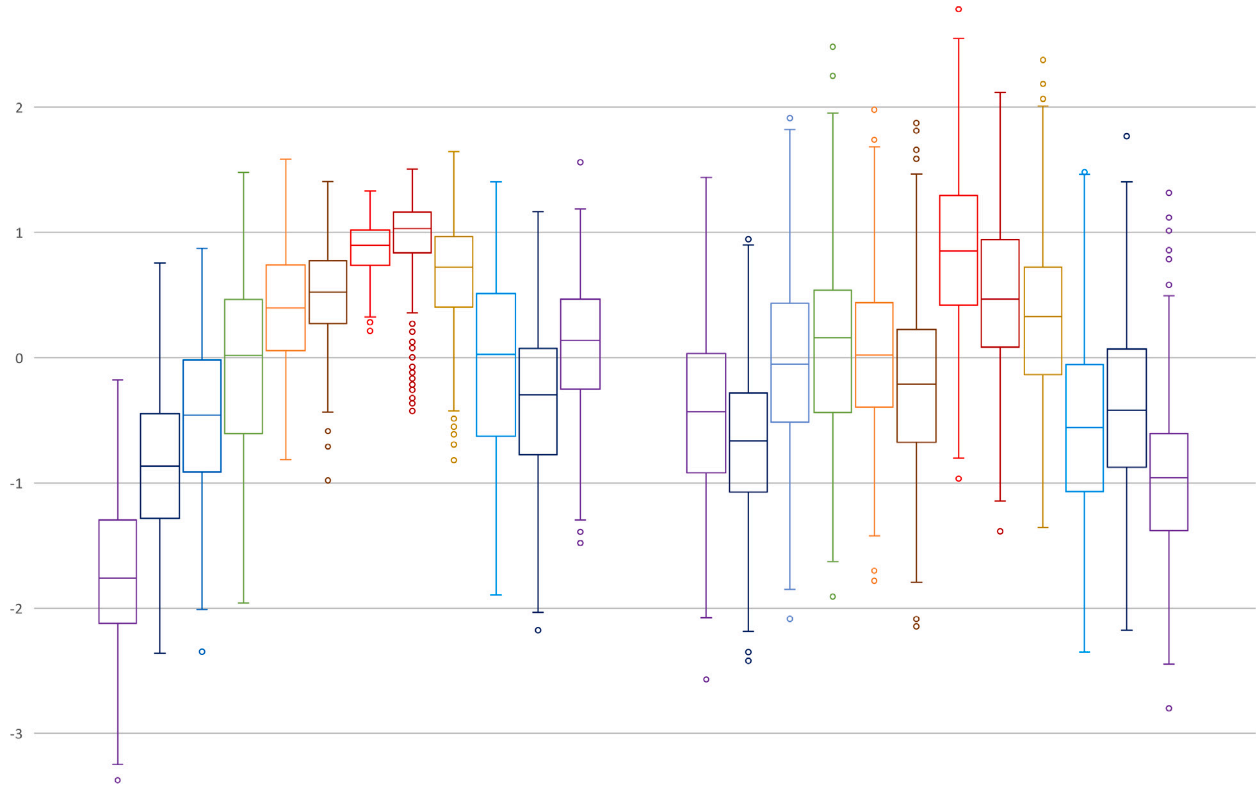

Fig. 10. Daily Supply/load balances (MW/h): The box plots in the left are balance of Solar PV for 12 months from January to December and those on the right are those of wind power.

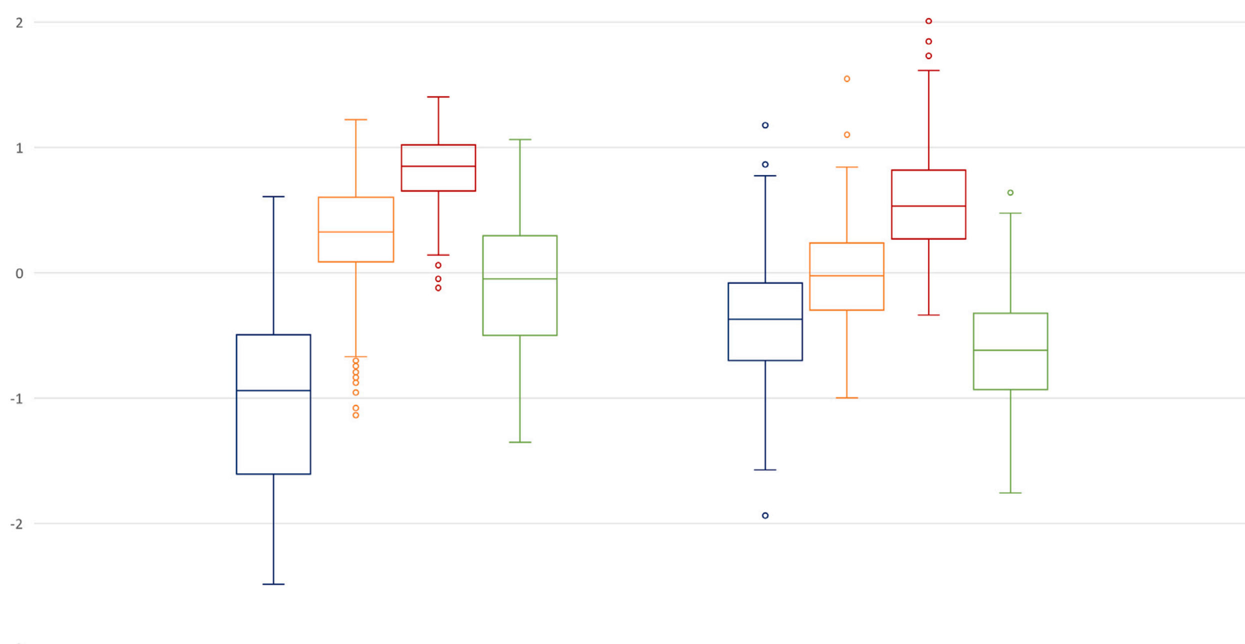

Fig. 11. Three-day supply/load balances (MW/h): The box plots in the left are the balance of Solar PV for four seasons: Jan–Mar, Apr–Jun, Jul–Sep, and Oct–Dec and those on the right are those of wind power.

the wind, live up to their reputations of being highly "intermittent", albeit in different ways. In the end, it is the details about storage and transmission cost and efficiency considerations, should help better inform the best course of actions, which will be detailed in the following subsections. We must remark that all the statistics above are based on based demand of 3.60. But considering high or low demand conditions require nothing but shifting the box plots up or down by differences between base load and those cases' averages. None of the above observations and comparisons change, but of course they might have significant ramifications for the storage and transmission decisions.

Our results highlight the challenges of balancing renewable energy supply and demand, especially in the presence of intermittent of solar and wind power. Both sources demonstrate limitations, i.e. solar PV shows a predictable daily pattern but comes with considerable surpluses during the day and deficits at night, making it unreliable during peak production hours. Wind power, though more consistently variable throughout the day, is difficult to predict over extended periods, potentially leading to longer gaps in generation.

For energy management, neither solar nor wind is independently viable without some form of base-load provision, storage infrastructure, or supplementary power, such as diesel generation. This is especially critical for island systems, where conventional base-load sources are less feasible. The integration of bulk storage systems becomes essential to compensate for these imbalances. The effectiveness of these storage options depends heavily on operational choices.

The results indicate that wind power may be a more effective renewable source in this context, with its variability being somewhat constant across seasons, except for increased variation in summer months. Solar power, while offering surpluses for four consecutive months, experiences significant deficits during three other months, making it less stable over the year. These early insights suggest that wind could play a more central role in the energy mix, but the integration of storage systems remains key to managing the overall balance. Our analysis also reveals the importance of considering storage and transmission costs and efficiencies when making long-term decisions about energy infrastructure.

5. Numerical experiments

In this section, we report on our numerical experiments and discussion of our results. Owing to the variety and detail of considerations, this section is presented in several parts. In what follows, we start with the remaining details of experimental settings, such as the main grid elements of concern, alternatives, and related cost and operational particulars, in addition to the load and generation particulars, some of which were explained in detail in the previous section.

The overarching purpose of these experiments is to develop managerial insights into storage systems under changing cost, technology, and generation/load balance scenarios. Such numerical results will conveniently be given in several subsections devoted to parts of experiments, and this section concludes with discussion of main results and managerial insights. The main body of these experiments is directed towards understanding the interplay between storage design decisions and the renewable source technologies under a variety of conditions. Although we take the Island of El Hierro as an example, it is only for illustration purposes because although some data are obtained from this island, much of the others are obtained from generic sources and synthetically generated. For example, at the time of the writing of this paper, El Hierro did not have a major solar PV production, but it did have a wind farm of five turbines with an installed total capacity of 11.5 MW and a PHS system that is essentially co-located with the farm.

5.1. Experimental settings

We choose Li-ion batteries and PHS as the options for battery and bulk storage systems, respectively. As mentioned earlier, both of them are the leading and most commonly used storage technologies in their own classes. The system has a RES site (wind or solar PV) that is accompanied by an on-site BESS system, which together is connected to the load site. Along the route, there may be a PHS installation opportunity and if taken up, the RES-complex is first connected to the PHS with a transmission line (first line) and then proceeds to the load site with another (second line). In some cases, these two essentially become one line; for example, if they are co-located with the RES or the load center or not employed at all. In the last case, BESS would be the only storage option employed. Fig. 12 depicts the setting of this simple island system under consideration.

