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A novel framework for development and optimisation of future electricity scenarios with high penetration of renewables and storage

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HIGHLIGHTS

- FuturES framework optimises electricity scenarios with high renewables penetration.
- Reservoir and concentrating solar power modelled based on storage value.
- Feasible scenarios created with 81–100% renewables by 2050.
- Long-term energy storage helps to achieve low electricity costs.

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ABSTRACT

Although electricity supply is still dominated by fossil fuels, it is expected that renewable sources will have a much larger contribution in the future due to the need to mitigate climate change. Therefore, this paper presents a new framework for developing Future Electricity Scenarios (FuturES) with high penetration of renewables. A multi-period linear programming model has been created for power-system expansion planning. This has been coupled with an economic dispatch model, PowerGAMA, to evaluate the technical and economic feasibility of the developed scenarios while matching supply and demand. Application of FuturES is demonstrated through the case of Chile which has ambitious plans to supply electricity using only renewable sources. Four cost-optimal scenarios have been developed for the year 2050 using FuturES: two Business as usual (BAU) and two Renewable electricity (RE) scenarios. The BAU scenarios are unconstrained in terms of the technology type and can include all 11 options considered. The RE scenarios aim to have only renewables in the mix, including storage. The results show that both BAU scenarios have a levelised cost of electricity (LCOE) lower than, or equal to, today's costs ($72.7–77.3 vs $77.6/MWh) and include 81–90% of renewables. The RE scenarios are slightly more expensive than today's costs ($81–87/MWh). The cumulative investment for the BAU scenarios is $123-$145 bn, compared to $147-$157 bn for the RE. The annual investment across the scenarios is estimated at $4.0 ± 0.4 bn. Both RE scenarios show sufficient flexibility in matching supply and demand, despite solar photovoltaics and wind power contributing around half of the total supply. Therefore, the FuturES framework is a powerful tool for aiding the design of cost-efficient power systems with high penetration of renewables.

1. Introduction

Electricity generation is responsible for approximately 25% of global greenhouse gas (GHG) emissions. As a result, the Intergovernmental Panel on Climate Change (IPCC) has highlighted the importance of the decarbonisation of electricity supply and deployment of renewables as key mitigation measures for the sector [1]. A recent study showed that, between 2014 and 2016, the global energy-related CO_2 emissions have remained constant after decades of increase [2]. The development of renewable technologies, such as solar photovoltaics (PV) and wind, has been crucial in achieving this, allowing them to become more competitive and triggering further increase in investment in recent years. This has also been stimulated by policy in different regions. For example, in the European Union (EU), the

