An Optimization Framework for Capacity Planning of Island Electricity Systems

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Abstract

Meeting decarbonization goals requires taking significant action on electricity systems, which are a major source of CO_2 emissions. Decarbonizing island electricity systems raises additional challenges due to their heavy historical dependence on fossil fuels and strict power-reserve and reliability requirements. To address this challenge, this paper presents a comprehensive optimization model for long-term capacity planning of island electricity systems. Our model determines an optimal mix of generation and transmission capacity to satisfy energy demand at least cost while respecting the strict technical constraints that are inherent in island systems. In addition, our model considers the use of thermal and renewable generation, electric vehicles providing electricity-system services, batteries, pumped-hydroelectric storage, and ac and high-voltage dc transmission lines.

We demonstrate our model with a case study of the Canary Islands archipelago. Our results show that combining the aforementioned technologies reduces generation costs by up to 25% and capacity requirements up to 50% (relative to a case without the technologies). In addition, without any mechanism to internalize the social cost of carbon, fossil-fueled thermal generation is the lowest-cost source of energy. Environmental considerations demonstrate the benefits of renewable generation and result in these carbon-free energy sources supplying about 40% of the energy mix.

Keywords: Generation planning, transmission planning, optimization, island electricity system, energy storage, electric vehicle

Word Count: 4663

Abbreviations

EV	Electric Vehicle
HVDC	High-Voltage dc
OC	Oil-Fired Combustion
OCC	Oil-Fired Combined Cycle
OS	Oil-Fired Steam
PHS	Pumped-Hydroelectric Energy Storage
PV	Photovoltaic
SOE	State of Energy

1. Introduction

Decarbonization calls for greater use of renewable electricity, which raises challenges around its uncertain and variable real-time supply. Spatial disaggregation, transmission interconnection, energy storage, and electric vehicles (EVs) providing electricity-system services can help address this challenge, which raises two questions. First is the optimal mix of the technologies. Second is how the resource mix should be operated. Capacity-planning models answer both questions simultaneously [1, 2].

Much of the capacity-planning literature [3–5] focuses on continental power systems. Models for island electricity systems is a gap that this paper addresses. Unique features of island electricity systems, which our model captures, include high costs due to low generating efficiencies and fuel-transportation needs and strict reserve requirements [6]. Our model captures also short-term and small-scale uncer-

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tainties, such as variable load and renewable-energy supply [7], and includes generation, energy storage, EVs, and transmission as technology options. Our model captures unit-commitment and energy-capacity decisions for energy storage [8] and co-optimizes charging cycles for EVs with electricity-system operations [9, 10]. EV-mobility patterns are modeled, which captures the spatial movement of these resources and loads.

We demonstrate our model using a case study of Canary Islands, which is European Union's outermost region with the highest economic growth and electricity consumption. Generation costs on the islands may be up to 10 times higher than in mainland Spain [11]. Current regulations do not allow renewable energy, energy storage, or EVs to provide reserves to the Canary Islands electricity system.[1] This regulation is addressed by building transmission between the islands. Allowing renewable energy, energy storage, or EVs to provide reserves may help address decarbonization goals, which our model assesses. Our case study considers diesel engines and oil-fired steam (OS), combustion (OC), and combined-cycle (OCC) units as thermal generation; wind, solar photovoltaic (PV), biogas, and hydroelectric units as renewable generation; and battery and pumped-hydroelectric (PHS) energy storage. We examine 19 variants of our case study, which assess the aforementioned technologies with and without carbon pricing.

Our work makes several contributions. It presents a capacity-planning model that is tailored to island electricity systems and captures the operation of flexibility sources, by representing small-scale uncertainty and variability in real-time renewable-energy availability and load. The model captures interday and spatial energy-shifting capabilities of EVs. Finally, our case study assesses transmission expansion and carbon pricing. In addition to assessing them individually, we find that combining all of the aforementioned technologies can reduce generation costs and capacity requirements by up to 25% and 50%, respectively, relative to a base case without the technologies.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature. Section 3 provides a qualitative description of our model. Appendix A provides the detailed model formulation. Section 4 summarizes case-study data and implementation, with further implementation details provided in Appendix B. Section 5 summarizes case-study results. Section 6 concludes.

2. Literature Review

Characteristics of continental and island electricity systems call for capacity-planning models that are tailored for the latter [12]. A distinct characteristic of the latter is their vulnerability to power-quality, -reliability, and -resilience issues, which yield operational and planning requirements that may be more stringent than those for the former.

Despite this need, there is scant literature that examines capacity planning for island electricity systems. Indeed, most models of island electricity systems focus on system operations with gross simplifications of operating requirements. Some works examine the impacts of energy storage, EVs, and transmission interconnections thereupon. However, most of the extant literature evaluates these technologies individually and do not assess combinations of them [13]. These are key gaps that our work addresses.

Kuang *et al.* [14] provide a review of electricity-system planning in island systems, with a particular focus on the use of renewable energy and energy storage. Liu and Wu [15] conduct a similar analysis, but focus on the case of Kinmen Island, China. Both of these works provide primarily descriptive and qualitative analyses, with the aim of assisting the planning of renewable energy in island electricity systems. However, these works lack quantitative modeling to support their results and findings.

PHS is a technology that is studied extensively in island electricity systems. Bueno and Carta [16] develop a model, with which to study a wind-powered PHS plant and apply it to a case study that is based in El Hierro. Subsequent works [17–19] expand upon this concept. These works consider relatively low renewable-energy penetrations and neglect electricity-system reserves and unit-commitment decisions for PHS-plant operations [1, 7]. Ma *et al.* [20] propose a model that optimizes the energy production of a hybrid system that consists of PV, wind, and PHS to achieve 100% energy autonomy for remote islands. Their work [20] does not optimize capacity-investment decisions, however.

Other energy-storage technologies are assessed in the literature. Demiroren and Yilmaz [21] analyze energy costs for a Turkish island that uses combinations of wind, PV, diesel engines, and batteries for electricity supply. This work [21] employs HOMER [22], as opposed to a tailored model, to optimize electricity-system operations. In addition, neither reserve requirements nor optimized capacity levels are captured. Blechinger *et al.* [23] develop a generic cost-optimization model to assess the potential for battery energy storage globally on small islands. Given the generic nature of the model, this work [23] does not consider the specific physical or other characteristics of any particular electricity system. Duić and da Graça Carvalho [24] examine the maximum penetration of renewable energy that hydrogen energy storage would allow in Porto Santo. Their work neglects capacity-investment decisions and reserves requirements are met in an heuristic manner by limiting the renewable-energy share to a maximum of 30% on an energy basis. This can be contrasted with our work, which adjusts reserve levels dynamically based on supply and demand conditions. Hoseinzadeh and Astiaso Garcia [25] use HOMER [22] to assess the techno-economic suitability of a hybrid electricity system that consists of PV, wind, and

[1] *cf.* Real Decreto 738/2015.

hydrogen energy storage. Both of these works [24, 25] find hydrogen energy storage to have exceedingly high costs that cannot be justified economically.

There are limited studies of using EVs for electricity-system services on islands. Two works [26, 27] examine such use of EVs, but do not consider EV mobility within the network. EV mobility may be important in island electricity systems, which may have weak transmission systems. Colmenar-Santos *et al.* [28] study EVs and charging and discharging patterns, but neglect electricity-system reserves, costs that are incurred by battery cycling, and EV mobility.

We find two types of works that examine interconnectors within island electricity systems. One set considers islands being connected to a continental system whereas the other considers interconnectors within or between islands. Many works of the first type analyze the role of continental connections to increase renewable-energy use or to reduce generation costs and examine case studies that are based on Greek islands. Kapsali *et al.* [29] use a unit-commitment model to investigate the economics of interconnecting the island of Lesbos to mainland Greece. Koltsaklis *et al.* [30] develop a planning model to assess the benefits of interconnection between continental Greece and Crete. Georgiou *et al.* [12] study the effect of interconnecting multiple islands to mainland Greece, with a specific emphasis on developing renewable-energy resources. Koltsaklis *et al.* [31] analyze interconnection of Cyclades and Crete to continental Greece and expansion of PHS resources. Other works [32, 33] apply commercial software packages to assess the development of an interconnected Greek electricity system. In addition to these Greek studies, Ries *et al.* [34] examine the economics of linking Malta, Sicily, and continental Europe.

The second body of works that considers interconnectors within or between islands is more limited than the first. Lobato *et al.* [6] examine transmission connections between the Spanish islands Lanzarote and Fuerteventura. However, they do not consider the role of energy storage, EVs, or other technologies as complements to or substitutes for interconnectors. Ramos-Real *et al.* [13] study the relative cost and emissions benefits of operating island electricity systems with energy storage as opposed to interconnectors.

Much of this extant literature simplifies operational constraints for the technologies that are considered, including especially energy storage and EVs. In addition, many of these works simplify system-wide constraints (*e.g.*, reserve requirements). In addition, much of the existing literature considers technology options and islands individually, as opposed to combinations of technologies deployed within a (potentially) interconnected island system. Our work aims to address these limitations.

3. Model Description

This section provides a qualitative description of our model. Appendix A provides a detailed mathematical formulation. Our model adapts to island systems the work of Boffino *et al.* [2], which is focused on modeling continental electricity systems. Our model represents two sets of decisions—the first pertains to investments (*i.e.*, generation, transmission, and energy storage that are built) and the second to operations (*i.e.*, how those assets are operated to serve energy demands, reserve constraints, and other operational requirements). Our model is static, in the sense that it assumes a single set of investment decisions, which are followed by a single set of operational decisions. Electricity-system operations are captured using a set of representative operating periods, which are taken in our case study to be week-long in duration and represented at hourly time steps, with appropriate weights. Our model structure is flexible in capturing different operating-period durations and temporal granularity. The model has cost minimization as its objective. The objective function has two major components—investment and operational costs.

Generation investments are continuous, meaning that any amount of capacity (which can be non-integer) can be built, whereas transmission investments are lumpy. There is a predetermined set of candidate transmission lines that connect given electricity-system nodes with given capacities and each line either is built or is not built. We include both ac and high-voltage dc (HVDC) lines, which have differences in how power flows are modeled. Energy-storage investments are continuous and involve two decisions—the energy and power capacity of each unit. We assume that the electricity system begins with existing transmission lines but no existing generation capacity. This assumption reflects a case in which investments are being planned far into the future by which time existing generation capacity surpasses its useful life, but existing transmission facilities remain usable. Model inputs that pertain to investment decisions include investment costs, which are given in €/MW for generating units, € for transmission lines, and €/MW and €/MWh, respectively, for the power- and energy-capacity components of energy storage. We impose resource (*e.g.*, land-use) and budget constraints on investments.

Operating decisions include power output of generators, charging and discharging of energy storage and EVs, load that is shed, resultant power flows, and the provision of operating reserves to the electricity system. EVs are classified into a set of archetypal fleets, each of which has its own mobility pattern and energy requirement for its associated EVs to serve their mobility roles. There are not investment costs modeled for EVs, because we assume that EV-purchase costs are incurred by their owners.