In the real data we have on El Hierro, the effective generation of the wind farm is around 3.60 MW per hour, as compared to the average load of 5.03 MW. This difference is substantial, considering the intermittency of wind and incurs a quite substantial diesel cost that obscures the dynamics that we like to capture. Hence, we have opted for calibrations of load data to create three scenarios of average loads as “Base” (3.60 MW), “Low” (3.20 MW), and “High” (4.00 MW). Hence, the latter cases intended for balances where the average deficits or surpluses constitute roughly 10% of the average power generation. In all these cases the average wind and solar production and the base load are fixed at 3.60 MW per hour, as described in detail in the previous section. For the high and low loads, we have just scaled the base case according to the averages.

Another major experimental design decision is concerned with the availability of PHS opportunities in the system. We first consider a setting that a PHS option is not available and hence, BESS is the only storage option. One of the main reasons for such a distinction, unlike El Hierro, a PHS might not be physically or economically feasible for some island systems and need to rely on batteries. Also, these BESS-only cases, untangled from the interactions with the PHS, allow a better initial exposition of the dynamics involved in such systems in these as well as in the more general setting. Finally, BESS adoption is almost nonexistent or insignificant when PHS option is available, even under the most favorable *realistic* cost scenarios in their current states. This is particularly the case for an island system that lack other cheaper sources of base load provision to manage the balances, the weight of which in the island system would rest on storage and diesel, neither of which is particularly inexpensive.

The next set of features of our experiments includes the related costs and related technical characteristics and the feasible locations for a PHS, if relevant. For both types of ESSs, investment costs related to power and energy were calculated at minimum, moderate, and maximum levels, as detailed in Table 3. These numbers are based on the ones reported by a detailed report of Mongird et al. (2019) and annualized for our problem setting. We have also introduced two additional investment cost scenarios for the Li-ion technology as reported in the last two columns of Table 3. These values are unrealistically low in the current state of battery technologies, but their main purpose is to explore the implications of some hypothetical improvements in batteries or similar flexible storage technologies in future.

The remaining features, some discussed above, are given in Table 4. Costs related to transmission lines, diesel, and storage O&M and storage efficiency rates are also obtained from the literature (Gioutsos et al., 2018; Qi, Liang, & Shen, 2015). Here, too, we have added the two cheaper Li-ion O&M cost scenarios for hypothetical purposes. A bulk storage facility such as PHS is viable only at certain geographical locations. To assess such locational restrictions would have an impact, we have considered five hypothetical scenarios. We first considered that the direct distance from RES to the load center is 30 miles and there are five alternatives including the extreme cases of co-location with the RES or the load center, and the other three chosen uniformly. At the extremes, there would essentially be a single transmission line, but in mid-cases, transmission line capacities may differ between the segments.

In all of our results, we have done our utmost, to give summaries of the results with respect to major aspects of the experimental design parameters. In many cases, certain parameters have no discernible effect on some results. In those cases, we then suppress those parameters (and give averages) to highlight the more important effects.

For example, both battery size and power rate decisions are quite robust to different O&M cost scenarios, but they change appreciably with respect to changing load and the investment costs. Hence, the numbers reported for these design decisions are averages under three O&M cost scenarios. Similarly, transmission line capacity decisions are only seriously affected by the load scenarios and very insensitive to the other scenario parameters and therefore, the capacities reported in the table are the averages of 15 scenarios under each load profile (five investment and three O&M cost scenarios).

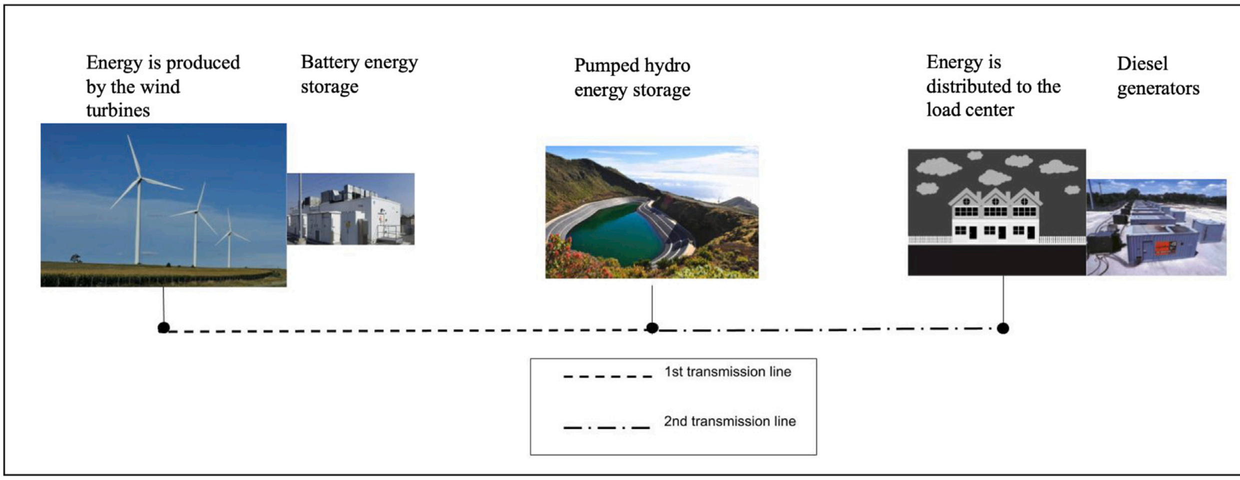

Fig. 12. Proposed island system.

Table 3
ESS size and power investment cost scenarios.

Technology		Minimum	Moderate	Maximum	Maximum/3	Maximum/10
Li-ion	Size ($/MWh-yr)	19,650	24,350	29,050	9,680	2,900
	Power ($/MW-yr)	78,500	97,300	116,100	38,700	11,610
PHS	Size ($/MWh-yr)	2,120	3,060	4,000	–	–
	Power ($/MW-yr)	34,000	49,000	64,000	–	–

Table 4
Sets of other parameters.

	Li-ion	PHS
Variable O&M ($/MWh)	30, 10, 3	0.25
Round-trip efficiency (%)	95	85
Diesel cost ($/MWh)	250	
Transmission line ($/MW-mile)	1,000	
PHS distance from RES (miles)	0, 7.5, 15, 22.5, 30	
Load (MW/h)	3.20, 3.60, 4.00 (Low, Base, High)	

Table 5
Design decisions: BESS-only.

Size (MWh)	Solar PV			Wind		
	Low	Base	High	Low	Base	High
2,905	59.6	63.6	67.4	40.5	41.7	36.8
9,680	47.3	52.3	56.2	23.9	24.8	22.6
19,650	43.6	48.7	52.9	16.5	17.0	16.2
24,350	42.8	47.7	51.0	14.6	15.1	14.4
29,050	42.1	46.6	46.9	13.1	13.6	12.9
Power (MW)						
11,610	11.2	11.9	12.6	5.6	5.8	5.7
38,700	8.3	9.3	10.1	4.8	5.0	4.9
78,500	6.9	7.9	8.6	4.1	4.4	4.4
97,300	6.6	7.5	8.1	3.9	4.1	4.2
116,100	6.3	7.1	7.3	3.7	3.9	4.0
Line (MW)	3.88	4.30	4.70	4.03	4.39	4.74
Cost ($/MWh)	4.15	4.09	4.02	4.31	4.18	4.06

5.2. BESS-only results

In this subsection, we start with the easy case that includes only the battery system as a storage technology. In our experiments, we have 45 instances for each solar and wind, determined by the three load scenarios and five investment and three O&M cost scenarios. We will start with optimal design decisions, followed by resulting costs, and conclude with a summary of operational aspects under various scenarios.

Table 5 reports on the results of the battery and transmission line design decisions. Under solar PV case, optimal BESS size and power rates increase with the load and decrease with the respective investment costs. This behavior, although present in all cases, is more clearly observed for high investment cost cases. The same results for wind, although sharing much of the same behavior as solar PV, present some peculiarity: size and power rates may actually *decrease* under some high-load conditions, as compared to the base-load. The explanation, essentially, rests on the balance statistics that are discussed at length in the previous section. In those high-load cases, wind power finds much more opportunity to supply directly, without needing as much storage. This conclusion is also well-supported by the uniformly larger transmission line capacities for wind power, which enable more renewable energy to be sent directly to the load center.

An interesting feature of the results given above is that O&M costs have no significant effect on these decisions at all. In retrospect, this should have been obvious: At its highest level of $30/MWh, supply from a battery is still a lot cheaper than diesel's cost of $250/MWh if the battery is sufficiently large. Hence, high operational costs would be no deterrence to larger storage capacities, which are only checked by their investment costs and their trade-off with the diesel. Transmission line capacity, likewise, is not at all affected by battery related costs, which is more sensitive to load conditions. If one consider the transmission line cost, given in the last line of the table, there are some economies of scale, but its sensitivity to load is moderated.