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Nomenclature

Parameters

- $B_{g,t}^{plan}$ scheduled new-build capacity of technology g in year t (MW)
- b_g learning rate (%)
- $C_{g,t}^{fuel}$ fuel cost of technology g in year t ($/unit fuel)
- $CF_{g,t}$ capacity factor of technology g in year t (%)
- CO_{2t}^{tax} carbon tax in year t ($/t)
- CO_{2g}^{emi} CO_2 emission factor for technology g (kg/MJ)
- cv_g calorific value of fuel used by technology g (MJ/unit fuel)
- $D_{g,t}^{total}$ total capacity of technology g decommissioned in year t (MW)
- $D_{g,t}^{plan}$ total capacity of technology g planned to be decommissioned in year t (MW)
- eff_g power plant efficiency for technology g (%)
- $E_{g,t}$ electricity generated by technology g in year t (MWh)
- E_t^{demand} electricity demand in year t (MWh)
- $f_{g,t}^{inv}$ annualised capital cost of technology g in year t ($/MWh)
- $f_{g,t}^{OM}$ operating and maintenance fixed cost for technology g in year t ($/MWh)
- $I_{g,t0}^{capital}$ initial capital cost of technology g ($/kW)
- $LCOE_{g,t}$ levelised cost of electricity for technology g in year t ($/MWh)
- N_g^{max} maximum annual new-build capacity allowed for technology g (MW)
- $P_{g,t}^{total}$ total installed capacity of technology g in year t (MW)
- $P_{g,init}^{total}$ initial total installed capacity of technology g (MW)
- PO_g^{max} maximum annual phase-out capacity of technology g (MW)
- $PO_{g,t}^{quota}$ phase-out quota capacity of technology g in year t (MW)
- $Q_t^{NCRE_{min}}$ minimum share of electricity from non-conventional renewable sources in year t (%)
- $Q_{g,t}^{tech_{max}}$ maximum share of electricity from technology g in year t (%)
- q share of the total phase-out electricity (%)
- r_g discount rate (%)
- S_g fraction of investment costs used to estimate operating and maintenance fixed costs (%)
- S_t^{loss} annual electricity loss in year t (%)
- $S^{NCRE_{min}}$ minimum share of non-conventional renewable electricity in the target year (%)
- $S_{t0}^{NCRE_{min}}$ minimum share of non-conventional renewable in the starting year (%)
- $S_g^{tech_{maxEnd}}$ maximum electricity share of technology g in the target year (%)
- $t^{NCRE_{min}}$ target year for non-conventional renewable electricity
- $t_g^{phaseout_{start}}$ starting year for the phase-out of technology g
- $t_g^{tech_{maxInit}}$ year when a maximun electricity share of technology g starts
- $v_{g,t}^{carbon}$ carbon tax payable for technology g in year t ($/MWh)
- $v_{g,t}^{fuel}$ fuel cost for technology g in year t ($/MWh)
- $v_{g,t}^{OM}$ operating and maintenance variable cost for technology g in year t ($/MWh)
- $W_{g,t}$ global cumulative installed capacity of technology g in year t (MW)
- $W_{g,t0}$ starting global cumulative installed capacity of technology g (MW)
- Z total system cost (objective function) ($)
- γ_g^{NCRE} binary parameter denoting if a technology is non-conventional renewable
- κ_g^{hydro} binary parameter denoting if a technology is hydropower
- $\lambda_g^{learning}$ binary parameter denoting if technology g has a learning rate
- τ_g lifespan of technology g (years)
- $\phi_g^{phaseout}$ binary parameter denoting if technology g is being phased-out
- $\omega_g^{tech_{max}}$ binary parameter denoting if technology g must achieve its maximum quota in a given year

Variables

- $Var_{g,t}^{new}$ new-build capacity of technology g in year t (MW)
- $Var_{g,t}^{phaseout}$ phase-out capacity of technology g in year t (MW)

Subscripts

- g technology type
- t year
- t_0 starting year
- t_{end} target year

Sets

- G set of technologies
- G_S set of technologies with storage
- T set of years in the planning horizon

Renewable Energy Directive [3] sets a target of 34% of renewable electricity by 2020. As a result, the share of renewable electricity in the EU reached 30% by 2016 [4]. In the US, for instance, the contribution of renewable electricity in the same year was 15% [5]. In both regions, wind and solar PV play a significant role, in addition to hydro power.

Renewable power options are predominantly capital-cost intensive as opposed to fossil-fuel technologies which are marginal-cost plants, driven by the operational and fuel costs. This poses new challenges to traditional electricity markets which are mostly based on marginal costs [6]. As renewables have variable costs close to zero, they can lead to low system marginal costs (or spot prices) which discourages investors to fund new projects [7,8]. This could result in a market failure in the absence of appropriate signals or mechanisms to stimulate investment. Some South American countries have experienced a similar situation due to a high contribution of hydropower which has high capital but very low marginal costs. They have resolved this issue through long-term contracts for investments while keeping short-term markets for energy trading to secure electricity dispatch at optimal costs at all times [7].

In addition to the market challenges, it is also crucial to ensure that future electricity systems dominated by renewables can provide reliable supply to match the demand. Achieving this requires sufficient flexibility in the system to mitigate against the variability, intermittency and unpredictability of supply from wind and solar PV [9]. In the last decades, flexibility has been achieved primarily via hydropower, pumped hydro storage systems and oil and gas power plants, with the support of base-load sources, such as nuclear, coal, biomass and run-of-river hydropower. In future power systems shaped by renewables, storage systems will play a key role in achieving flexibility [10]. Nowadays, depending on energy resource availability and geography, countries can take advantage of reservoir and pumped hydropower or concentrating solar power (CSP) thermal storage. Others that lack such natural resources can rely on battery energy storage solutions. With the expected significant increase of renewables in future electricity systems, it will become progressively more important to develop optimal system configurations with sufficient flexibility to ensure security of supply.