There are four categories of operational costs. First, there are operational costs for generating units. Some units (*e.g.*, thermal generation) incur a fixed per-unit cost for power output in addition to fixed costs when they are shutdown or started-up. As such, we model unit-commitment decisions for such units [35–37]. Other units (*e.g.*, most renewable generators) have only a fixed per-unit cost of power output and we do not model unit-commitment decisions for such units. We include a fixed per-unit carbon-emissions price and carbon-emissions rate for generating units, which can capture cases with explicit carbon pricing as a climate-change-mitigation policy. The second operational-cost category is the cost of load curtailment, which incurs a fixed cost per unit of demand that is unserved. Third, there is a fixed cost on energy-storage discharging, which can capture the actual cost of energy-storage use on cycle-life degradation (*e.g.*, of a battery) [38, 39]. Fourth, there is a fixed cost on EV discharging, which can capture cycle-life degradation or perceived costs to EV owners from their vehicles having a lower state of energy (SOE) [9, 40].

There are six sets of operational constraints, the first three of which pertain to the electricity system as a whole. The first imposes hourly nodal load balance, by ensuring that the sum of power that is supplied at and imported (in net) to each node during each hour equals exactly nodal demand (which is a model input) less load that is shed.

The second constraint set pertains to operating-reserve requirements. We model three operating-reserve types—upward and downward spinning and upward non-spinning reserves—and set the reserve requirements based on operational procedures of the Canary Islands electricity system [5, 6, 13, 41]. Specifically, the hourly upward-spinning-reserve requirement for each island is equal to half of the highest scheduled hourly dispatch of any single generating unit that is located on that island. Downward-spinning-reserve requirements are set in an analogous manner. The total of upward spinning and non-spinning reserves that are procured on each island during each hour must be at least twice the highest scheduled dispatch during that hour of any single generating unit that is located on that island. Furthermore, the sum of upward spinning and non-spinning reserves that are procured on each island during each hour must be at least as great as the scheduled increase in total load on that island between the hour and the previous hour. Finally, the total of upward spinning and non-spinning reserves that are procured on each island during each hour must be at least as great as the scheduled hourly inflow into the island from each interconnector.

Following practice in the Canary Islands electricity system, we allow thermal generators to provide all three types of reserves and renewable generators to provide downward spinning reserves only [5, 6, 13, 41]. Our model could be adapted to allow renewable generators to provide all three types of reserves, for instance to understand the benefits of such a change in operating practice for greater use of renewable energy. Unlike current practice in the Canary Islands electricity system, we allow energy storage to provide all three reserve products and EVs to provide spinning reserves. By allowing energy storage and EVs to provide reserves, we examine how relaxing current rules can ease decarbonization of island electricity systems.

The third set of operational constraints is power-flow limits on transmission lines. Power flows along ac lines are represented using a linearization of Kirchhoff's laws. Conversely, power flows along HVDC lines are modeled using a pipeline assumption, whereby power flows can be directed along each line independently of other power flows.

The fourth set of operational constraints pertain to generating units. Each generating unit has a maximum capacity, which limits the total of power and reserves that it can provide. A unit's maximum capacity is determined from the (endogenously determined) amount of capacity that is built and a fixed per-unit time-variant availability factor (*e.g.*, to represent weather-dependent renewable generators). Units for which we model unit-commitment decisions have exogenously fixed minimum-load requirements when they are online, whereas power and upward and downward spinning reserves that they provide are constrained to equal zero when they are offline. Units for which unit-commitment decisions are not modeled have zero as their minimum-output levels. Generators have fixed upward and downward ramping limits, which constrain the amount that their output can change from one hour to the next. Upward and downward reserves that can be provided by each generating unit are constrained to ensure that capacity and ramping constraints are not violated if the unit is called during real-time.

The fifth set of constraints relate to energy-storage operations. Each energy-storage unit has a power limit that constrains the amount that it can be charged and discharged during any given hour and an energy limit that constrains its maximum SOE. These limits are set endogenously from the corresponding investment decisions. These constraints ensure that the deployment of reserves would not violate the power and energy limits. We include constraints that prevent simultaneous charging and discharging of each energy-storage unit. We use standard inventory constraints, which account for fixed efficiency factors on charging and discharging, to model the evolution of the SOE of each energy-storage unit from one hour to the next [42–44]. We impose boundary conditions which fix the starting SOE of each energy-storage unit to be 50% of its energy limit as of the beginning of each representative operating period and require the ending SOE as of the end of each operating period to be at least 50%. Such boundary conditions are an heuristic approach to ascribe value to storing energy from one operating period to another [45, 46].

The final set of operational constraints pertain to EVs. To a large extent, EVs are modeled similarly to energy-storage units [9, 10, 47]. One key difference is that the power and energy capacities of the EV fleets are fixed. These parameters are determined by the configuration of the EVs, the number of EVs that owned and operated by drivers on the islands, and the configuration of the EV-charging stations. Another key difference is that we represent the mobility of EV fleets, which are given exogenously. The mobility patterns impact EVs operations in three important ways. First, each EV has a minimum-

SOE requirement on its battery as of the beginning of each vehicle trip. Second, EVs are unavailable to be charged, discharged, or provide reserves while they are driven. We assume that EVs are grid connected and available for these purposes when they are not being driven. Third, EVs can move from one electricity-system node to another during a vehicle trip. This characteristic makes EVs a mobile form of energy storage.

4. Case-Study Data and Implementation

4.1. System Topology and Transmission Data

Fig. 1 summarizes the case-study topology. The islands are indicated by blue rectangles with rounded corners and the nodes by bars, which are numbered as $n = 1$ through $n = 13$. Solid, dotted, and dashed links between islands indicate existing, planned, and proposed transmission lines, respectively. Transmission lines that are within islands are not shown.

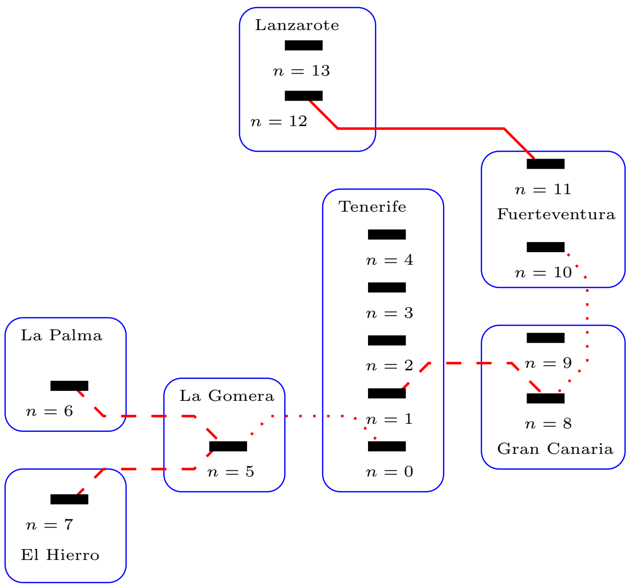

Figure 1: Case-study topology. Blue boxes indicate islands. Solid, dotted, and dashed links between islands indicate existing, planned, and proposed transmission lines, respectively.

Table 1 provides transmission-line data. Lines that are labeled as 'existing' in Table 1 are the existing lines in our model. The others are candidates that can be built. Investment costs for ac and HVDC transmission lines are obtained from publicly available transmission-project data from Red Eléctrica de España, the Spanish transmission system operator, and other studies [29, 48], respectively.

4.2. Load Data

Each island's year-2017 load data are obtained from Red Eléctrica de España. These loads are ascribed to electricity-system nodes based on the proportion of each island's population that is served by the node. Table 2 summarizes these proportions.

Table 2: Proportion of each island's node that is ascribed to each electricity-system node.

Node	Proportion of Load (%)
Tenerife	
0	28
1	12
2	23
3	24
4	13
Gran Canaria	
8	26
9	74
Fuerteventura	
10	42
11	58
Lanzarote	
12	41
13	59
La Palma	
6	100
La Gomera	
5	100
El Hierro	
7	100

4.3. Generator Data

Generating-unit costs vary. Table 3 lists average un-annualized costs and carbon-emissions rates of the candidate generation technologies [49–52]. Table 4 summarizes the maximum capacity of the candidate technologies and nodes at which they can be built. Maximum thermal-generation capacity is the installed capacity as of 2017 and is spread between 83 units, which we retain in unit-commitment modeling [51]. Maximum renewable-generation capacity is based on projections of renewable-energy development in Canary Islands, which is 3.8 times the available capacity as of 2017 [53]. The hourly availability factors for the renewable generators are based on year-2017 data.

4.4. Energy-Storage Data

There is an existing 11.2-MW, 112-MWh PHS plant on El Hierro with a 68.88% roundtrip efficiency. Tables 5–6 summarize the characteristics of the candidate energy-storage technologies [8, 26, 27, 54]. The maximum energy capacity of each energy-storage unit is 10 times the maximum power capacity that can be built. Energy storage can be operated over its full SOE range.

PHS plants use an integrated turbine and pump, which can operate in only one of the corresponding modes during any given time [46]. Such restrictions do not apply to batteries. Thus, for batteries we relax the constraints in the model that restrict energy-storage units from charging and discharging simultaneously. We allow battery energy

Table 1: Transmission-system data.

Line Number	Sending-End Node of Line	Receiving-End Node of Line	Transmission-Line Capacity (MW)	Type	Status	Un-annualized Cost (€ million)
1	0	1	628	ac	Existing	n/a
2	0	4	107	ac	Existing	n/a
3	1	2	575	ac	Existing	n/a
4	1	3	107	ac	Existing	n/a
5	1	4	107	ac	Existing	n/a
6	2	3	107	ac	Existing	n/a
7	3	4	107	ac	Existing	n/a
8	0	4	107	ac	Planned	5.1
9	2	3	575	ac	Planned	0.8
10	8	9	682	ac	Existing	n/a
11	8	9	287	ac	Planned	5.9
12	10	11	53	ac	Existing	n/a
13	10	11	321	ac	Planned	11
14	12	13	53	ac	Existing	n/a
15	12	13	321	ac	Planned	4.6
16	0	5	106	ac	Planned	24
17	1	9	321	ac	Proposed	54
18	9	10	213	ac	Planned	75
19	5	6	66	ac	Proposed	49
20	5	7	33	ac	Proposed	49
21	11	12	66	ac	Existing	n/a
22	0	5	50	HVDC	Planned	45
23	1	9	200	HVDC	Proposed	67
24	9	10	100	HVDC	Planned	70
25	5	6	50	HVDC	Proposed	45
26	5	7	10	HVDC	Proposed	49

Table 3: CO_2-emissions rates and average costs of generation technologies.

Technology	Un-annualized Investment Cost (€/kW)	Operating Cost (€/MWh)	CO_2-Emissions Rate (t/MWh)
Diesel	1 180	34.55	0.65
OS	1 320	6.29	0.90
OC	500	30.66	1.12
OCC	1 090	18.16	0.60
Wind	1 050	0.00	0.00
PV	1 680	0.00	0.00
Hydroelectric	910	1.24	0.00
Biogas	1 550	9.10	0.60

Table 4: Maximum capacities of generation technologies that can be built in each island and nodes at which they can be built.