Overall, the advantages of wind over solar PV on an island system are already clear. For most realistic scenarios (recall that the two lowest battery cost scenarios are hypothetical, as explained above), solar PV requires on average about three times the size of wind (about 2.6 to 3.6, to be precise) and about 80% more power rate. As one moves on to the hypothetical cases, the differences move on opposite directions; the ratio of sizes gets much lower and ratio of power rates get larger, although PV still needs larger capacities across all scenarios and power rates substantially more than the capacity of transmission lines. Hence, as expected, high power rate of solar is used mainly for charging the batteries, rather than discharges, which are restricted by power rate as well as line capacity.

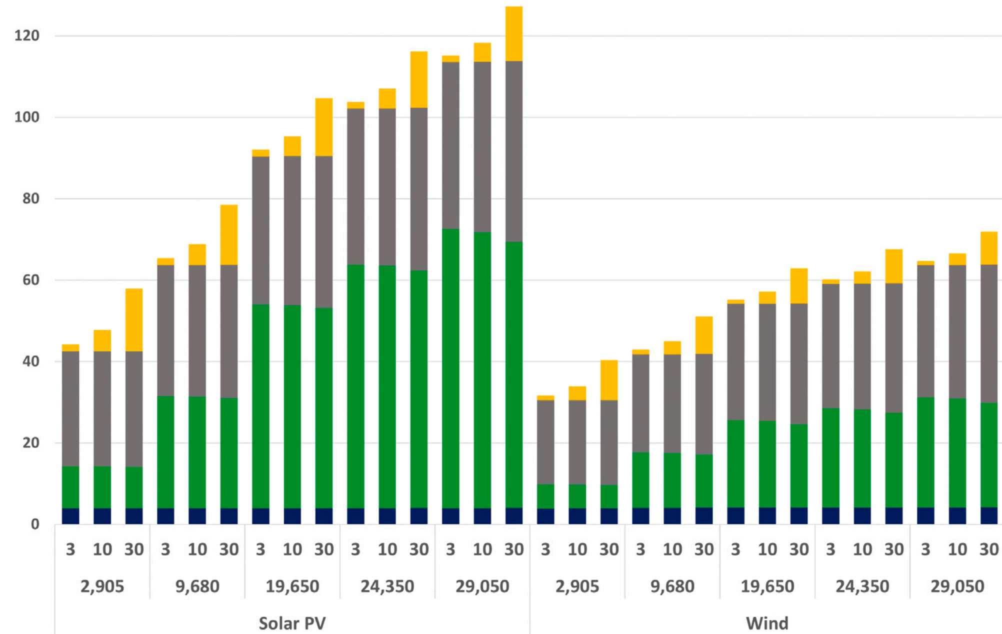

Fig. 13. Average cost per MWh load (from bottom to top): Transmission cost, storage investment cost, diesel cost, and battery O&M.

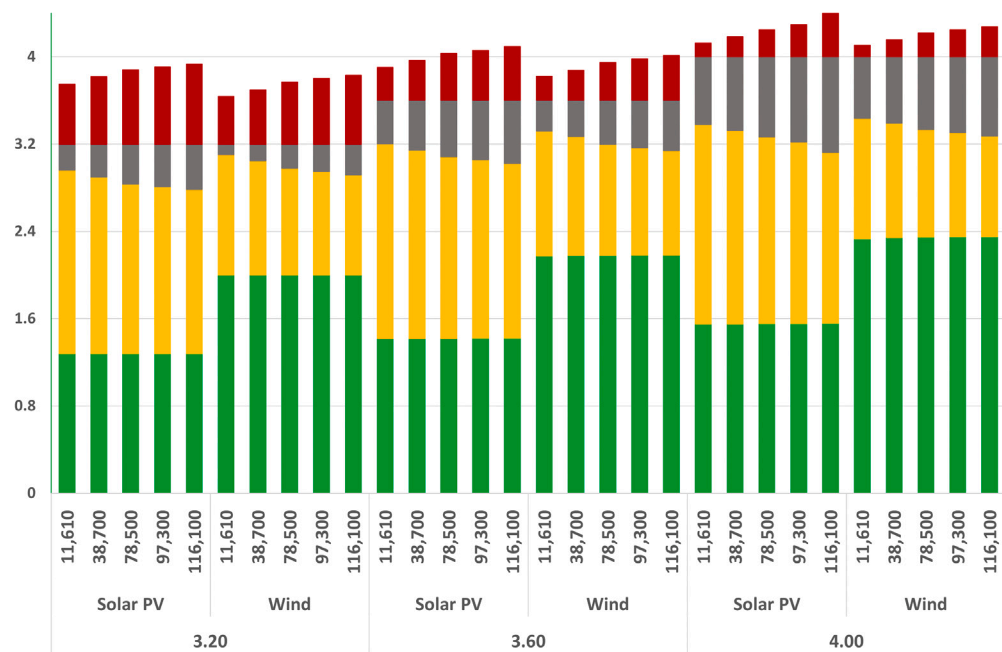

Fig. 14. Average hourly supply profile (all in MWs; from bottom to top): Direct from renewable, discharge from battery, diesel generation, and dumped (unused) renewable energy.

Given the observations on design decisions, the rest of them will further the same conclusion. For example, total cost per MW of demand is about 40% to 80% more expensive for solar than wind. When we look at the cost breakdown under some scenarios, given in Fig. 13, transmission cost differences are barely discernible in comparison to the total, due mainly to the short distance assumed here on an island. The investment costs show a slight decrease with the O&M costs, total of which are (per MW) provided at the tip of each bar in the chart. Although it is also visually discern, except the O&M cost part of each set of scenarios the sum of the other three cost terms are virtually identical. Again we like to emphasize that this result is due to large unit cost diesel, if the island had another base-load providing option, O&M costs would have also played some role in these decisions.

Finally, Fig. 14 depicts the hourly supply/demand balance for each load scenario, where side-by side comparison of solar and wind is emphasized. On average, the direct flow from renewable facility to the load site, is almost constant, which actually depends only on the capacity of the transmission line, but largely it is the result of inherent hourly supply/demand balances in the system. Here the advantage of wind is quite obvious. However, one must keep in mind that these per hour statistics are average values for the entire year; obviously, under both solar and wind there would be wide variations of direct supply on an hourly basis. The rest of the results are, consequently, not also favorable to solar PV. Battery usage, diesel usage, and dumped renewable energy are all higher in solar *vis-a-vis* in wind. A higher level of battery usage is also a disadvantage, because battery lives shorten with more frequent usage. However, the proportional differences in all quantities seem to be lessening as the loads increase, which suggests that solar may be a poor choice for an island, but it might be more economically competitive with wind, if renewables are relied upon for a smaller portion of the load.

5.3. Results with PHS and BESS

With the availability of bulk storage system such as PHS, the variety of scenarios multiply greatly. In addition to the scenarios explored in the BESS-only cases, the addition of the three PHS investment cost and five site alternative scenarios swells to 675 instances each, for solar PV and wind cases.

If one had a free choice of a bulk storage system, the most preferable location would be at the renewable generation site, or very close to it. While BESS can certainly be located anywhere, geography alone would dictate PHS location, which otherwise would not be feasible either technically or economically. Hence, it is important to see how hypothetical, but reasonable, PHS location alternatives affect the overall system decisions and costs. Given the considerable variety of scenarios and more complex trade-offs involved, some results will necessarily be far more detailed in this section. For example, we will observe that battery O&M costs will show some prominent effects on the results, because now it is also confronted with another and sometimes much cheaper option, i.e., PHS. We now proceed with the similar flow of presentation, starting with the optimal design decisions, followed by optimal cost and some operational statistics.

Tables 6 and 7 summarize the battery size and power rate decisions for solar PV and wind, respectively. In these and some subsequent tabular results, we make occasional use of the asterisk sign (∗), which refers to all or the remaining set scenarios that not explicitly specified in the table. For example, the aforementioned tables display the results in segments. Optimal total storage size and power rates are given in the tables on the left and the share of PHS of the corresponding values on the right hand. In the first use of asterisk sign in Table 6 (essentially the first column of the results), the average storage values are listed for different PHS costs and loads, which are applicable regardless of values of BESS investment and O&M costs, other than the indicated ones in the same rows. The first column of the table on the right essentially indicates that the entire storage requirements for all those cases are provided as PHS, i.e., no BESS of any size employed at all.

Hence, except for the lowest (and hypothetical) BESS cost scenarios, in all other scenarios of BESS investment and O&M costs, PHS is the sole storage provider for solar and nearly so for the wind in the optimal solutions. Only when BESS gets cheaper, it gradually increases its share and later overtakes the PHS as the sole storage option. In these cases, one can also clearly see the effect of battery O&M costs in those two low-cost investment cost scenarios. In general, as BESS investment becomes more economically viable, it has a moderating effect on the size, presumably now a portfolio of storage options and relatively higher efficiency of BESS, find it sufficient to lower the total storage slightly. However, it rebounds later as the BESS costs get even lower further down. Here the location of PHS and portfolio of storage decisions have intricate trade-offs, which are also affected by the location and hence, the cost of transmission lines. Under wind power, similar and many times the exact behavior observed for the solar, although at a much lower scale and variation and sometimes with slight exceptions.