In an attempt to contribute to this effort, this paper proposes a new framework – Future Electricity Scenarios (FuturES) – with the aim of designing optimal power systems dominated by renewables. The FuturES framework integrates systems optimisation with an economic dispatch model. The optimisation model, developed as part of this study, is a deterministic power system expansion model which generates optimised electricity scenarios by minimising total system costs under perfect market competition conditions. The economic dispatch model PowerGAMA (Power Grid and Market Analysis) [11] evaluates the extent to which the resulting optimised scenarios can operate with flexibility by implementing the storage value approach [12] for water reservoirs and CSP with storage. Therefore, FuturES allows the modelling and optimisation of future electricity scenarios where CSP and hydropower act as backup options in systems with high penetration of renewables. The framework is generic and can be used in different regions and countries. To demonstrate its application, Chile is considered as an illustrative case, as the country has very ambitious plans for increasing the contribution of renewables in the electricity mix up to 100% by 2050. This is the first study of its kind for Chile, aimed at providing guidance to the energy sector and policy makers on designing techno-economically optimal electricity systems with high penetration of renewables, capable of matching supply and demand.

The framework is presented in Section 3, followed by its application in Section 4. Prior to that, the next section gives an overview of literature, focusing on challenges in power system modelling and optimisation.

2. Literature review

Optimisation of power systems has been used extensively over the years for a range of purposes, including power system planning, trading and monitoring of market performance [13–15]. Typically, linear