Technology	Electricity-System Nodes	Maximum Capacity (MW)
Tenerife		
Diesel	0, 1	66.55
OS	0, 1	223.04
OC	0, 1	194.12
OCC	0	432.30
Wind	0, 4	402.00
PV	0, 1, 2, 3, 4	300.00
Hydroelectric	4	6.20
Biogas	0	43.00
Gran Canaria		
Diesel	9	66.55
OS	8, 9	259.60
OC	8, 9	147.00
OCC	8	433.10
Wind	8, 9	411.00
PV	8, 9	61.52
Hydroelectric	8	1.00
Biogas	8	40.00
Fuerteventura		
Diesel	11	96.28
OC	11	62.89
Wind	10, 11	81.00
PV	10, 11	22.50
Biogas	11	11.50
Lanzarote		
Diesel	13	135.28
OC	13	51.94
Wind	12, 13	81.00
PV	12, 13	22.50
Biogas	13	11.50
La Palma		
Diesel	6	74.84
OC	6	21.60
Wind	6	28.00
PV	6	7.93
Hydroelectric	6	6.40
Biogas	6	3.00
La Gomera		
Diesel	5	14.90
Wind	5	8.00
PV	5	5.00
El Hierro		
Diesel	7	11.18
Wind	7	14.00
PV	7	2.00
Biogas	7	0.50

Table 5: Characteristics of energy-storage technologies.

Technology	Un-annualized Investment Costs		Discharging Cost (€/MWh)	Efficiency (p.u.)	
	Power-Related (€/kW)	Energy-Related (€/kWh)		Charging	Discharging
PHS (El Hierro)	2 870	5	5.86	0.84	0.82
PHS (Other Islands)	440	5	5.86	0.84	0.82
Battery	400	150	8.00	0.95	0.95

Table 6: Maximum capacities of energy-storage technologies that can be built in each island and nodes at which they can be built.

Technology	Electricity-System Nodes	Maximum Capacity (MW)
Tenerife		
PHS	0, 1, 2, 3, 4	90.0
Battery	1, 2, 3, 4	200.0
Gran Canaria		
PHS	8, 9	164.0
Battery	8, 9	200.0
Fuerteventura		
Battery	10, 11	40.0
Lanzarote		
Battery	12, 13	40.0
La Palma		
PHS	6	30.0
Battery	6	40.0
La Gomera		
PHS	5	15.0
Battery	5	20.0
El Hierro		
PHS	7	11.2
Battery	7	10.0

storage and PHS to provide spinning reserves and spinning and non-spinning reserves, respectively.

4.5. EV Data

We model 25 000 EVs on Tenerife, which is about 5% of its vehicle fleet, and use mobility data for Tenerife, which provide 10 archetypal driving profiles [26, 28]. Mobility data for other islands are unavailable. The mobility data define vehicle flows between origins and destinations, which we map to Tenerife's five electricity-system nodes. The mobility data provide means and standard deviations of driving distances between origins and destinations. Assuming Gaussian distributions, we use these statistics to generate random driving distances for each EV fleet.

Table 7 summarizes the fleets' characteristics. Each fleet has two daily trips, which constitute a round-trip from origin to destination and back. Driving distances are converted into energy use by assuming a 0.25-kWh/km efficiency [3, 5]. Each EV has a 40-kWh battery and uses a 66-kW charger which has 86% charging and discharging efficiencies [26, 55]. To mitigate degradation, we impose a 25% minimum SOE on EV batteries and assume a €40/MWh cost on discharging EVs for electricity-system services [55]. To avoid range anxiety [40, 56, 57], we require that EV-battery SOEs be at least 70% and 30%, respectively, as of the beginning of the two daily vehicle trips.

4.6. Cases Analyzed

We examine 19 cases. First, we calibrate our case study by fixing capacities equal to the levels that were in Canary Islands during 2017. This case allows understanding differences between our model results and how the electricity system actually was operated during 2017.

Next, we model three business-as-usual cases (with no, ac, and HVDC candidate transmission lines), in which capacities are not fixed but cannot be greater than the amounts that were in Canary Islands during 2017. These cases allow assessing if the Canary Islands electricity system is overcapacitated and the role of transmission lines *vis-à-vis* capacity planning.

Next, we analyze three sets of technology-option cases, which consider the same three transmission candidates. First, we examine cases that allow additional renewable-energy resources. Next, we consider cases that allow additional energy-storage capacity. Finally, we have cases that include EVs. These cases allow us to understand the role of each technology individually. A final pair of cases consider all three technology options simultaneously with ac and HVDC candidate transmission lines.

Finally, we consider four cases with all three technology options, ac candidate transmission lines, and €5.83/t, €24.75/t, €50.00/t, and €100.00/t carbon prices. These prices correspond to average actual year-2017 and -2020 prices and projections of future prices, respectively.

We set the investment budgets under all of the cases sufficiently high that they do not restrict any investment decisions.

4.7. Case-Study Implementation

Our model is programmed with Python 3.6.8 and it is solved with Gurobi 9.1.2 with default settings on a workstation with two Intel Xeon E5-2697 v4 processors, each of which has 18 2.30-GHz cores, and 270 GB of memory.

Table 7: Characteristics of EV fleets.

Fleet Number	Number of EVs	Nodes: Origin	Nodes: Destination	Driving Distance (km)	Trip 1 Hours: Departure	Trip 1 Hours: Arrival	Trip 2 Hours: Departure	Trip 2 Hours: Arrival
0	1 692	0	0	8.75	7	8	15	16
1	1 692	0	0	12.35	13	14	22	23
2	1 308	0	0	7.46	8	9	12	13
3	1 308	0	0	9.59	17	18	22	23
4	26	1	2	15.39	7	8	15	16
5	26	1	2	18.01	13	14	22	23
6	13	1	2	16.12	8	9	12	13
7	13	1	2	16.48	17	18	22	23
8	10	1	3	17.54	7	8	15	16
9	10	1	3	20.27	13	14	22	23
10	5	1	3	16.81	8	9	12	13
10	5	1	3	16.81	8	9	12	13
11	5	1	3	15.02	17	18	22	23
12	10	1	0	27.03	7	8	15	16
13	10	1	0	28.56	13	14	22	23
14	10	1	0	26.11	8	9	12	13
15	10	1	0	26.99	17	18	22	23
16	44	1	1	4.92	7	8	15	16
17	44	1	1	6.25	13	14	22	23
18	23	1	1	7.03	8	9	12	13
19	23	1	1	4.35	17	18	22	23
20	1 231	2	2	5.78	7	8	15	16
21	1 231	2	2	5.82	13	14	22	23
22	989	2	2	5.30	8	9	12	13
23	989	2	2	6.44	17	18	22	23
24	433	2	3	9.69	7	8	15	16
25	433	2	3	10.42	13	14	22	23
26	348	2	3	9.28	8	9	12	13
27	348	2	3	9.67	17	18	22	23
28	432	3	2	11.18	7	8	15	16
29	432	3	2	9.59	13	14	22	23
30	302	3	2	11.00	8	9	12	13
31	302	3	2	11.29	17	18	22	23
32	1 039	3	3	2.45	7	8	15	16
33	1 039	3	3	1.88	13	14	22	23
34	726	3	3	1.18	8	9	12	13
35	726	3	3	2.67	17	18	22	23
36	140	4	2	16.17	7	8	15	16
37	140	4	2	21.01	13	14	22	23
38	132	4	2	15.42	8	9	12	13
39	132	4	2	18.85	17	18	22	23
40	194	4	3	19.17	7	8	15	16
41	194	4	3	18.43	13	14	22	23
42	183	4	3	19.12	8	9	12	13
43	183	4	3	17.35	17	18	22	23
44	1 272	4	4	18.37	7	8	15	16
45	1 272	4	4	18.03	13	14	22	23
46	1 203	4	4	19.53	8	9	12	13
47	1 203	4	4	18.42	17	18	22	23

Table 12: Historic energy mix (%) that was supplied in Canary Islands during 2017.

Technology	Energy Mix
Diesel	3.42
OS	31.00
OC	33.00
OCC	25.00
Wind	4.26
PV	2.94
Hydroelectric	0.03
Biogas	0.10

Appendix B provides details regarding how the representative weeks that are used to capture electricity-system operations are selected.

5. Case-Study Results

Tables 8–11 summarize case-study results. Insights that are drawn from the 19 cases are provided in the subsequent discussion.

5.1. *Case-Study Calibration*

The first row of Table 8 shows Canary Islands's actual generation mix during 2017 and Table 12 summarizes the corresponding *actual* generation mix. Contrasting Table 12 with the first row of Table 9 shows that our case study overestimates and underestimates energy from diesel and OC units, respectively. This discrepancy may be due to differences between how we model operational costs and regulations that govern the operation of Canary Islands's electricity system. Regulations consider fixed operation and maintenance and fuel-logistic costs, which are distinct from fuel costs. Our objective function follows other works [2, 48]. Our omission of these costs means that our model weighs fuel costs differently than is done under current practice [6, 13, 41]. Despite the differences between Tables 9 and 12, the optimized costs that are reported in the first row of Table 10 are within 1% of actual estimates of the cost of Canary Islands's electricity system.

5.2. *Business As Usual and the Role of Transmission*

Table 8 reveals two major differences between *actual* year-2017 generation capacity and optimized business-as-usual capacity. Actual capacity is about 44%–46% higher than optimized levels, with differences in the capacity mix. There was about 412 MW of renewable-energy capacity during 2017 as opposed to optimized capacities of 20 MW–24 MW. The optimized capacity mixes include a subset of relatively low-investment-cost OS units. The optimized capacity mixes rely more on OC as opposed to diesel units, due to high investment costs of the latter. The optimized capacity mixes build less OCC capacity than existed during 2017.

Table 9 shows similar energy-supply mixes with actual and optimized capacity mixes, with one notable difference. With the actual year-2017 capacity mix, the optimized energy mix relies more upon renewable units, compared to the energy mix that results from the optimized business-as-usual capacity levels.

Developing renewable energy in Canary Islands cannot be justified solely by pecuniary cost. Indeed, renewable-energy resources incur additional ancillary costs, due to the treatment of renewable-energy units in the reserve requirements. For example, consider a candidate wind generator with the case study's 27% annual-average capacity factor. 3.70 MW of capacity must be built for such a unit to produce 1.00 MWh of energy. The reserve criteria require an additional 2.00 MW of capacity from a resource that can provide upward reserves, giving a 5.70-MW capacity requirement. Conversely, 3.00 MW of thermal capacity provides the same energy and reserves. Thus, renewable resources in Canary Islands are deployed for reasons other than cost. The business-as-usual cases show that OCC units are used predominantly for reserves. Other case-study variants that yield more renewable generation have more OCC units to meet reserve requirements.

Table 11 shows that business as usual sees lines connecting either Tenerife and La Gomera or Gran Canaria and Fuerteventura, which are interconnectors that are proposed currently by Red Eléctrica de España, being built. These lines allow for about 3% cost decreases compared to no transmission investment. These cost savings arise mainly from using relatively low-cost OCC capacity to meet energy needs of islands with higher-cost local generation.

5.3. *The Role of Renewable Energy*

The renewable-energy cases yield (relative to business as usual) higher renewable-resource penetrations. The additional candidate renewable-generation units are economically favorable compared to resources in Canary Islands during 2017. The amount of thermal generation built decreases (relative to business as usual) in the renewable-energy cases, especially without transmission investment. Relative to no transmission investment, transmission results in less renewable-generation capacity, which is displaced by oil-fired generation, which is built on larger islands to supply smaller islands.