The last three rows of Tables 6 and 7 summarize the optimal power rate decisions, which in general, show less variation across the instances than the storage size decisions, which allowed us to present them at a more aggregated fashion without losing the necessary detail. In general, as the BESS is employed more (lower BESS cost cases), the optimal power rates mimic those of the corresponding BESS-only cases. As the PHS increase its share and overtakes as the sole storage options, the optimal power rates decrease, which might be anywhere from 10%–25%, between the most extreme cases. This result is facilitated by the larger storage sizes, which allows a higher level of stored energy on average and does not force the system to charge "in a hurry". Again, solar and wind shows the same patterns, but these observations are less pronounced for the latter.

Finally, we have also observed a peculiar contrast between solar and wind when it comes to power rate decisions. Although BESS-dominated instances mirror those of the BESS-only cases discussed above, in instances where PHS is exclusively or predominantly employed, those decisions behave somewhat differently. In those solar cases, the optimal power rate depends almost entirely on the load level, while the power rate cost of PHS has no discernible effect. In contrast, in the corresponding wind instance, those roles are reversed. Although perplexing at first, this observation is another reflection of the different intermittency characteristics of solar and wind. In solar, there are systemic diurnal balance patterns, albeit with some daytime variability, hence the function of the storage is to accommodate large surplus during daytime, consistent deficits during evening times, and the variability. The intermittency of wind is quite different, although it may be more variable, in general, that is only what the storage needs to deal without the aggravation of systemic balance imbalances, however predictable they may be.

Transmission line decisions, summarized in Tables 8 and 9, are even much more varied due to interactions caused by PHS accompanied by cost and location scenarios. However, there are some expected effects prominently displayed similar to the BESS-only cases for solar as well as wind, albeit with some moderation in the latter. For example, the first line of each table represent those instances where PHS is the sole, nearly so for wind, storage option employed in the system. As the feasible PHS location moves further away from the renewable power site, the need for the first transmission line capacity necessarily increase to accommodate energy storage, and further the distance higher the transmission cost. On the other hand, when the entire storage can be set up at the RES site (i.e., when the PHS can be co-located with the RES or the BESS is considerably cheaper than PHS), the transmission investments are nearly identical to the BESS-only case discussed above (these cases can be observed in the first columns and the last rows respectively).

We must remark that each entry in these two tables represent the total investment cost per unit of load to be comparable to the BESS-only case (i.e., the values given in the very last row of Table 5), as reporting individual line capacities would make the tables bloated, without adding much to the overall understanding. What remains in the bulk of the tables is when both storage systems employed with some appreciable shares (i.e., those cases with batteries have 9680 size cost scenarios). Here there are mainly three trends worthy of notice: (i) When the PHS facility is relatively closer to the RES site (i.e., 7.5 and 15 mile cases), there is a balanced portfolio such that transmission line expenditure per MWh of load is relatively stable with respect to the load. (ii) The line cost increases with the increased share of PHS (when it enjoys higher investment and to some extent O&M cost advantages), but the line cost decreases as the share of BESS increases (as one goes further down in tables). (iii) These dynamics are also observed when PHS site is more distant from the RES site (i.e., 22.5 and 30 mile cases), but this time load also have a prominent effect, which necessitate the first, and in these instances longer part of the line, to have higher capacity, which leads to higher transmission costs overall. In the end, as the PHS's cost advantage diminishes, the results approach to the BESS-only cases.

We now turn to the optimal cost and operational characteristics of the instances. Fig. 15, summarizes the unit total cost and its breakdown among the components. Here we focus on the effects of the renewable source, load, and the feasible PHS site. Each bar in the figure represents the average values of 45 instances, defined by the combination of BESS and PHS cost combinations. Hence, there ate actually quite a cost difference among those instances, but the general trends are best summarized with this aggregation. For example, in instances with cheaper storage there is less diesel usage and more storage supply, but

Table 6
PHS and BESS Design decisions summary—Solar PV.

	BESS	*	9,680			2,905			*	9,680			2,905		
	O&M	*	30	10	3	30	10	3	*	30	10	3	30	10	3
PHS	Load	Total storage size (MWh)							PHS share (%)						
2,120	Low	58	58	58	57	64	60	60	100	100	97	93	61	1.3	0.1
	Base	64	64	64	64	68	64	64	100	100	94	83	47	0.5	0.1
	High	63	63	63	63	68	68	68	100	100	87	70	23	0.4	0.1
3,060	Low	55	55	54	52	61	60	60	100	97	82	58	24	–	–
	Base	60	60	59	57	64	64	64	100	96	69	45	9	–	–
	High	61	61	60	60	67	68	68	100	95	53	32	0	–	–
4,000	Low	53	53	50	48	59	60	60	100	89	40	12	0	–	–
	Base	57	58	55	54	63	64	64	100	85	28	11	–	–	–
	High	59	59	58	57	67	68	68	100	77	17	7	–	–	–
PHS	Load	Total power rate (MW)							PHS share (%)						
*	Low	8.5	8.8	8.8	8.8	11.3	11.3	11.3	100	91	66	49	19.8	0.25	0.03
*	Base	9.5	9.8	9.9	9.8	12.0	12.0	12.0	100	88	55	39	13.1	0.10	0.01
*	High	10.1	10.4	10.5	10.5	12.5	12.7	12.7	100	84	44	29	5.1	0.04	0.01

Table 7
PHS and BESS Design decisions summary—Wind Power.

	BESS	*	9,680			2,905			*	9,680			2,905		
	O&M	*	30	10	3	30	10	3	*	30	10	3	30	10	3
PHS	Load	Total storage size (MWh)							PHS share (%)						
2120	Low	44	44	45	44	46	43	42	100	99	94	89	81	31	5.3
	Base	44	44	44	44	45	44	43	100	99	89	83	70	17	1.6
	High	37	37	38	38	38	37	38	100	99	83	76	49	1.6	–
3060	Low	39	39	38	37	41	40	41	100	96	85	76	49	0.2	–
	Base	39	39	38	38	40	42	43	100	95	77	70	19	–	–
	High	32	32	33	32	35	37	38	100	93	69	61	–	–	–
4000	Low	35	35	34	33	40	40	41	100	90	71	59	10	–	–
	Base	35	35	34	33	40	42	43	99	88	61	51	–	–	–
	High	29	29	29	28	35	37	38	98	82	49	41	–	–	–
PHS	Load	Total power rate (MW)							PHS share (%)						
34,000	*	5.1	5.2	5.3	5.4	5.9	5.8	5.7	100	94	61	48	37	5.2	0.5
49,000	*	4.9	5.1	5.2	5.2	5.8	5.7	5.7	99	80	42	30	15	0.1	–
64,000	*	4.7	5.0	5.1	5.1	5.7	5.7	5.7	97	61	25	17	3.4	–	–

Table 8
Transmission line cost—Solar PV ($/MWh).

	Miles to RES		0	7.5	15	22.5			30		
BESS	O&M	PHS	*	*	*	Low	Base	High	Low	Base	High
*	*	*	4.1	6.3	8.5	10.7	10.6	10.2	12.6	12.4	12.0
9,680	30	2,120	4.0	6.5	8.7	11.1	10.9	10.4	13.0	12.6	11.9
		3,060	4.1	6.3	8.3	10.1	9.7	9.3	11.4	10.9	10.2
		4,000	4.1	5.9	7.3	9.1	8.6	7.4	10.2	9.0	7.2
	10	2,120	4.0	6.5	8.5	10.7	9.6	8.3	11.4	10.1	8.0
		3,060	4.1	5.7	6.6	8.4	6.8	5.6	8.0	6.4	5.3
		4,000	4.1	4.8	4.9	4.9	4.5	4.1	4.3	4.2	4.1
	3	2,120	4.0	6.3	7.7	9.7	8.0	6.5	9.8	7.7	6.4
		3,060	4.1	5.2	5.5	6.0	5.4	4.9	5.2	4.9	4.5
		4,000	4.1	4.3	4.1	4.1	4.1	4.0	4.1	4.1	4.0
2,905	*	*	4.1	4.2	4.3	4.5	4.2	4.0	4.4	4.1	4.0

Table 9
Transmission line cost—Wind ($/MWh).