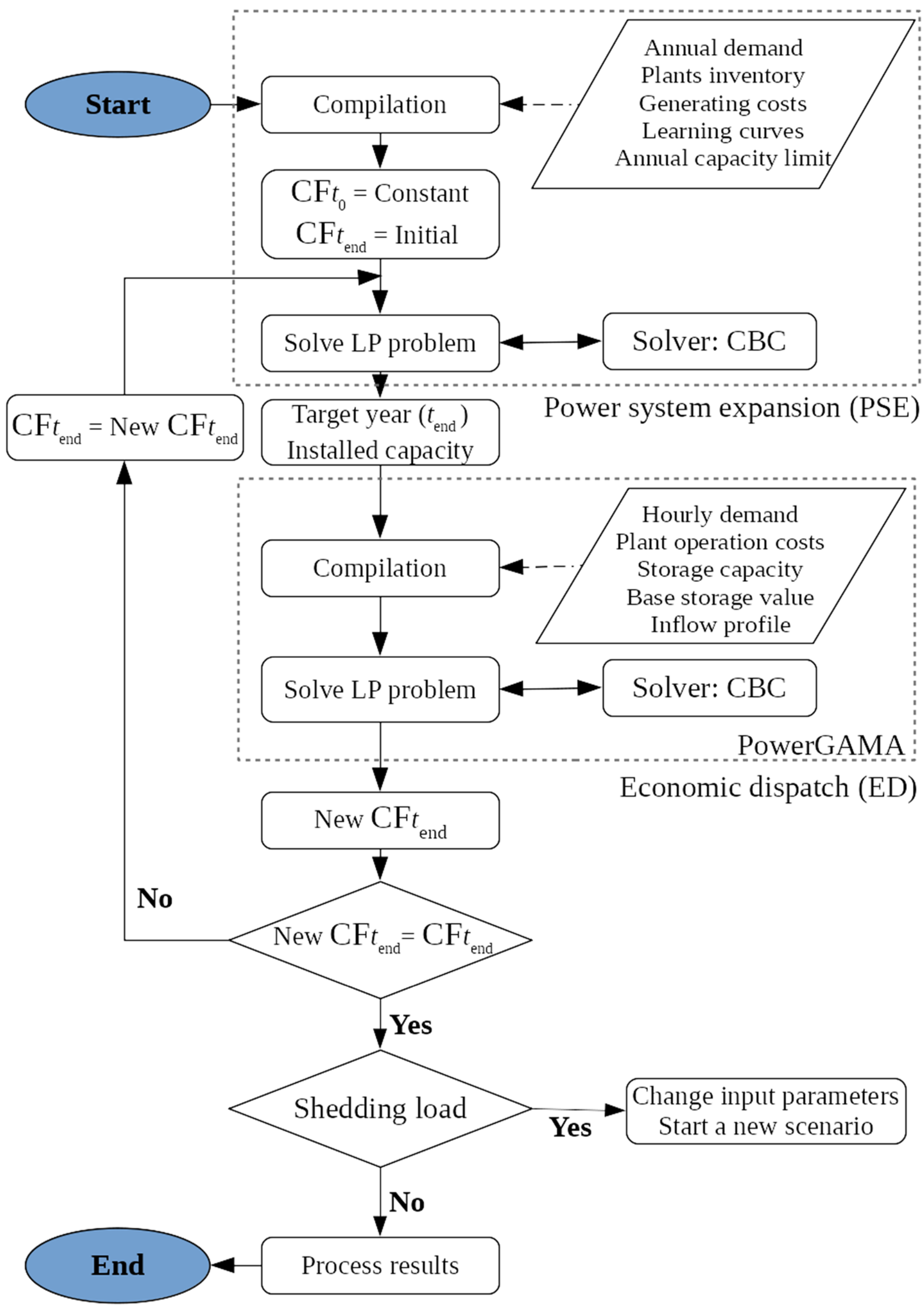

Fig. 1. FuturES framework for defining optimal power scenarios. [CFt_0: capacity factor at starting period, CFt_{end}: capacity factor at target year, LP: linear programming, CBC: COIN-OR Branch-and-Cut mixed integer linear programming solver with an integral linear programming solver.]

programming (LP) is used for optimisation of power systems. A wide variety of LP models exists, of which MARKAL [16] and its successor TIMES [17] are probably the most widely used commercial models. They both enable optimisation of future scenarios at a national level based on supply and demand requirements. Equivalent open-source models are also available, including OSeMOSYS [18], an optimisation model for long-term energy planning, and PyPSA [19], an open-source toolbox for simulating and optimising power systems. Furthermore, Switch 2.0 [20] provides a modelling platform for planning transitions to low-emission electric power grids. Finally, Calliope [21] and URBS [22] model energy systems to satisfy heat, power and gas demand with a focus on planning and flexibility of the systems at different spatial resolutions.

Currently, the main challenge in power system optimisation is to design future systems capable of operating reliably with high penetration of renewables [23]. Given the large heterogeneity of countries and regions with respect to renewable resources, each power system may require different models to represent differing conditions.

A further challenge is modelling of energy storage [24]. This is largely due to two main reasons. First, storage dispatch may vary significantly with high capacity of variable-supply technologies, requiring the model to be able to deal with short-term storage. Secondly, high contribution of storage may act as a price-maker, as is the case, for example, with water reservoirs.

Various methods have been developed to deal with these challenges, as described by Schill and Zerrahn [25]. For example, Hemmati et al. [26] developed a generation expansion planning model where energy storage systems enable flexibility by replacing peak-load fossil fuel options. A similar approach was considered by Balducci et al. [27] who proposed a taxonomy for assigning benefits of services provided by energy storage systems.

Hydropower from reservoirs is considered a long-term storage option that can play an important role in power systems where it has a significant contribution, such as in Norway [12]. Wolfgang et al. [12] highlighted that the marginal value of water for different reservoir levels, periods and zones enables an optimal dispatch of hydropower by exploiting the long-term storage characteristics of reservoirs. To determine the water storage value and allow an optimal dispatch in hydrothermal power systems, different stochastic optimisation models have been developed [28], with that developed by Pereira being one of the most used models for this purpose [29]. Stochastic methods can be used where the installed capacity and the energy storage of hydropower plants are known. However, they have high computational requirements when determining the optimal capacity of technologies in a generation expansion planning model [20].