5.4. *Additional Energy-Storage Capacity*

The energy-storage-technology cases yield reductions (relative to business as usual) in the amount of generation capacity that is built. Energy storage provides operating reserves, which reduces the need for generation capacity. There are some changes in the energy mix, which means that energy storage impacts generation-fleet operation. The energy-storage-technology cases see 237 MW–292 MW and 290 MW–300 MW, respectively, of battery energy storage and PHS built. This can be contrasted with

Table 8: Optimized generation capacity (MW) that is built in 19 variants of case study.

Case	Diesel	OS	OC	OCC	Wind	PV	Hydroelectric	Biogas
Calibration	465.6	482.6	477.6	865.4	223.9	182.0	1.9	3.7
Business-as-Usual	366.5	423.4	469.9	596.4	18.9	1.3	1.9	0.0
Business-as-Usual + ac	339.5	413.2	475.3	612.1	22.0	0.0	1.9	0.0
Business-as-Usual + HVDC	296.5	403.6	476.1	648.7	18.5	0.0	1.9	0.0
Renewable	331.4	306.1	458.6	638.6	160.0	20.0	13.6	4.8
Renewable + ac	332.4	412.5	476.1	606.9	34.1	2.0	13.5	0.0
Renewable + HVDC	275.0	416.3	477.6	641.2	12.1	4.1	13.6	0.0
Energy Storage	203.5	409.6	357.8	337.6	13.7	0.0	1.9	0.0
Energy Storage + ac	206.7	404.2	357.8	382.9	14.8	0.0	1.9	0.0
Energy Storage + HVDC	145.1	424.4	357.3	413.9	15.4	0.0	1.9	0.0
EV	342.9	409.6	417.6	556.4	21.0	0.0	1.9	0.0
EV + ac	342.5	417.9	415.5	550.1	22.6	0.0	1.9	0.0
EV + HVDC	293.3	406.0	412.1	596.3	18.5	0.0	1.9	0.0
All Technology + ac	177.3	417.1	350.9	398.8	42.9	4.8	13.6	0.0
All Technology + HVDC	199.6	410.2	354.8	336.1	36.0	1.4	13.6	0.0
€5.83/t Carbon Price + ac	465.6	482.6	477.6	865.4	1 025.0	426.5	13.6	109.5
€24.75/t Carbon Price + ac	465.6	482.6	477.6	865.4	1 025.0	426.5	13.6	109.5
€50.00/t Carbon Price + ac	465.6	482.6	477.6	865.4	1 025.0	426.5	13.6	109.5
€100.00/t Carbon Price + ac	465.6	482.6	477.6	865.4	1 025.0	426.5	13.6	109.5

Table 9: Optimized energy mix (%) that is supplied in 19 variants of case study.

Case	Diesel	OS	OC	OCC	Wind	PV	Hydroelectric	Biogas
Calibration	17.2	44.6	6.2	22.9	6.0	2.9	0.2	0.1
Business-as-Usual	17.6	40.0	6.7	35.1	0.4	0.0	0.2	0.0
Business-as-Usual + ac	16.7	39.2	5.8	37.7	0.5	0.0	0.2	0.0
Business-as-Usual + HVDC	12.4	38.6	5.0	43.4	0.4	0.0	0.2	0.0
Renewable	14.1	39.0	5.2	36.2	4.2	0.3	1.1	0.0
Renewable + ac	16.0	39.1	6.2	36.6	0.9	0.0	1.1	0.0
Renewable + HVDC	11.1	39.6	4.6	42.3	1.2	0.1	1.1	0.0
Energy Storage	15.9	39.5	15.5	28.5	0.4	0.0	0.2	0.0
Energy Storage + ac	16.1	39.0	12.5	31.8	0.4	0.0	0.2	0.0
Energy Storage + HVDC	9.4	40.7	13.0	36.4	0.4	0.0	0.2	0.0
EV	17.4	38.9	7.4	35.6	0.5	0.0	0.2	0.0
EV + ac	17.4	39.4	7.0	35.5	0.5	0.0	0.2	0.0
EV + HVDC	12.1	38.5	6.1	42.6	0.4	0.0	0.2	0.0
All Technology + ac	11.6	40.0	12.0	34.0	1.2	0.1	1.1	0.0
All Technology + HVDC	15.2	39.3	14.6	28.6	1.1	0.0	1.1	0.0
€5.83/t Carbon Price + ac	14.6	36.3	1.3	11.2	25.6	6.8	1.0	3.1
€24.75/t Carbon Price + ac	14.9	33.5	0.5	12.3	25.9	6.9	1.1	4.9
€50.00/t Carbon Price + ac	14.8	4.3	0.3	42.1	25.8	6.9	1.1	4.7
€100.00/t Carbon Price + ac	15.6	1.2	0.0	44.6	25.9	6.9	1.1	4.6

Table 10: Breakdown of optimized cost (€ million) in 19 variants of case study.

Case	Investment	Operation	Carbon
Calibration	271.9	122.2	n/a
Business-as-Usual	179.1	149.6	n/a
Business-as-Usual + ac	177.5	142.6	n/a
Business-as-Usual + HVDC	177.3	142.4	n/a
Renewable	192.6	132.9	n/a
Renewable + ac	178.2	139.6	n/a
Renewable + HVDC	179.4	136.8	n/a
Energy Storage	148.4	151.3	n/a
Energy Storage + ac	153.6	147.3	n/a
Energy Storage + HVDC	164.5	141.8	n/a
EV	165.8	146.5	n/a
EV + ac	167.0	145.4	n/a
EV + HVDC	167.4	144.3	n/a
All Technology + ac	154.3	141.5	n/a
All Technology + HVDC	144.2	147.5	n/a
€5.83/t Carbon Price + ac	401.9	83.9	27.3
€24.75/t Carbon Price + ac	404.0	91.1	109.4
€50.00/t Carbon Price + ac	402.8	130.6	180.2
€100.00/t Carbon Price + ac	411.7	146.6	350.4

Table 11: Transmission lines that are built (indicated by '+') in 11 variants of case study that allow transmission investment.

Case	$0 \leftrightarrow 4$	$8 \leftrightarrow 9$	$12 \leftrightarrow 13$	$0 \leftrightarrow 5$	$1 \leftrightarrow 9$	$9 \leftrightarrow 10$	$11 \leftrightarrow 12$
Calibration							+
Business-as-Usual + ac	+			+			+
Business-as-Usual + HVDC	+					+	+
Renewable + ac			+	+			+
Renewable + HVDC	+					+	+
Energy Storage + ac	+			+			+
Energy Storage + HVDC				+	+	+	+
EV + ac			+				+
EV + HVDC						+	+
All Technology + ac		+				+	+
All Technology + HVDC							+

about 11 MW under business as usual. Our cases see more PHS as opposed to battery energy storage built, which is contrary to other analyses [13] and may stem from our optimizing both the energy and power capacities of the energy-storage units. Other works optimize power capacities only.

5.5. EVs and the Provision of Electricity-System Services

Adding EVs that provide electricity-system services reduces the amount of generating capacity that is built relative to business as usual and the renewable-technology cases. More renewable-energy capacity is built with EVs relative to the energy-storage-technology cases, suggesting that electricity-system services from EVs aid renewable-energy integration. EV charging does not require added generating capacity (relative to business as usual), because EV charging is timed and co-ordinated with electricity-system operations. Thus, subject to constraints surrounding mobility usage, EV charging is scheduled to use available generation capacity during off-peak periods.

Fig. 2 shows optimized hourly electricity-system operations during the first representative operating week under case EV + ac. The positive bars indicate power that is provided by resources and the negative bars indicate power that is consumed for EV charging. The figure shows that EV charging is scheduled during off-peak overnight hours.

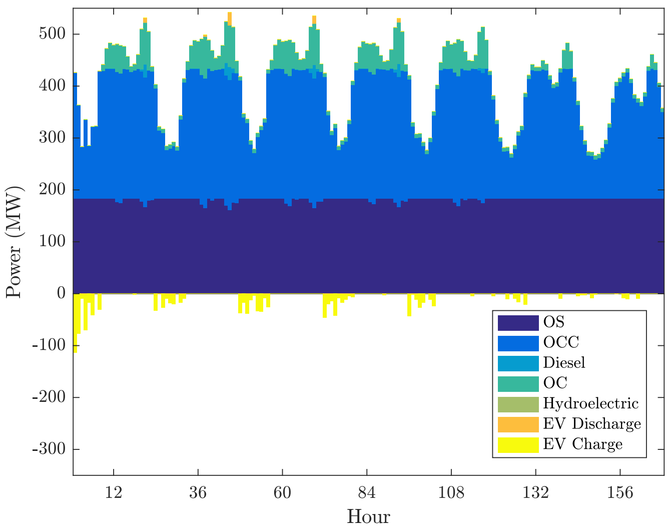

Figure 2: Optimized hourly operation of electricity system during first representative operating week under case EV + ac.

Fig. 2 shows that EVs discharge very little to the electricity system. The primary electricity-system benefit of EVs is providing operating reserves, which is consistent with some analyses [9, 47] and contrary to others [26, 27]. These differences may be due to some works using simpler representations of electricity-system operations compared to our model. Current regulations do not allow EVs to provide operating reserves to the Canary Islands electricity system. Our results suggest that relaxing these rules can provide cost savings.

Despite needing charging energy, EVs provide about 2% cost saving relative to business as usual. Avoided generation-capacity investments outweigh the cost of EV-charging energy. Total costs are lower under the energy-storage-technology compared to the EV-technology cases, because the limited number of EVs do not allow the same reduction in generation-capacity investment that energy storage allows. Thus, if there is a larger EV fleet, there may be additional cost savings, especially because EV owners bear the costs of their vehicle batteries.

5.6. All Technology Options

All-technology-case costs are about 5% lower than the renewable-technology cases, which are the least costly of the aforementioned cases. There is more renewable-energy and less energy-storage capacity, respectively, under the all-technology cases than under the renewable- and energy-storage-technology cases. With candidate ac transmission lines, the energy-storage-technology cases yield 237 MW and 298 MW of battery energy storage and PHS, respectively. With candidate HVDC transmission lines these investment levels are 291 MW and 292 MW, respectively. These values decrease to 126 MW, 280 MW, 160 MW, and 291 MW, respectively, in the all-technology cases with candidate ac and HVDC lines.

The combination of energy storage and EVs providing electricity-system services accommodates more renewable energy than either technology does individually. EVs providing electricity-system services reduces the amount of energy-storage capacity that must be built. EVs and energy storage providing operating reserves obviates the need to build transmission lines to deliver reserves to other nodes. For instance, one transmission line is built under the all-technology + HVDC case, whereas two or more are built under all of the other cases.

5.7. Carbon Pricing

Carbon pricing yields all of the candidate units being built and very similar energy mixes between the four price levels. Carbon pricing necessitates a shift towards using renewable energy, with the operating-reserve requirements increasing the need for fossil-fueled capacity.