	Miles to RES		0	7.5	15	22.5			30		
BESS	O&M	PHS	*	*	*	Low	Base	High	Low	Base	High
*	*	*	4.1	5.3	6.3	7.8	7.3	6.8	8.8	8.2	7.5
9680	30	2120	4.0	5.3	6.4	7.8	7.2	6.7	8.2	7.5	6.9
		3060	4.1	5.1	5.9	6.9	6.4	5.9	7.4	6.9	6.2
		4000	4.1	4.9	5.5	6.5	5.9	5.3	6.8	6.1	5.2
	10	2120	4.0	4.9	5.5	6.6	5.8	5.2	6.9	6.0	5.2
		3060	4.1	4.7	5.1	5.9	5.2	4.7	5.9	5.2	4.6
		4000	4.1	4.5	4.7	5.2	4.7	4.3	5.1	4.6	4.3
	3	2120	4.0	4.7	5.2	6.1	5.4	4.9	6.1	5.4	4.9
		3060	4.1	4.5	4.8	5.3	4.9	4.5	5.3	4.8	4.4
		4000	4.1	4.3	4.5	4.8	4.5	4.2	4.7	4.4	4.2
2,905	*	*	4.0	4.2	4.2	4.5	4.1	3.9	4.5	4.1	3.9

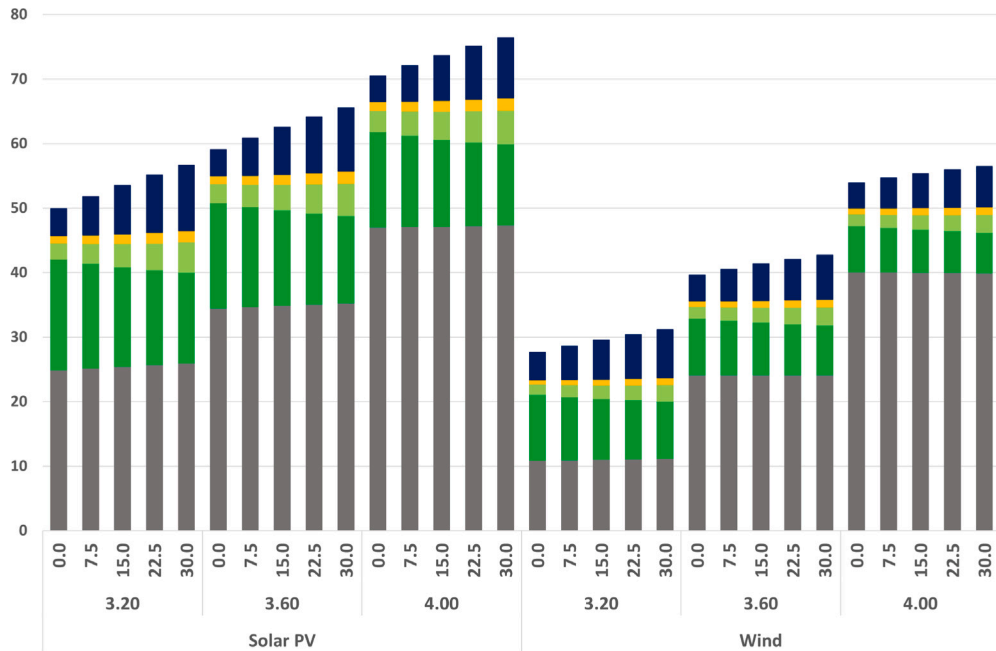

Fig. 15. Average cost per MWh load (from bottom to top): Diesel cost, PHS investment cost, BESS investment cost, storage O&M, and transmission line cost.

despite the magnitude differences the overall trends are replicas of this graph in form.

First and foremost, these results suggest that the level of diesel cost is virtually unaffected by the PHS location, while supply/load balance is the main factor along with the storage investment costs (not shown in the figure). Likewise, the total storage related costs are also insensitive to the PHS location, but as it gets further away from the RES site, PHS's share in the storage portfolio decreases. Unit transmission cost (that is, per MWh) steadily increase with the distance, which further signify the importance of having a storage location close to the RES. While certainly, having an effect, the PHS location has not much interaction between the storage costs and diesel costs.

On the whole, however, availability of PHS has a substantial effect on the cost of the system. In the optimal solutions the average total costs per MWh range from about from $50 to about $75 for PV and $30 to a little over $60 for wind (the same averages in the BESS only cases range from about $40 and close to $130 for PV and more than $30 to over $70). PHS is more beneficial to solar than wind, where the cost reduction is rather modest.

Finally, Fig. 16 depicts the portfolio of the load provision. At the outset there is certainly some reduction in the dumped energy at the RES from as little as some 15% to as much as 80% (as compared to the BESS-only cases), which has an average of a little over 40% across all cases. This is certainly what can be termed as only a modest gain. On the whole, however, despite providing a much cheaper alternative, PHS investment costs, is still substantial to make a greater stride towards elimination of diesel. On the brighter side, the presence of a cheaper storage alternative, in general, increases the transmission capacity and hence, facilitate more direct supply from RES, which in turn decreases battery usage, extending the life of batteries. Although direct supply increases as PHS is farther away from the RES, provision from battery decreases, and depending on the costs, there may be slight increase or decrease of diesel. But whatever these trends are, they are barely noticeable in the figure and also hardly significant to report them numerically.

Overall, the results indicate that integrating PHS with BESS can significantly decrease costs and improve operational efficiency in renewable energy setups. The location of PHS is crucial; co-locating it with RES minimizes transmission costs, while greater distances increase these costs. As BESS costs decrease, they take a larger share of the storage portfolio, but PHS often remains the preferred option due to its lower operational expenses, particularly for solar energy systems.

In terms of overall costs, incorporating PHS can reduce the total cost per MWh for solar from 40–130 in BESS-only scenarios to 50–75 when PHS is used. Additionally, the presence of PHS decreases reliance on diesel generators, though it may not fully eliminate their use. Overall, decision-makers should prioritize optimal locations for PHS and consider BESS cost trends to enhance system design and efficiency while lowering transmission investments.

5.4. Miscellaneous results

In this section, we will present the results of a few additional experiments to further understand the design decisions and our solution approach. Owing to the proliferation of the of instances with these additional experimental design settings, our experiments will be much more limited in some way; otherwise, computational effort as well as discussion may quickly become insurmountable. Hence, the results here should also be interpreted with caution, although connections with the main body of experiments will further enhance the understanding, they necessarily have to be limited in scope. There are three sets of results we like to discuss here: the impact of diesel cost, the impact of mixed RES sources, and the sensitivity of the results to the scenarios.

5.4.1. Punitive diesel cost

In the main set of experiments, we have used an approximated diesel cost of $250 from the literature. This is already a fairly large variable cost of electricity; as mainland grids ordinarily have a variety of sources that are far cheaper. Our results also show that large BESS O&M cost ($30 is the highest of the scenarios) is not an impediment for storage decisions, but rather it is the trade-off between diesel costs and storage investment costs that eventually impact those design decisions. Here, we like to explore how some of the design decisions, costs, and operational characteristics change with an imputed penalty surcharge on diesel use, which is an essence considered as a proxy for giving incentives to the RES usage. For this purpose, we have re-solved the BESS-only instances with a diesel cost of $1250, five times the original estimate. Admittedly, this is rather an arbitrary amount, but its purpose is only illustrative rather than suggestive. We have also restricted our

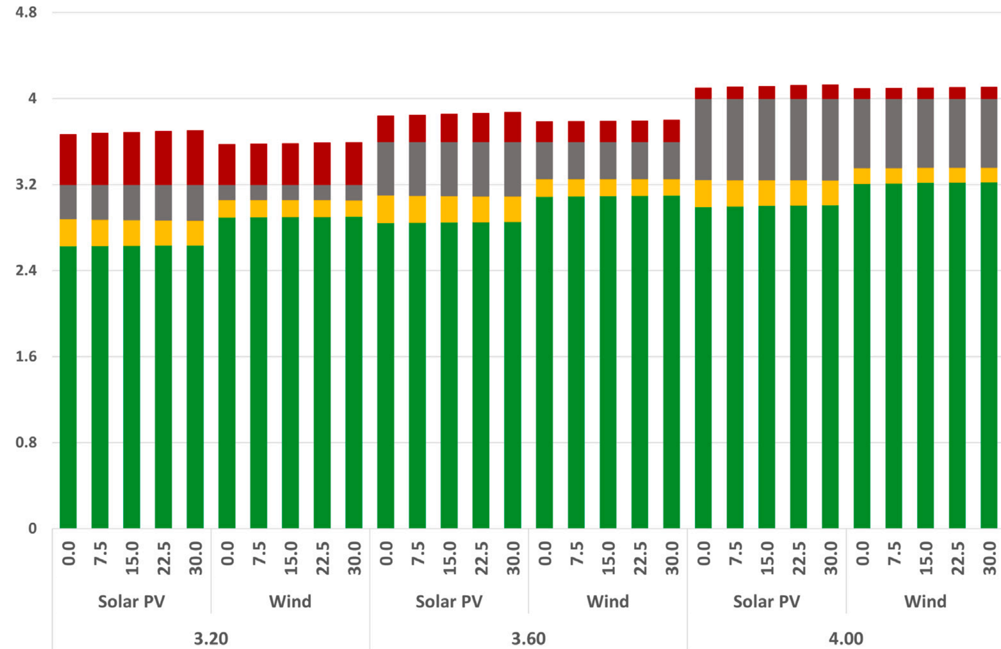

Fig. 16. Average hourly generation/load profile (from bottom to top): Direct from renewable, discharges from storage systems, diesel generation, and dumped (unused) renewable energy.

Table 10
Increases in BESS design decisions under punitive diesel cost.

Size ratio	Solar PV					Wind				
	2,905	9,680	19,650	24,350	29,050	2,905	9,680	19,650	24,350	29,050
Low	2.34	1.41	1.28	1.26	1.25	1.92	1.98	2.26	2.37	2.46
Base	1.51	1.31	1.26	1.24	1.23	1.76	1.98	2.15	2.26	2.36
High	1.52	1.30	1.22	1.22	1.29	1.63	1.89	2.08	2.15	2.25
Power ratio										
Low	1.36	1.48	1.52	1.53	1.55	1.14	1.21	1.33	1.37	1.42
Base	1.29	1.40	1.44	1.46	1.47	1.12	1.20	1.29	1.33	1.37
High	1.24	1.34	1.39	1.43	1.54	1.11	1.20	1.27	1.30	1.34
Line increase (%)										
Low	5.0	5.2	5.5	5.5	5.4	3.4	3.9	4.6	4.7	4.7
Base	4.5	5.0	5.1	5.0	4.9	3.1	2.0	2.0	2.3	2.6
High	4.1	4.8	4.9	4.8	4.1	5.6	1.9	1.9	1.6	1.1

choice to the BESS-only instances, because introduction of PHS make many results far more complicated to interpret, without adding much to the insights into these decisions and outcomes.