Higher carbon prices result in more energy-storage capacity being built to reduce the use of fossil-fueled generation. However, less energy storage is built compared to the energy-storage- and all-technology cases, because fossil-fueled capacity must be built with carbon pricing to meet operating-reserve requirements. All available energy storage is not built. Thus, an expanded set of candidate renewable-energy units may yield more renewable-energy and energy-storage investment compared to the levels that we observe. No transmission lines are built with carbon pricing. Without carbon pricing, transmission lines are used to deliver low-cost fossil-fueled generation from Tenerife to other islands. With carbon pricing, such use of transmission lines is uneconomic.

Costs are higher with as opposed to without carbon pricing. Carbon pricing has an indirect effect on investments by requiring more generation capacity. Carbon pricing has a more direct effect in increasing the operating cost of fossil-fueled generation. If the carbon price internalizes the social cost of carbon, this direct cost is not a social-welfare loss. Rather, the carbon price is a wealth transfer from the carbon emitter to whomever collects the payment and should be excluded from considering the social cost of carbon pricing [58].

6. Conclusions

Our model optimizes capacity planning for island electricity systems and capture numerous technology options. Clustered weeks, which outperform clustered days *vis-à-vis* capturing energy storage and electricity-system flexibility, are used to represent electricity-system operations [59]. We apply our model to a case study that is based on Canary Islands, which allows us to understand how its operating-reserve restrictions impact planning and decarbonization. Technologies are assessed individually and together, with the key finding that without internalizing the social cost of carbon, fossil-fueled generation is the predominantly used technology. We do not opine on a 'correct' carbon price, as this depends upon the societal cost of carbon emissions.

OCC and OS units are the primary technologies that are used to meet operating-reserve and energy requirements, respectively. On average, they account for 31% and 25% of installed capacity and supply about 40% and 36% of the energy mix, respectively. Transmission lines should be assessed carefully. Their primary value is in serving loads on remote islands with fossil-fueled generation from larger islands, which yields modest cost savings of 3% compared to cases with no transmission investment. This value of transmission erodes with carbon policy. Energy-storage technologies allow up to 50% and 23% reductions in needed generation capacity and total costs, respectively. The value of energy storage is maximized if its power- and energy-capacities are optimized and the associated costs are considered. The primary electricity-system benefit of EVs is providing operating reserves. Thus, relaxing restrictions on such use of EVs would be valuable. Combining all of the technologies that we consider provides cost savings close to 25% compared to actual system costs. However, absent explicit carbon policy, the share of renewable energy does not increase significantly. Indeed, carbon pricing increases renewable-energy use, up to a maximum of about 40% on an energy basis, with a commensurate increase in fossil-fueled capacity to meet operating-reserve requirements.

This work develops a capacity-planning model that is tailored to island electricity systems. Future work could develop a dynamic variant of the model, whereby there are multiple investment stages [1]. Further case studies could examine a broader set of technology options, including alternative energy-storage and renewable-energy systems (*e.g.*, offshore wind, ocean, and geothermal energy). Finally, the effects of relaxing operational constraints on renewable penetration and power reliability and quality should be addressed.

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Appendix A. Mathematical Model Formulation

Appendix A.1. Model Notation

We begin by defining the following model indices.

c, c'	indices of thermal units
e	index of EV fleets
g, g'	indices of renewable units
i	index of islands
l	index of transmission lines
n, n'	indices of electricity-system nodes
o	index of operating conditions
ref	index of reference electricity-system node
s	index of energy-storage units
t	index of hours that correspond to an operating condition
ψ	index of EV trips

Next, we define the following model sets.

$\mathcal{I}$	set of islands
$\mathcal{N}$	set of electricity-system nodes
$\mathcal{N}_i$	set of electricity-system nodes that are located on island i
$\mathcal{O}$	set of operating conditions
$\mathcal{T}$	set of hours that correspond to an operating condition
Ψ	set of EV trips
Ω_n^C	set of thermal units that are located at node n
$\Omega_{n,o,t}^E$	set of EV fleets that are located at node n during hour t of operating condition o
Ω_n^G	set of renewable units that are located at node n
Ω^L	set of existing transmission lines
Ω^{L+}	set of candidate transmission lines
$\Omega^{L,\mathrm{ac}}$	set of existing and candidate ac transmission lines
Ω_n^S	set of energy-storage units that are located at node n

We divide the ac and HVDC transmission lines into existing and candidate lines [2]. The set, $\Omega_{n,o,t}^E$, is time dependent to represent spatial mobility. EVs are used for mobility during a set, Ψ, of trips, during which time they are available for neither discharging to the electricity system nor charging. EVs are grid-connected and available for charging and discharging while they are not being driven.

Next, we define the following model parameters.

B_l	susceptance of transmission line l (S)
$C_c^{C,\kappa}$	shutdown cost of thermal unit c (€)
$C_c^{C,\lambda}$	start-up cost of thermal unit c (€)
$\bar{F}_l^{\max}$	capacity of transmission line l (MW)
$f_{g,o,t}$	hour-t capacity factor of renewable unit g during operating condition o (p.u.)
I_c^C	investment cost of thermal unit c (€/MW)
$I^{C,\max}$	investment budget for thermal units (€)
I_g^G	investment cost of renewable unit g (€/MW)
$I^{G,\max}$	investment budget for renewable units (€)
I_l^L	investment cost of transmission line l (€)
$I^{L,\max}$	investment budget for transmission lines (€)
$I_s^{S,\gamma}$	investment cost of power capacity of energy-storage unit s (€/MW)
$I_s^{S,\xi}$	investment cost of energy capacity of energy-storage unit s (€/MWh)
$I^{S,\max}$	investment budget for energy-storage units (€)
K_c^C	generation cost of thermal unit c (€/MWh)
K^D	load-shedding cost (€/MWh)
$K_e^{E,T}$	discharging cost of EV fleet e (€/MWh)
K_g^G	generation cost of renewable unit g (€/MWh)
$K_s^{S,T}$	cost of discharging energy from energy-storage unit s (€/MWh)
M	a large constant
$\bar{P}_c^{C,\max}$	maximum capacity of thermal unit c that can be built (MW)
$\bar{p}_c^{C,\min}$	minimum operating point of thermal unit c while it is online (MW)
$P_{n,o,t}^{D,\max}$	hour-t load at node n during operating condition o (MW)
$\bar{P}_e^{E,\max}$	charging and discharging capacity of EV fleet e (MW)
$\bar{P}_g^{G,\max}$	maximum capacity of renewable unit g that can be built (MW)
$\bar{p}_g^{G,\min}$	minimum operating point of renewable unit g while it is online (MW)
$\bar{P}_s^{S,\gamma,\max}$	maximum power capacity of energy-storage unit s that can be built (MW)
$\bar{P}_s^{S,\xi,\max}$	maximum energy capacity of energy-storage unit s that can be built (MW)
$R_c^{C,-}$	maximum ramp-down rate of thermal unit c (MW/hour)
$R_c^{C,+}$	maximum ramp-up rate of thermal unit c (MW/hour)
$R_g^{G,-}$	maximum ramp-down rate of renewable unit g (MW/hour)
$R_g^{G,+}$	maximum ramp-up rate of renewable unit g (MW/hour)
$\bar{\xi}_s^{S,\min}$	minimum state of energy (SOE) of energy-storage unit s (MWh)
ϵ_c^C	output-based carbon-emission rate of thermal unit c (t/MWh)
ϵ_g^G	output-based carbon-emission rate of renewable unit g (t/MWh)
ζ_l^r	receiving-end node of transmission line l
ζ_l^s	sending-end node of transmission line l
$\eta_e^{E,P}$	charging efficiency of EV fleet e (p.u.)
$\eta_e^{E,T}$	discharging efficiency of EV fleet e (p.u.)
$\eta_s^{S,P}$	charging efficiency of energy-storage unit s (p.u.)
$\eta_s^{S,T}$	discharging efficiency of energy-storage unit s (p.u.)
$\bar{\rho}_e^{E,\max}$	maximum SOE of EV fleet e (MWh)
$\bar{\rho}_e^{E,\min}$	minimum SOE of EV fleet e (MWh)
$\bar{\rho}_e^{E,\min,\psi}$	minimum SOE of EV fleet e as of the beginning of its ψth trip (MWh)
$\sigma_{e,o,t}^E$	hour-t mobility-related energy consumption of EV fleet e during operating condition o (MWh)
Υ_o	weight of operating condition o (weeks)
$\phi_e^{A,\psi}$	arrival time of EV fleet e for its ψth trip (h)
$\phi_e^{D,\psi}$	departure time of EV fleet e for its ψth trip (h)
χ	carbon-emissions price (€/t)

Finally, we define the following decision variables.

$p_{c,o,t}^C$	hour-t production of thermal unit c during operating condition o (MW)
$p_c^{C,\max}$	capacity of thermal unit c that is built (MW)
$p_{n,o,t}^D$	hour-t load at node n that is curtailed during operating condition o (MW)
$p_{g,o,t}^G$	hour-t production of renewable unit g during operating condition o (MW)
$p_g^{G,\max}$	capacity of renewable unit g that is built (MW)
$p_{l,o,t}^L$	hour-t power flow through transmission line l during operating condition o (MW)
$p_s^{S,\gamma,\max}$	power capacity of energy-storage unit s that is built (MW)
$p_s^{S,\xi,\max}$	energy capacity of energy-storage unit s that is built (MW)
$r_{c,o,t}^{C,\text{down}}$	hour-t downward spinning reserve that is provided by thermal unit c during operating condition o (MW)
$r_{c,o,t}^{C,\text{up}}$	hour-t upward spinning reserve that is provided by thermal unit c during operating condition o (MW)
$r_{e,o,t}^{E,\text{down}}$	hour-t downward spinning reserve that is provided by EV fleet e during operating condition o (MW)
$r_{e,o,t}^{E,\text{up}}$	hour-t upward spinning reserve that is provided by EV fleet e during operating condition o (MW)
$r_{g,o,t}^{G,\text{down}}$	hour-t downward spinning reserve that is provided by renewable unit g during operating condition o (MW)
$r_{s,o,t}^{S,\text{down}}$	hour-t downward spinning reserve that is provided by energy-storage unit s during operating condition o (MW)
$r_{s,o,t}^{S,\text{up}}$	hour-t upward spinning reserve that is provided

by energy-storage unit s during operating condition o (MW)

$w^{C}_{c,o,t}$ hour-t upward non-spinning reserve that is provided by thermal unit c during operating condition o (MW)

$w^{S}_{s,o,t}$ hour-t upward non-spinning reserve that is provided by energy-storage unit s during operating condition o (MW)

x^{L}_{l} equals 1 if candidate transmission line l is built and equals 0 otherwise

$\gamma^{S,P}_{s,o,t}$ hour-t charging of energy-storage unit s during operating condition o (MW)

$\gamma^{S,T}_{s,o,t}$ hour-t discharging of energy-storage unit s during operating condition o (MW)

$\delta^{C}_{c,o,t}$ equals 1 if thermal unit c is online during hour t of operating condition o and equals 0 otherwise

$\theta_{n,o,t}$ hour-t phase angle of node n during operating condition o (rad)

$\kappa^{C}_{c,o,t}$ equals 1 if thermal unit c shuts-down during hour t of operating condition o and equals 0 otherwise

$\lambda^{C}_{c,o,t}$ equals 1 if thermal unit c starts-up during hour t of operating condition o and equals 0 otherwise

$\lambda^{S}_{s,o,t}$ equals 1 if energy-storage unit s is charging during hour t of operating condition o and equals 0 otherwise

$\xi^{S}_{s,o,t}$ ending hour-t SOE of energy-storage unit s during operating condition o (MWh)

$\rho^{E,L}_{e,o,t}$ ending hour-t SOE of EV fleet e during operating condition o (MWh)

$\rho^{E,P}_{e,o,t}$ hour-t charging of EV fleet e during operating condition o (MW)

$\rho^{E,T}_{e,o,t}$ hour-t discharging of EV fleet e during operating condition o (MW)

Appendix A.2. Model Formulation

Our model formulation is:

$$\begin{aligned}\min \sum_{l\in\Omega^{L+}} I^{L}_{l}x^{L}_{l} + \sum_{n\in\mathcal{N}} \Bigg\{ &\sum_{c\in\Omega^{C}_{n}} I^{C}_{c}p^{C,\max}_{c} \\ &+ \sum_{g\in\Omega^{G}_{n}} I^{G}_{g}p^{G,\max}_{g} \\ &+ \sum_{s\in\Omega^{S}_{n}} \left(I^{S,\gamma}_{s}p^{S,\gamma,\max}_{s} + I^{S,\xi}_{s}p^{S,\xi,\max}_{s}\right) \\ &+ \sum_{o\in\mathcal{O},t\in\mathcal{T}} \Upsilon_{o}\cdot\Bigg\{\sum_{c\in\Omega^{C}_{n}} \left[\left(K^{C}_{c}+\epsilon^{C}_{c}\chi\right)p^{C}_{c,o,t} \right.\\ &\left. + C^{C,\kappa}_{c}\kappa^{C}_{c,o,t} + C^{C,\lambda}_{c}\lambda^{C}_{c,o,t}\right] \\ &+ \sum_{g\in\Omega^{G}_{n}} \left(K^{G}_{g}+\epsilon^{G}_{g}\chi\right)p^{G}_{g,o,t} + K^{D}p^{D}_{n,o,t} \\ &+ \sum_{s\in\Omega^{S}_{n}} K^{S,T}_{s}\gamma^{S,T}_{s,o,t} + \sum_{e\in\Omega^{E}_{n,o,t}} K^{E,T}_{e}\rho^{E,T}_{e,o,t}\Bigg\}\Bigg\}\end{aligned} \tag{A.1}$$

$$\text{s.t. } 0 \le p^{C,\max}_{c} \le \bar{P}^{C,\max}_{c}; \forall n\in\mathcal{N}, c\in\Omega^{C}_{n} \tag{A.2}$$

$$0 \le p^{G,\max}_{g} \le \bar{P}^{G,\max}_{g}; \forall n\in\mathcal{N}, g\in\Omega^{G}_{n} \tag{A.3}$$

$$0 \le p^{S,\gamma,\max}_{s} \le \bar{P}^{S,\gamma,\max}_{s}; \forall n\in\mathcal{N}, s\in\Omega^{S}_{n} \tag{A.4}$$

$$0 \le p^{S,\xi,\max}_{s} \le \bar{P}^{S,\xi,\max}_{s}; \forall n\in\mathcal{N}, s\in\Omega^{S}_{n} \tag{A.5}$$

$$\sum_{n\in\mathcal{N},c\in\Omega^{C}_{n}} I^{C}_{c}p^{C,\max}_{c} \le I^{C,\max} \tag{A.6}$$

$$\sum_{n\in\mathcal{N},g\in\Omega^{G}_{n}} I^{G}_{g}p^{G,\max}_{g} \le I^{G,\max} \tag{A.7}$$

$$\sum_{l\in\Omega^{L+}} I^{L}_{l}x^{L}_{l} \le I^{L,\max} \tag{A.8}$$

$$\sum_{n\in\mathcal{N},s\in\Omega^{S}_{n}} \left(I^{S,\gamma}_{s}p^{S,\gamma,\max}_{s} + I^{S,\xi}_{s}p^{S,\xi,\max}_{s}\right) \le I^{S,\max} \tag{A.9}$$

$$\begin{aligned}&\sum_{c\in\Omega^{C}_{n}} p^{C}_{c,o,t} + \sum_{g\in\Omega^{G}_{n}} p^{G}_{g,o,t} \\ &+ \sum_{s\in\Omega^{S}_{n}} \left(\gamma^{S,T}_{s,o,t} - \gamma^{S,P}_{s,o,t}\right) + \sum_{e\in\Omega^{E}_{n,o,t}} \left(\rho^{E,T}_{e,o,t} - \rho^{E,P}_{e,o,t}\right) \\ &+ \sum_{l\in\Omega^{L}\cup\Omega^{L+}:\zeta^{r}_{l}=n} p^{L}_{l,o,t} - \sum_{l\in\Omega^{L}\cup\Omega^{L+}:\zeta^{s}_{l}=n} p^{L}_{l,o,t} \\ &= P^{D,\max}_{n,o,t} - p^{D}_{n,o,t}; \forall n\in\mathcal{N}, o\in\mathcal{O}, t\in\mathcal{T}\end{aligned} \tag{A.10}$$

$$0 \le p^{D}_{n,o,t} \le P^{D,\max}_{n,o,t}; \forall n\in\mathcal{N}, o\in\mathcal{O}, t\in\mathcal{T} \tag{A.11}$$

$$\begin{aligned}&\sum_{n\in\mathcal{N}_{i}} \left(\sum_{c\in\Omega^{C}_{n}} r^{C,\mathrm{up}}_{c,o,t} + \sum_{e\in\Omega^{E}_{n,o,t}} r^{E,\mathrm{up}}_{e,o,t} \right.\\ &\left. + \sum_{s\in\Omega^{S}_{n}} r^{S,\mathrm{up}}_{s,o,t}\right) \ge 0.5p^{C}_{c',o,t}; \\ &\forall i\in\mathcal{I}, n'\in\mathcal{N}_{i}, c'\in\Omega^{C}_{n'}, o\in\mathcal{O}, t\in\mathcal{T}\end{aligned} \tag{A.12}$$

$$\begin{aligned}&\sum_{n\in\mathcal{N}_{i}} \left(\sum_{c\in\Omega^{C}_{n}} r^{C,\mathrm{up}}_{c,o,t} + \sum_{e\in\Omega^{E}_{n,o,t}} r^{E,\mathrm{up}}_{e,o,t} \right.\\ &\left. + \sum_{s\in\Omega^{S}_{n}} r^{S,\mathrm{up}}_{s,o,t}\right) \ge 0.5p^{G}_{g',o,t}; \\ &\forall i\in\mathcal{I}, n'\in\mathcal{N}_{i}, g'\in\Omega^{G}_{n'}, o\in\mathcal{O}, t\in\mathcal{T}\end{aligned} \tag{A.13}$$

$$\begin{aligned}&\sum_{n\in\mathcal{N}_{i}} \left[\sum_{c\in\Omega^{C}_{n}} \left(r^{C,\mathrm{up}}_{c,o,t} + w^{C}_{c,o,t}\right) + \sum_{e\in\Omega^{E}_{n,o,t}} r^{E,\mathrm{up}}_{e,o,t} \right.\\ &\left. + \sum_{s\in\Omega^{S}_{n}} \left(r^{S,\mathrm{up}}_{s,o,t} + w^{S}_{s,o,t}\right)\right] \ge 2p^{C}_{c',o,t}; \\ &\forall i\in\mathcal{I}, n'\in\mathcal{N}_{i}, c'\in\Omega^{C}_{n'}, o\in\mathcal{O}, t\in\mathcal{T}\end{aligned} \tag{A.14}$$

$$\sum_{n\in\mathcal{N}_{i}} \left[\sum_{c\in\Omega^{C}_{n}} \left(r^{C,\mathrm{up}}_{c,o,t} + w^{C}_{c,o,t}\right) + \sum_{e\in\Omega^{E}_{n,o,t}} r^{E,\mathrm{up}}_{e,o,t} \right. \tag{A.15}$$

$$+\sum_{s\in\Omega_n^S}\left(r_{s,o,t}^{S,\mathrm{up}}+w_{s,o,t}^S\right)\Bigg]\geq 2p_{g',o,t}^G;$$
$$\forall i\in\mathcal{I},n'\in\mathcal{N}_i,g'\in\Omega_{n'}^G,o\in\mathcal{O},t\in\mathcal{T}$$

$$\sum_{n\in\mathcal{N}_i}\Bigg[\sum_{c\in\Omega_n^C}\left(r_{c,o,t}^{C,\mathrm{up}}+w_{c,o,t}^C\right)+\sum_{e\in\Omega_{n,o,t}^E}r_{e,o,t}^{E,\mathrm{up}} \tag{A.16}$$
$$+\sum_{s\in\Omega_n^S}\left(r_{s,o,t}^{S,\mathrm{up}}+w_{s,o,t}^S\right)\Bigg]$$
$$\geq\sum_{n\in\mathcal{N}_i}\left(P_{n,o,t+1}^{D,\max}-P_{n,o,t}^{D,\max}\right);\forall i\in\mathcal{I},o\in\mathcal{O},t\in\mathcal{T}$$

$$\sum_{n\in\mathcal{N}_i}\Bigg[\sum_{c\in\Omega_n^C}\left(r_{c,o,t}^{C,\mathrm{up}}+w_{c,o,t}^C\right)+\sum_{e\in\Omega_{n,o,t}^E}r_{e,o,t}^{E,\mathrm{up}} \tag{A.17}$$
$$+\sum_{s\in\Omega_n^S}\left(r_{s,o,t}^{S,\mathrm{up}}+w_{s,o,t}^S\right)\Bigg]\geq p_{l,o,t}^L;\forall i\in\mathcal{I},o\in\mathcal{O},$$
$$t\in\mathcal{T},l\in\Omega^L\cup\Omega^{L+}:\zeta_l^r\in\mathcal{N}_i,\zeta_l^s\notin\mathcal{N}_i$$

$$\sum_{n\in\mathcal{N}_i}\Bigg(\sum_{c\in\Omega_n^C}r_{c,o,t}^{C,\mathrm{down}}+\sum_{e\in\Omega_{n,o,t}^E}r_{e,o,t}^{E,\mathrm{down}} \tag{A.18}$$
$$+\sum_{g\in\Omega_n^G}r_{g,o,t}^{G,\mathrm{down}}+\sum_{s\in\Omega_n^S}r_{s,o,t}^{S,\mathrm{down}}\Bigg)\geq 0.5p_{c',o,t}^C;$$
$$\forall i\in\mathcal{I},n'\in\mathcal{N}_i,c'\in\Omega_{n'}^C,o\in\mathcal{O},t\in\mathcal{T}$$