Table 10 summarizes the changes in the BESS storage and transmission decisions. As in the previous cases, BESS O&M costs virtually have no discernible effect on any decision and therefore, each value in the table is the average of three instances that only change in their O&M costs. The size and power rate values are the ratios of the decisions under inflated DC cost to those under the original case of $250. As expected, there is an increase in all those decisions for each instance, but there are also interesting contrasts between solar PV and wind. While the BESS size decision is far more responsive to the imposed penalty under wind (except the instances low load and BESS investment costs at their lowest), BESS power rates, which were already high under solar PV than under wind, gets even more so with a larger increase. This is somewhat expected, because in the face of large seasonal and diurnal differences in solar PV incentives are used more towards reducing the dumped energy via larger charge capacity. On the other hand, the need for charge rate increase is lesser for wind, but reduction in dumped energy is achieved more by increases in storage sizes to accommodate longer periods of imbalances, primarily of draughts. In general, we observe some trends in battery decisions, in power rate and also in storage size, however the latter has shown some reverse trends (e.g., solar PV under high load). Here, the trade-off between capacity decisions (size vs. power) depends on many factors not limited to the relative costs, nature of balances, and all the other parameters.

As for the transmission line capacities, solar PV is ahead of the expansion, not only in the expansion rate, but except for once instance, it also overtakes wind with overall larger line capacities. In general, however, transmission line decisions are far more robust to various cost parameters in the system, including the penalty cost among others. However, for the same reason, slight changes in some costs, would invalidate some of our conclusions. For example, under a lower punitive diesel cost, wind cases might have still had larger capacities in most, if not all, instances considered here. Likewise, under a higher penalty cost, solar PV would probably extend its lead. These results also suggest that if PHS option available, especially at some distance from the RES site, solar would allocate more portion of the incentives for transmission capacity.

The next set of results, given in Table 11 pertain to the operational characteristics as a result of an additional penalty cost on diesel; its effect on ultimate cost of energy supply and reduction in diesel usage. In the first portion of the table, "cost ratio" represents the ratio of nominal incurred costs (i.e., without the additional punitive portion) between the corresponding instances that differ only in the diesel cost. The middle portion of the table gives average diesel reduction per day,

Table 11
Operational changes under punitive diesel cost.

Cost ratio	Solar PV					Wind				
	2,905	9,680	19,650	24,350	29,050	2,905	9,680	19,650	24,350	29,050
Low	1.16	1.11	1.12	1.12	1.13	1.11	1.14	1.20	1.22	1.24
Base	1.05	1.07	1.09	1.10	1.10	1.05	1.10	1.14	1.16	1.18
High	1.04	1.06	1.07	1.08	1.08	1.02	1.06	1.10	1.11	1.12
Diesel reduction (MWh/day)										
Low	1.21	1.88	2.81	3.20	3.63	0.62	1.56	2.88	3.45	3.99
Base	0.72	1.69	2.73	3.21	3.82	0.58	1.51	2.75	3.35	3.88
High	0.74	1.63	2.65	3.51	5.63	0.48	1.33	2.41	2.92	3.45
Unit diesel reduction cost ($/MWh)										
Low	408	274	286	293	302	296	240	258	267	270
Base	304	264	290	293	274	253	263	250	254	264
High	291	279	280	247	183	229	251	268	263	261

followed by how much extra for each unit of diesel usage reduction (MWh) incurred, again in nominal values.

As the storage costs get higher, there is proportionally more diesel reduced with the penalty cost, even though ultimate cost also increase with an increasing rate, however slight that may be. These results also shown what has been the general theme so far: solar PV and wind results usually show the same trends, albeit with larger variations than wind. On a *per unit basis*, the greatest benefits are obtained when the load is high in both solar PV and wind. This is quite encouraging, because such incentives can actually be used more effectively in the cases of systemic negative imbalances and for PV, it is even more so for the solar PV when the storage is expensive. The latter result does not hold for wind, but as mentioned earlier, there is very little variance in wind cases, which appears to have more uniform effectiveness. In the end, our choice of punitive diesel cost along with other parameters when changed slightly may result in differing outcomes, and it is possible to find the circumstances and the proper level of incentives to maximize renewable usage and reduce diesel. However, on the whole, an island system with a systemic negative balance and high storage costs are exactly the ones that may benefit most from well-designed incentives.

5.4.2. Mixed solar PV and wind

Complementarity of renewable sources have a long history of research and practice (see for example a small sample of recent papers by Harrison-Atlas, Murphy, Schleifer, & Grue, 2022; Kapica, Canales, & Jurasz, 2021; Schindler, Behr, & Jung, 2020; Weschenfelder et al., 2020). Although correlation measures between these sources has a literature of its own, just for reporting purposes, we computed the simple Pearson correlation coefficient, which was nearly zero in our data of 10 scenarios (around +0.003 when we include only the hours at which solar PV is productive). Despite the absence of complementarity in production, these two sources obviously complement each other during times when there is no solar energy production. Our aim in this part is to investigate this issue in a rather crude way in our island system. The simple question is what would be the outcome, if there were co-located "mixed" solar PV and wind farms that, on average, has equal effective production rates, i.e., a 50–50 split of 3.60 MW/h.

Table 12 reports on the comparison of design decisions of this mix farm to those of solar PV and wind. The numbers leave us with little to report: There are many cases with decreases in all investments of battery size, power rate, and transmission capacity with respect to both solar PV or wind and in the cases with mixed results, the reductions with respect to one source (mainly solar) outweighs the increases with respect to the other (mainly wind).

There are certainly gains from such a portfolio of renewables, and we can clearly see the operational outcomes in Table 13. Again, either there are improvements in all important measures such as cost, diesel usage, and dump reduction with respect to both solar PV and wind, or the gains in one far outweighs the losses in the other. These results suggest that it is quite possible that with a properly designed portfolio one can certainly improve the viability of renewables in terms of the storage and transmission infrastructure.

5.4.3. Robustness to number of scenarios

In the previous sections, we have reported results of our extensive numerical experiments of the SMIP model with 10 scenarios. Before we have undertaken this large set of experiments, we have investigated if 10 scenarios are sufficient to make meaningful inferences. Obviously, the larger the number of scenarios the more accurate the inferences are expected to be, but so are the computational times, which increase tremendously as the number of scenarios grows larger. For example, on average, each instance is solved within a time frame of 40-60 min for the 10-scenario case. However, when the number of scenarios increases to 25 or 50, the solution time experiences a significant surge; varying between 80-100 min for each instance of the former and approximately 6-7 h for those of the latter. In this section, we like to report on a small set of numerical experiments to investigate the impact of the number of scenarios on the solution quality, which eventually led to our choice of 10.

As previously stated, there are 675 distinct instances to solve for the configuration involving both PHS and BESS under wind case. Clearly, we could not undertake even a major fraction of those instances in this study and therefore, we have chosen 15 instances in a quasi-random way and generated 25 and 50 instances of generation and load data and solved those instances. Table 14 summarizes comparison of 25 and 50 scenario instances with the corresponding 10 scenario ones of these 15 instances. To make sure that we have proportional instances where only PHS, only BESS, and both are employed, we have chosen those instances with distinct storage investment costs. For example, the first line of the reported result pertains to two instances where only BESS is employed, followed, in the second line, by one instance where both storage types are employed, and the remainder of the table summarizes results of a total of nine instances each where only PHS employed.

As an indicator of solution quality, we consider the investment decisions of ESSs and total costs (differences in transmission lines were even more insignificant). First, we like to point out that major investment decisions remain unchanged across all instances; specifically, whether only BESS or PHS or both types employed in a 10-scenario instance is exactly the same one prescribed in the respective the 25 and 50-scenario cases. Moreover, we observe negligible differences in total costs and storage investment decisions, which are reported as the mean absolute percentage differences with respect to the minimum of those values prescribed by any pair of scenario instances. Therefore, with such a minimal disparity of around 1%–2%, and consistency in major results, we opted for experiments with 10 scenarios, particularly when considering solution time constraints and large sets of instances to be solved. Finally, we also like to point out that much of results of qualitative nature would remain unchanged as they are robust to such small levels of errors.

Table 12
Design decision changes under mixed source (averages of respective ratios).

BESS size	Mixed vs PV					Mixed vs Wind				
	2,905	9,680	19,650	24,350	29,050	2,905	9,680	19,650	24,350	29,050
Low	0.57	0.57	0.51	0.48	0.45	0.84	1.13	1.35	1.41	1.45
Base	0.61	0.59	0.52	0.48	0.45	0.93	1.24	1.48	1.54	1.54
High	0.62	0.57	0.49	0.45	0.44	1.13	1.40	1.58	1.61	1.59
Power rate										
Low	0.55	0.52	0.49	0.48	0.46	1.11	0.91	0.84	0.82	0.79
Base	0.58	0.57	0.51	0.49	0.46	1.20	1.05	0.93	0.89	0.84
High	0.59	0.58	0.52	0.49	0.47	1.30	1.19	1.02	0.95	0.86
Line	0.989	0.995	1.003	1.006	1.007	0.993	0.976	0.973	0.974	0.974

Table 13
Operational characteristics under mixed source (averages of respective values).

Cost savings	Mixed vs. PV					Mixed vs. Wind				
($/MWh)	2,905	9,680	19,650	24,350	29,050	2,905	9,680	19,650	24,350	29,050
Low	16.8	26.3	39.0	45.0	51.1	(1.09)	(0.86)	(1.68)	(2.21)	(2.72)
Base	16.4	25.0	37.0	42.8	48.9	1.35	0.23	(2.06)	(3.05)	(3.88)
High	13.8	22.1	34.1	40.0	45.9	2.76	0.39	(2.87)	(4.08)	(4.98)
Diesel reduction (MWh/day)										
Low	2.61	3.18	3.28	3.17	2.93	(0.78)	(0.43)	(0.14)	(0.13)	(0.24)
Base	3.09	3.53	3.26	3.00	2.73	0.28	0.57	0.50	0.33	(0.09)
High	2.58	2.87	2.42	2.33	3.16	1.25	1.31	0.77	0.28	(0.51)
Dump reduction (%)										
Low	12.5	15.0	14.2	13.0	11.1	(9.9)	(5.7)	(2.7)	(2.5)	(3.2)
Base	28.6	28.9	21.8	18.0	14.3	1.1	5.6	3.6	1.3	(3.3)
High	50.7	41.3	22.5	17.5	21.9	42.3	30.9	11.3	1.4	(11.4)

Table 14
Mean Absolute Percent Differences for 15 Sample Instances (% of the minimums).

BESS	PHS	10 vs. 25 Scenarios			10 vs. 50 Scenarios		
		Cost	Size	Power	Cost	Size	Power
2,905	2,120	1.23	2.37	0.63	1.23	0.11	0.85
2,905	*	1.21	1.12	0.84	1.21	0.06	1.05
*	2,120	1.23	3.41	0.94	1.64	0.81	0.94
*	3,060	1.15	2.14	0.78	1.54	0.90	1.30
9,680	4,000	0.76	2.78	1.76	1.14	2.39	2.28
*	4,000	0.73	1.86	1.75	1.09	2.26	2.35

Table 15
Ratios of design decisions and consequences under deterministic model to stochastic model.

Load[a]	Wind			Solar PV		
	Low	Base	High	Low	Base	High
Total cost	2.16	2.13	2.62	1.01	1.01	1.62
Diesel	5.52	3.30	3.49	1.12	1.09	2.09
Dumped energy	2.74	5.12	8.21	1.08	1.17	0.96
Energy rate	0.19	0.18	0.15	0.96	0.96	0.96
Power rate	0.33	1.04	1.04	1.01	0.99	0.91
Transmission	0.82	0.83	0.85	0.97	0.97	0.96

[a] Each cell represents averages of 15 different PHS cost and location combinations.

5.4.4. *Impact of uncertainty*

In the preceding section, we have observed that using as few as 10 scenarios can provide sufficient accuracy compared to using as many as 50 scenarios. In this section, we explore whether considering uncertainty is even needed at all. To investigate this, we conducted a limited set of experiments that revealed some important findings.

Towards this end, we consider the instances where BESS costs are restricted as $9680/MWh for energy rate, $38,700/MW for power rate, and $10/MWh for variable O&M costs. This selection is mainly motivated by the observation that such instances result in a range of decision outcomes regarding storage technologies. As also reported in Tables 6 and 7, the storage decisions vary significantly, with the shares of PHS and BESS fluctuating across these instances.

In total, we solved 45 instances for both wind and solar PV, covering three load scenarios, three PHS cost scenarios, and five PHS location scenarios. We already had solutions for these instances under the stochastic model with 10 scenarios representing hourly load and renewable generation rates. Next, we solved each instance using a deterministic model by averaging the data from these 10 scenarios, using only the expected values for load and generation data. After determining storage and transmission design decisions using the deterministic model, we re-solved the stochastic model with these design decisions fixed to obtain total costs and other key metrics.

Table 15 summarizes the most important findings related to design decisions, costs, and other outcomes. Since the results did not vary considerably across different PHS cost and location scenarios, we found it more convenient to present them based on renewable technology and load. Each cell contains the average ratios from 15 instances. To simplify the presentation, we aggregated the storage facilities, as the main themes were strong enough that reporting PHS and BESS separately would be redundant.

The impact of ignoring uncertainty in wind power can only be described as severe. Total costs more than double or even triple, while diesel usage and dumped energy increase dramatically. The main reason for this is significant underinvestment in both storage and transmission lines, particularly in energy rates. Even slight increases in power rate investments offer almost no mitigating effect. By contrast, ignoring uncertainty for solar PV does not result in significant damage, except in cases of high loads. The design variables in the deterministic model are quite similar to those in the stochastic model, so the deterioration in costs and performance measures is minimal. High-load cases are an exception, but even then, the negative impacts are not as severe as they are under wind power.

These findings align with expectations given the different natures of variability in these two renewable energy sources' intermittencies. Solar PV has strong diurnal and seasonal patterns that are relatively predictable, making the use of expected values for generation effective in capturing variability. Ignoring uncertainty in solar PV becomes a

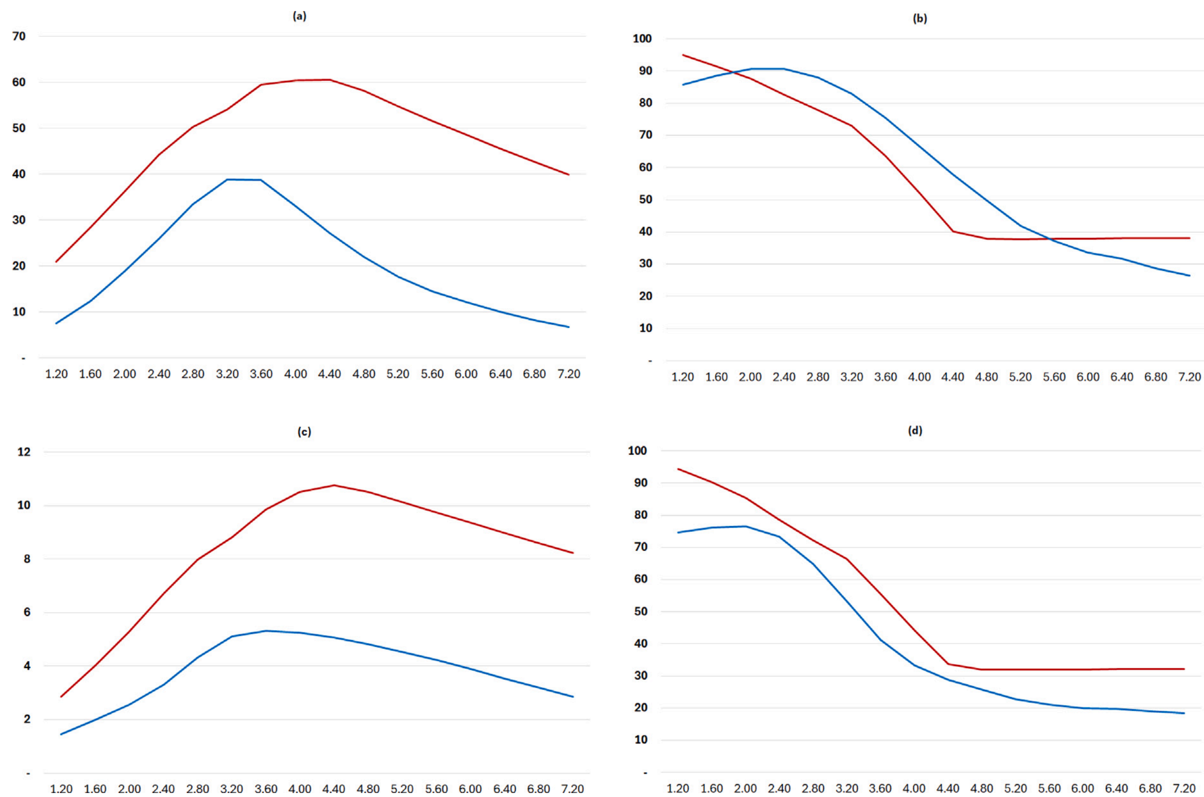

Fig. 17. Storage size decisions (reds are of solar PV, blues are of wind): (a) Total energy rate, (b) PHS percentage of energy rate, (c) Total power rate, (d) PHS percentage of total power rate.

serious drawback when loads are high, requiring increased storage to reduce diesel usage—a task in which the deterministic model performs poorly. Wind, on the other hand, has no dominant predictable patterns and a deterministic model such as the one we have applied fails disastrously. However, our findings for wind should be interpreted with caution. Averaging across 10 scenarios may significantly reduce variability, and selecting a single scenario instead could potentially mitigate the negative outcomes.

5.4.5. Larger imbalances

Much of our experiments have focused on cases where generation and load imbalances are rather small. The reason for these settings is that this work is inspired by the case of El Hierro Island, where the wind farm supplies a significant portion of the island's demand, and imbalances are minimal. In this section, we explore the impact of more imbalanced systems on design and operational decisions.