$$\sum_{n\in\mathcal{N}_i}\Bigg(\sum_{c\in\Omega_n^C}r_{c,o,t}^{C,\mathrm{down}}+\sum_{e\in\Omega_{n,o,t}^E}r_{e,o,t}^{E,\mathrm{down}} \tag{A.19}$$
$$+\sum_{g\in\Omega_n^G}r_{g,o,t}^{G,\mathrm{down}}+\sum_{s\in\Omega_n^S}r_{s,o,t}^{S,\mathrm{down}}\Bigg)\geq 0.5p_{g',o,t}^G;$$
$$\forall i\in\mathcal{I},n'\in\mathcal{N}_i,g'\in\Omega_{n'}^G,o\in\mathcal{O},t\in\mathcal{T}$$

$$-\bar{F}_l^{\max}\leq p_{l,o,t}^L\leq\bar{F}_l^{\max}; \tag{A.20}$$
$$\forall l\in\Omega^L,o\in\mathcal{O},t\in\mathcal{T}$$

$$-\bar{F}_l^{\max}x_l^L\leq p_{l,o,t}^L\leq\bar{F}_l^{\max}x_l^L; \tag{A.21}$$
$$\forall l\in\Omega^{L+},o\in\mathcal{O},t\in\mathcal{T}$$

$$p_{l,o,t}^L=B_l\cdot\left(\theta_{\zeta_l^s,o,t}-\theta_{\zeta_l^r,o,t}\right); \tag{A.22}$$
$$\forall l\in\Omega^L\cap\Omega^{L,\mathrm{ac}},o\in\mathcal{O},t\in\mathcal{T}$$

$$-M\cdot\left(1-x_l^L\right)\leq p_{l,o,t}^L \tag{A.23}$$
$$-B_l\cdot\left(\theta_{\zeta_l^s,o,t}-\theta_{\zeta_l^r,o,t}\right)\leq M\cdot\left(1-x_l^L\right);$$
$$\forall l\in\Omega^{L+}\cap\Omega^{L,\mathrm{ac}},o\in\mathcal{O},t\in\mathcal{T}$$

$$-\pi\leq\theta_{n,o,t}\leq\pi;\forall n\in\mathcal{N},o\in\mathcal{O},t\in\mathcal{T} \tag{A.24}$$

$$\theta_{\mathrm{ref},o,t}=0;\forall o\in\mathcal{O},t\in\mathcal{T} \tag{A.25}$$

$$0\leq p_{c,o,t}^C\leq p_c^{C,\max}; \tag{A.26}$$
$$\forall n\in\mathcal{N},c\in\Omega_n^C,o\in\mathcal{O},t\in\mathcal{T}$$

$$p_{c,o,t}^C+r_{c,o,t}^{C,\mathrm{up}}\leq p_c^{C,\max}\delta_{c,o,t}^C; \tag{A.27}$$
$$\forall n\in\mathcal{N},c\in\Omega_n^C,o\in\mathcal{O},t\in\mathcal{T}$$

$$p_{c,o,t}^C+r_{c,o,t}^{C,\mathrm{up}}+w_{c,o,t}^C\leq p_c^{C,\max}; \tag{A.28}$$
$$\forall n\in\mathcal{N},c\in\Omega_n^C,o\in\mathcal{O},t\in\mathcal{T}$$

$$\bar{p}_c^{C,\min}\delta_{c,o,t}^C\leq p_{c,o,t}^C-r_{c,o,t}^{C,\mathrm{down}}; \tag{A.29}$$
$$\forall n\in\mathcal{N},c\in\Omega_n^C,o\in\mathcal{O},t\in\mathcal{T}$$

$$0\leq r_{c,o,t}^{C,\mathrm{up}}\leq p_c^{C,\max}; \tag{A.30}$$
$$\forall n\in\mathcal{N},c\in\Omega_n^C,o\in\mathcal{O},t\in\mathcal{T}$$

$$0\leq w_{c,o,t}^C\leq p_c^{C,\max}; \tag{A.31}$$
$$\forall n\in\mathcal{N},c\in\Omega_n^C,o\in\mathcal{O},t\in\mathcal{T}$$

$$0\leq r_{c,o,t}^{C,\mathrm{down}}\leq p_c^{C,\max}; \tag{A.32}$$
$$\forall n\in\mathcal{N},c\in\Omega_n^C,o\in\mathcal{O},t\in\mathcal{T}$$

$$p_{c,o,t}^C+r_{c,o,t}^{C,\mathrm{up}}+w_{c,o,t}^C-p_{c,o,t-1}^C\leq R_c^{C,+}; \tag{A.33}$$
$$\forall n\in\mathcal{N},c\in\Omega_n^C,o\in\mathcal{O},t\in\mathcal{T}$$

$$-R_c^{C,-}\leq p_{c,o,t}^C-r_{c,o,t}^{C,\mathrm{down}}-p_{c,o,t-1}^C; \tag{A.34}$$
$$\forall n\in\mathcal{N},c\in\Omega_n^C,o\in\mathcal{O},t\in\mathcal{T}$$

$$\delta_{c,o,t}^C-\delta_{c,o,t-1}^C=\lambda_{c,o,t}^C-\kappa_{c,o,t}^C; \tag{A.35}$$
$$\forall n\in\mathcal{N},c\in\Omega_n^C,o\in\mathcal{O},t\in\mathcal{T}$$

$$0\leq p_{g,o,t}^G\leq f_{g,o,t}p_g^{G,\max}; \tag{A.36}$$
$$\forall n\in\mathcal{N},g\in\Omega_n^G,o\in\mathcal{O},t\in\mathcal{T}$$

$$\bar{p}_g^{G,\min}f_{g,o,t}\leq p_{g,o,t}^G-r_{g,o,t}^{G,\mathrm{down}}; \tag{A.37}$$
$$\forall n\in\mathcal{N},g\in\Omega_n^G,o\in\mathcal{O},t\in\mathcal{T}$$

$$0\leq r_{g,o,t}^{G,\mathrm{down}}\leq f_{g,o,t}p_g^{G,\max}; \tag{A.38}$$
$$\forall n\in\mathcal{N},g\in\Omega_n^G,o\in\mathcal{O},t\in\mathcal{T}$$

$$p_{g,o,t}^G-p_{g,o,t-1}^G\leq R_g^{G,+}; \tag{A.39}$$
$$\forall n\in\mathcal{N},g\in\Omega_n^G,o\in\mathcal{O},t\in\mathcal{T}$$

$$-R_g^{G,-}\leq p_{g,o,t}^G-r_{g,o,t}^{G,\mathrm{down}}-p_{g,o,t-1}^G; \tag{A.40}$$
$$\forall n\in\mathcal{N},g\in\Omega_n^G,o\in\mathcal{O},t\in\mathcal{T}$$

$$0\leq\gamma_{s,o,t}^{S,P}\leq p_s^{S,\gamma,\max}\lambda_{s,o,t}^S; \tag{A.41}$$
$$\forall n\in\mathcal{N},s\in\Omega_n^S,o\in\mathcal{O},t\in\mathcal{T}$$

$$0\leq\gamma_{s,o,t}^{S,T}/\eta_s^{S,T}\leq p_s^{S,\gamma,\max}\cdot(1-\lambda_{s,o,t}^S); \tag{A.42}$$
$$\forall n\in\mathcal{N},s\in\Omega_n^S,o\in\mathcal{O},t\in\mathcal{T}$$

$$\bar{\xi}_s^{S,\min}\leq\xi_{s,o,t}^S\leq p_s^{S,\xi,\max}; \tag{A.43}$$
$$\forall n\in\mathcal{N},s\in\Omega_n^S,o\in\mathcal{O},t\in\mathcal{T}$$

$$\xi_{s,o,t}^S=\xi_{s,o,t-1}^S+\eta_s^{S,P}\gamma_{s,o,t}^{S,P}-\gamma_{s,o,t}^{S,T}/\eta_s^{S,T}; \tag{A.44}$$
$$\forall n\in\mathcal{N},s\in\Omega_n^S,o\in\mathcal{O},t\in\mathcal{T}$$

$$\xi_{s,o,|\mathcal{T}|}^S\geq\xi_{s,o,0}^S=0.5p_s^{S,\xi,\max}; \tag{A.45}$$
$$\forall n\in\mathcal{N},s\in\Omega_n^S,o\in\mathcal{O}$$

$$\left(r_{s,o,t}^{S,\mathrm{up}}+w_{s,o,t}^S\right)/\eta_s^{S,T}\leq\xi_{s,o,t}^S-\bar{\xi}_s^{S,\min}; \tag{A.46}$$
$$\forall n\in\mathcal{N},s\in\Omega_n^S,o\in\mathcal{O},t\in\mathcal{T}$$

$$\left(\gamma^{S,T}_{s,o,t} + r^{S,\mathrm{up}}_{s,o,t} + w^{S}_{s,o,t}\right)/\eta^{S,T}_{s} \leq p^{S,\gamma,\max}_{s}; \tag{A.47}$$
$$\forall n \in \mathcal{N}, s \in \Omega^{S}_{n}, o \in \mathcal{O}, t \in \mathcal{T}$$

$$r^{S,\mathrm{down}}_{s,o,t} \leq p^{S,\xi,\max}_{s} - \xi^{S}_{s,o,t}; \tag{A.48}$$
$$\forall n \in \mathcal{N}, s \in \Omega^{S}_{n}, o \in \mathcal{O}, t \in \mathcal{T}$$

$$\gamma^{S,P}_{s,o,t} + r^{S,\mathrm{down}}_{s,o,t} \leq p^{S,\gamma,\max}_{s}; \tag{A.49}$$
$$\forall n \in \mathcal{N}, s \in \Omega^{S}_{n}, o \in \mathcal{O}, t \in \mathcal{T}$$

$$0 \leq \rho^{E,P}_{e,o,t} \leq \bar{P}^{E,\max}_{e}; \tag{A.50}$$
$$\forall n \in \mathcal{N}, o \in \mathcal{O}, t \in \mathcal{T}, e \in \Omega^{E}_{n,o,t}$$

$$0 \leq \rho^{E,T}_{e,o,t}/\eta^{E,T}_{e} \leq \bar{P}^{E,\max}_{e}; \tag{A.51}$$
$$\forall n \in \mathcal{N}, o \in \mathcal{O}, t \in \mathcal{T}, e \in \Omega^{E}_{n,o,t}$$

$$\bar{\rho}^{E,\min}_{e} \leq \rho^{E,L}_{e,o,t} \leq \bar{\rho}^{E,\max}_{e}; \tag{A.52}$$
$$\forall n \in \mathcal{N}, o \in \mathcal{O}, t \in \mathcal{T}, e \in \Omega^{E}_{n,o,t}$$

$$\rho^{E,L}_{e,o,t} = \rho^{E,L}_{e,o,t-1} + \eta^{E,P}_{e}\rho^{E,P}_{e,o,t} - \rho^{E,T}_{e,o,t}/\eta^{E,T}_{e} \tag{A.53}$$
$$- \sigma^{E}_{e,o,t}; \forall n \in \mathcal{N}, o \in \mathcal{O}, t \in \mathcal{T}, e \in \Omega^{E}_{n,o,t}$$

$$\rho^{E,L}_{e,o,|\mathcal{T}|} \geq \rho^{E,L}_{e,o,0} = 0.5\bar{\rho}^{E,\max}_{e}; \tag{A.54}$$
$$\forall n \in \mathcal{N}, o \in \mathcal{O}, e \in \Omega^{E}_{n,o,0} \cup \Omega^{E}_{n,o,|\mathcal{T}|}$$