To do this, we again limited our analysis to a subset of the instances used in the previous section. Specifically, we considered only cases where BESS costs were set at \$9680/MWh for energy rate, \$38,700/MW for power rate, and \$10/MWh for variable O&M costs. However, we adjusted the load values to range from 1.20 to 7.20 in increments of 0.40, while maintaining an average generation of 3.60. Therefore, this range captures scenarios from ample renewable supply to substantial deficits. The main design and operational decisions are summarized in Figs. 17–19. We report the average results from 15 instances for each of the 16 load scenarios (covering three PHS cost and five location scenarios), as there were no significant differences in the key outcomes among these scenarios.

Fig. 17 reveals several important observations. First, for both solar PV and wind, storage investments increase with load growth as more renewable energy needs to be stored to meet demand. This trend eventually levels off and then declines, which makes sense since, as loads become larger, more renewable energy is used directly to meet demand, leaving less available for storage. As observed earlier, solar PV consistently requires more storage investment, especially under high-load conditions compared to wind. The share of PHS in storage is noteworthy: under solar, PHS starts with a dominant share at lower loads and gradually decreases before stabilizing, even as storage sizes begin to decline. A similar pattern is seen under wind, where PHS maintains a high share at lower loads, grows as the load increases, and then declines more sharply. In general, it is reasonable to conclude that storage investments decrease when there is a significant shortage or oversupply of renewable power; however, while PHS tends to dominate in cases of shortage, more BESS is employed in cases of oversupply.

These trends are further illustrated in Fig. 18, which breaks down the unit cost of energy provision. Apart from the already mentioned results, we observe that despite increased transmission and storage investments, solar PV still relies more on diesel and incurs higher costs, although both factors are mitigated as loads increase. Thus, when renewables provide, on average, less than half of the total load, the cost advantage of wind over solar is minimal. Finally, Fig. 19 shows the average hourly energy supply profile, which recaptures some of the earlier remarks. It highlights that under lower loads, wind uses and dumps slightly more renewable energy than solar, though the differences are marginal and do not persist as load increases. Overall, more wind energy is utilized directly, while solar energy is used more through storage.

6. Conclusion

In this study, we investigated an island system offering two energy storage solutions: a battery system and a bulk storage system. The high cost of battery storage has posed a significant challenge to the widespread adoption of renewable energy systems. Moreover, when contemplating bulk storage solutions like PHS, it is crucial to acknowledge that potential bulk storage locations might differ from the generation sites. Therefore, we aimed to derive realistic cost estimates for relevant energy storage technologies, transmission line sizes, and

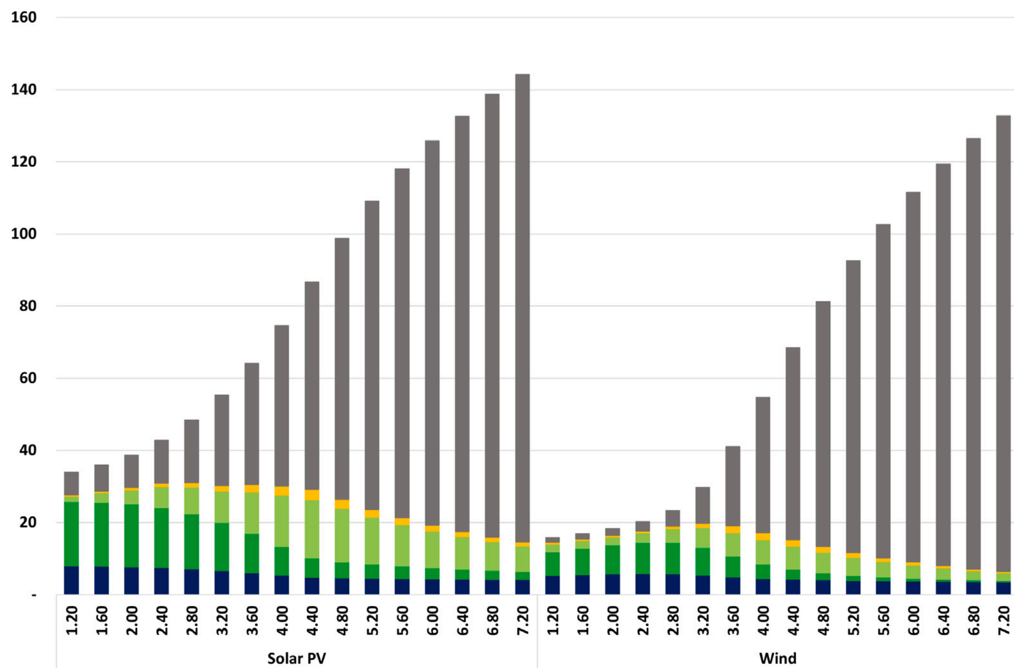

Fig. 18. Average cost per MWh load (from bottom to top): Transmission line cost, PHS investment cost, BESS investment cost, storage O&M, and diesel cost.

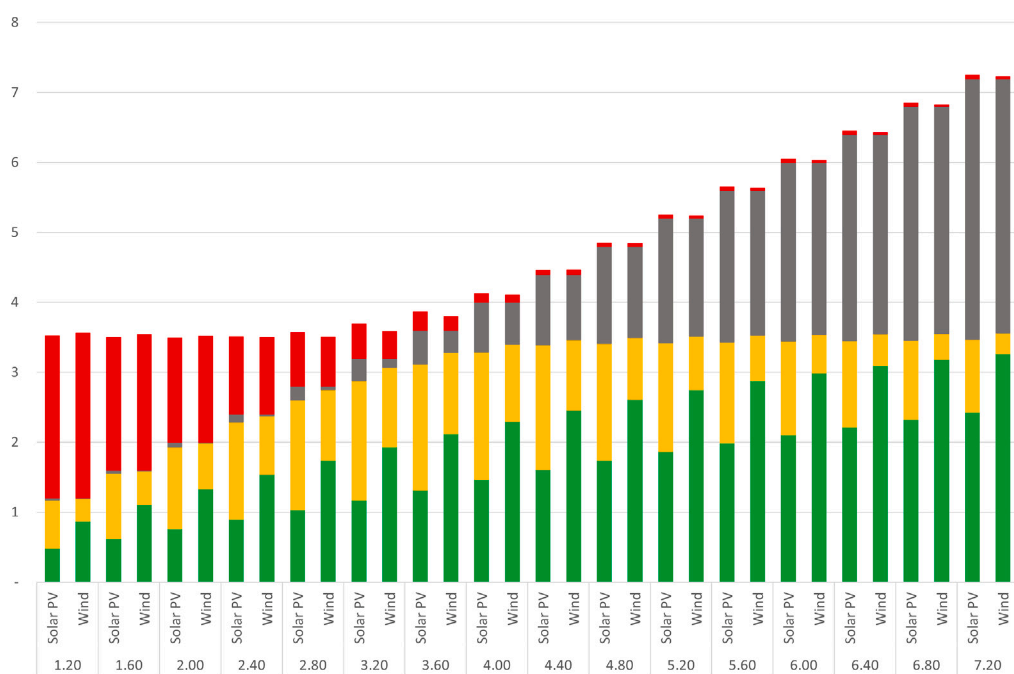

Fig. 19. Average hourly generation/load profile (from bottom to top): Direct from renewable, discharges from storage systems, diesel generation, and dumped (unused) renewable energy.

other critical parameters such as demand and supply. Our numerical results indicate that deploying battery systems economically remains challenging. This suggests that considerable time and progress in battery technologies are necessary, while advancements in bulk storage solutions must also be taken into account, for batteries to become economically attractive options.

The findings from our additional experiments provide critical managerial insights into the dynamics of ESSs, particularly concerning diesel costs and mixed renewable energy sources. The results indicate that while diesel costs significantly influence operational decisions, particularly under punitive scenarios, the O&M costs of BESS play a minimal role. Managers should be aware that increasing diesel costs can encourage the adoption of RESs by incentivizing more efficient storage and transmission strategies. Additionally, the complementarity between solar and wind energy can enhance overall system efficiency, leading to reduced costs and lower diesel dependency. This suggests that diversifying renewable energy portfolios can be a practical approach to maximizing resource utilization. Furthermore, we observe that more storage investment is required under more balanced renewable energy and load conditions, while relatively less storage may be sufficient for large imbalances. Then there is an oversupply of renewable it is more economical to invest in mass-storage technologies, but expensive BESSs are still justified if renewable capacities are not overwhelming.

While we focused on wind and PV energy and employed specific data generation techniques, the model's adaptability allows it to be applied to various renewable energy systems. Developers only need to obtain sufficient data to create appropriate generation scenarios. An implicit assumption in our formulation is that the path from the generation site to the load center already includes the PHS location. However, if the PHS location deviates significantly from the direct route between the generator and the load center, alternative pathways must be considered. Although our current formulation allows for solving the problem twice and comparing the results, a more comprehensive formulation considering these factors would be beneficial. This revision would be especially valuable for examining systems like seawater PHS and deep-sea PHS.

CRediT authorship contribution statement

Arya Sevgen Misic: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Conceptualization. **Mumtaz Karatas:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Abdullah Dasci:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Conceptualization.

Data availability

Data will be made available on request.

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