$$\rho^{E,L}_{e,o,\phi^{D,\psi}_{e}} \geq \bar{\rho}^{E,\min,\psi}_{e}; \tag{A.55}$$
$$\forall n \in \mathcal{N}, o \in \mathcal{O}, \psi \in \Psi, e \in \Omega^{E}_{n,o,\phi^{D,\psi}_{e}}$$

$$r^{E,\mathrm{up}}_{e,o,t}/\eta^{E,T}_{e} \leq \rho^{E,L}_{e,o,t} - \bar{\rho}^{E,\min}_{e}; \tag{A.56}$$
$$\forall n \in \mathcal{N}, o \in \mathcal{O}, t \in \mathcal{T}, e \in \Omega^{E}_{n,o,t}$$

$$\left(\rho^{E,T}_{e,o,t} + r^{E,\mathrm{up}}_{e,o,t}\right)/\eta^{E,T}_{e} \leq \bar{P}^{E,\max}_{e}; \tag{A.57}$$
$$\forall n \in \mathcal{N}, o \in \mathcal{O}, t \in \mathcal{T}, e \in \Omega^{E}_{n,o,t}$$

$$r^{E,\mathrm{down}}_{e,o,t} \leq \bar{\rho}^{E,\max}_{e} - \rho^{E,L}_{e,o,t}; \tag{A.58}$$
$$\forall n \in \mathcal{N}, o \in \mathcal{O}, t \in \mathcal{T}, e \in \Omega^{E}_{n,o,t}$$

$$\rho^{E,P}_{e,o,t} + r^{E,\mathrm{down}}_{e,o,t} \leq \bar{P}^{E,\max}_{e}; \tag{A.59}$$
$$\forall n \in \mathcal{N}, o \in \mathcal{O}, t \in \mathcal{T}, e \in \Omega^{E}_{n,o,t}$$

$$r^{E,\mathrm{down}}_{e,o,t}, r^{E,\mathrm{up}}_{e,o,t}, \rho^{E,P}_{e,o,t}, \rho^{E,T}_{e,o,t} = 0; \tag{A.60}$$
$$\forall n \in \mathcal{N}, o \in \mathcal{O}, t \in \bigcup_{\psi \in \Psi}\left[\phi^{D,\psi}_{e}, \phi^{A,\psi}_{e}\right], e \in \Omega^{E}_{n,o,t}$$

$$x^{L}_{l} \in \{0,1\}; \forall l \in \Omega^{L+} \tag{A.61}$$

$$\delta^{C}_{c,o,t}, \kappa^{C}_{c,o,t}, \lambda^{C}_{c,o,t} \in \{0,1\}; \tag{A.62}$$
$$\forall n \in \mathcal{N}, c \in \Omega^{C}_{n}, o \in \mathcal{O}, t \in \mathcal{T}$$

$$\lambda^{S}_{s,o,t} \in \{0,1\}; \forall n \in \mathcal{N}, s \in \Omega^{S}_{n}, o \in \mathcal{O}, t \in \mathcal{T} \tag{A.63}$$

$$r^{S,\mathrm{down}}_{s,o,t}, r^{S,\mathrm{up}}_{s,o,t}, w^{S}_{s,o,t} \geq 0; \tag{A.64}$$
$$\forall n \in \mathcal{N}, s \in \Omega^{S}_{n}, o \in \mathcal{O}, t \in \mathcal{T}$$

$$r^{E,\mathrm{down}}_{e,o,t}, r^{E,\mathrm{up}}_{e,o,t} \geq 0; \tag{A.65}$$
$$\forall n \in \mathcal{N}, o \in \mathcal{O}, t \in \mathcal{T}, e \in \Omega^{E}_{n,o,t}.$$

Objective function (A.1) minimizes cost. Investment-cost parameters, I^{C}_{c}, I^{G}_{g}, I^{L}_{l}, and I^{S}_{s}, are annualized by:

$$\frac{j \cdot (1+j)^{y}}{(1+j)^{y} - 1};$$

where y is the asset lifetime and j is the real interest rate.

Constraints (A.2)–(A.9) and (A.61) restrict investment decisions and the remaining restrict operating decisions. Constraints (A.2)–(A.9) impose resource and budget restrictions on investments. Transmission investments are restricted to be binary by (A.61).

Constraints (A.10) impose load balance and (A.11) restrict curtailed load to be no greater than demand.

Constraints (A.12)–(A.19) impose requirements for upward and downward spinning and upward non-spinning reserves on each individual island, based on procedures for Canary Islands [5, 6, 13, 41]. Constraints (A.12)–(A.13) require that upward spinning reserves on each island be at least half of the highest scheduled dispatch of any generator within that island. Constraints (A.14)–(A.15) set similar requirements for total upward reserves, which must be at least twice the highest scheduled dispatch of a generator within each island. Additionally, (A.16) requires that total upward reserves for each island be at least as great as the scheduled increase in the island's electricity demand from one hour to the next. Finally, (A.17) requires that total upward reserves for each island be at least as great as scheduled inflow into the island from each interconnector. Downward-reserve requirements are set analogously by (A.18)–(A.19) to how (A.12)–(A.13) set upward-reserve requirements.

Thermal generators can provide all three reserve types and renewable generators can provide downward reserves, which follows current practice [5, 6, 13, 41]. We allow energy storage to provide all three reserve types and EVs to provide spinning reserves to assess the value of these resources as sources of operating reserves.

Constraints (A.20)–(A.21) impose power-flow limits. Constraints (A.22)–(A.23) are linearizations of Kirchhoff's laws and apply only to ac lines, because HVDC lines are modeled using a pipeline assumption. Big-M method is used in (A.23) to enforce Kirchhoff's laws only for candidate lines that are built [60]. Constraints (A.24) bound the phase angles and (A.25) fix the reference-node phase angles.

Constraints (A.26)–(A.35) and (A.62) restrict thermal-unit operations. Constraints (A.26)–(A.28) require non-negative power output, impose capacity restrictions on the sum of power and upward reserves, and ensure no power output and spinning reserves while a unit is offline. Constraints (A.29) ensure that minimum-load levels are met if downward spinning reserves are called and that they are provided only while units are online. Constraints (A.30)–(A.32) impose non-negativity and capacity restrictions on reserves. Constraints (A.33)–(A.34) are ramping restrictions. Constraints (A.35) define the start-up and shut-down variables from the online variables and (A.62) imposes integrality on the commitment decisions.

Constraints (A.36)–(A.40) are similar to (A.26)–(A.34) and restrict renewable-unit operations. Constraints (A.36) impose capacity and non-negativity restrictions on power outputs. Constraints (A.37) enforce minimum-load levels and (A.38) limit downward-reserve levels. Ramping restrictions are imposed by (A.39)–(A.40).

Constraints (A.41)–(A.49) and (A.63)–(A.64) restrict energy-storage use [42–44]. Power limits and restrictions against simultaneous charging and discharging of energy-storage units are imposed by (A.41)–(A.42) and (A.63). SOE limits are imposed by (A.43) and (A.44) define SOE evolution. Constraints (A.45) are boundary conditions on energy-storage units' SOE, which is an heuristic to ascribe value to carrying energy from one period to another [45, 46]. Constraints (A.46)–(A.49) and (A.64) impose SOE, power, and non-negativity restrictions on reserves.

Constraints (A.50)–(A.60) and (A.65) restrict EV use. Constraints (A.50)–(A.51) impose power constraints on EV charging and discharging. Constraints (A.52) impose physical limits on EV SOEs and (A.53) define how the SOEs evolve. Constraints (A.54) are boundary conditions on EV SOEs. Constraints (A.55) impose SOE requirements on each EV fleet as of the departure time of each trip. Constraints (A.56)–(A.59) and (A.65) impose SOE, power, and non-negativity limits on reserves provided. Finally, (A.60) ensure that EVs are not charged, discharged, or providing reserves while they are being used for mobility.

Appendix B. Selection of Operating Conditions

The elements of $\mathcal{O}$ are selected by applying hierarchical clustering, which requires metrics between weeks and between clusters, to the weeks of the full year [7, 61]. To define these metrics, we represent each week as a vector of hourly load and solar- and wind-availability features. We use Euclidean distance and minimax linkage as the metrics between weeks and clusters, respectively [62]. Minimax linkage provides each cluster's prototype, which is the week from the unclustered data that is closest to the cluster center. The cluster prototype is used in modeling the corresponding operating condition, by providing the corresponding values of $f_{g,o,t}$ and $P^{D,\max}_{n,o,t}$. The values of Υ_o, $\forall o \in \mathcal{O}$ are given by the number of weeks in the clusters that correspond to the operating conditions.

Linear scaling is applied to the features before clustering. A generic feature, μ, is re-scaled to:

$$\frac{\mu - \mu^{\min}}{\mu^{\max} - \mu^{\min}};$$

where $\mu^{\min}$ and $\mu^{\max}$ are the minimum and maximum values, respectively, of the feature that are observed in the unclustered data.

We determine $|\mathcal{O}|$ based on how well (A.1)–(A.65) performs using the clustered compared to unclustered data.

Table B.14: Representative operating weeks that are selected.

Week of Year	Dates
8	20 February–26 February
21	22 May–28 May
27	3 July–9 July
35	28 August–3 September
43	23 October–29 October
52	25 December–31 December

Solving (A.1)–(A.65) with the unclustered data is computationally intractable. Thus, we use a reduced case study, in which co-located generators with similar characteristics are grouped together and represented as a single archetypal generating unit [63, 64], to calibrate $\mathcal{O}$. The clustered generators are diesel-fired units at nodes 0, 1, 6–9, 11, and 13, OS units at nodes 0, 1, 8, and 9, and OC units at nodes 0, 1, 8, 9, and 13.

We verify in two ways model fidelity with grouped generating units. First, we compare variants of (A.1)–(A.65) with fixed capacity levels with grouped and ungrouped generators. Second, we compare variants of (A.1)–(A.65) for each island individually with grouped and ungrouped generators. These comparisons show that grouped and ungrouped generating units yields similar costs, investment decisions, and electricity-system reliability.

Table B.13 summarizes optimized costs of operating the electricity system from solving (A.1)–(A.65) and corresponding computation times with different choices of $|\mathcal{O}|$. Based on these results, we use the six weeks that are listed in Table B.14 in our case study, as six operating weeks provides balance between model fidelity and tractability. The weeks that are selected are spread across the year, meaning that a variety of conditions that correspond to different seasons are represented in the clustered data.

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Table B.13: Optimized electricity-system costs and computation time to solve (A.1)–(A.65) with different numbers of operating weeks.

Number of Weeks	Costs (€ million)			Computation Time (min)
	Investment	Operating	Total	
52	232.96	167.27	400.23	2 989.0
10	228.17	167.27	395.44	38.5
9	228.19	167.32	395.51	84.0
8	228.18	167.43	395.61	13.0
7	228.31	169.26	397.51	10.5
6	228.36	169.30	397.66	8.2
5	228.53	169.40	397.93	9.5
4	221.32	163.93	385.25	3.5
3	219.78	164.27	384.06	1.5
2	222.58	162.39	384.97	2.0
1	228.33	155.63	383.96	0.5

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