Several models focus on long-term storage value of hydropower and oversimplify short-term storage of CSP. The latter is addressed well by PowerGAMA [11] which extends previous models to consider short-term storage in CSP and flexible load. Therefore, this model has been selected for use in the optimisation framework proposed here, in combination with linear programming (LP).

Various other optimisation and decision-support frameworks have been developed previously focusing on electricity. However, most are aimed at either local or regional levels, or focus on single or a limited number of technologies. For example, Fichera at al. [30] developed a tool combining spatial and energy issues with optimisation for aiding urban planners in developing energy strategies. The authors showed how local production of electricity can be determined due to the introduction of renewable energy. Saber et al. [31] focused on wind energy only, proposing a multi-objective framework for expansion of energy storage in systems with high wind penetration. Concentrating on biomass only, Vadenbo et al. [32] combined optimisation with consequential life cycle assessment to evaluate future bioenergy scenarios for Switzerland for the year 2035. A scenario-generation approach has also been proposed for integrating wind, solar PV and small hydropower systems [33]. A two-stage stochastic optimisation model is used for this purpose to minimise the probability of failing to deploy reserve in real-time. An example study that went beyond single or few technologies to consider a full electricity system at the national level is that carried out for the UK [34]. The authors developed a multi-period mixed-integer optimisation to determine the most sustainable 2050 electricity scenarios with respect to life cycle costs and environmental impacts. Another study at the national level, based in Germany [35], integrated battery storage into an optimisation model to determine the optimal configuration of the German electricity system for the year 2040.

However, as far as the authors are aware, there are no optimisation frameworks that enable consideration of future integrated electricity scenarios with high penetration of renewables at a national level as proposed in this work. This is detailed in the next section.

3. Methodology

3.1. FuturES framework

As can be seen in Fig. 1, the FuturES framework consists of two models: an LP power system expansion (PSE) model and an economic dispatch (ED) model. The former has been developed in this study (Section 3.1.1) and the latter is based on the open-source PowerGAMA model (Section 3.1.2).

The PSE model generates optimal scenarios for future electricity systems by minimising total system costs. The main variable in this model is the new-build capacity for each technology, which is decided by the model based on each technology's levelised cost of electricity (LCOE) and power output. These two are in turn dependent on capacity factors. Previous studies have assumed constant capacity factors [34,36]. However, this assumption holds only if the electricity mix remains similar over time – if new technologies are included, it is likely that the capacity factors will change. To overcome this problem, a second model based on minimisation of marginal costs through economic dispatch (ED) is coupled with the PSE model. The ED model integrates the outputs from PSE (the total capacity of each technology) with technical parameters, such as variable or marginal costs of technologies, wind profiles, solar radiation and water inflow. It uses these parameters to determine the capacity factor of each technology, hourly marginal costs, filling levels of storage systems, energy spillage (solar, wind and run-of-river energy harvested but not dispatched) and load shedding.

The load shedding and capacity factors are considered indicators of flexibility. When there is no load shedding and the resulting capacity factors from the ED model are equal to the capacity factors assumed in the PSE model, then the scenario is considered to be feasible. If the capacity factors are different, the LCOE initially estimated in the PSE model will be inconsistent with their expected operation. This leads to an under– or overestimation of the costs of some technologies. Therefore, the capacity factors of the PSE model are replaced by the capacity factors obtained from the ED model and a new iteration begins, as shown in Fig. 1. The starting year (t_0) of the PSE model maintains the actual capacity factors of the technologies in that year. The resulting capacity factors of the optimal ED model are set as the capacity factors for the last year (t_{end}) of the evaluating period and the capacity factors between years t_0 and t_{end} are estimated through linear interpolation. Consequently, the combined PSE and ED models continue to iterate until the model converges. In other words, the two models run until the capacity factors of PSE and ED by year t_{end} are similar and reach the condition of feasibility of no load shedding.

The PSE model has been developed using Pyomo, an open-source tool for optimisation applications [37] with a COIN-OR Branch-and-Cut (CBC) mixed integer linear solver, which also contains a linear programming solver [38]. PowerGAMA [11], used for the ED model, was developed using the Python programming language. Each model is described in turn in the next sections.

3.1.1. Power system expansion model

A linear programming problem can generally be formulated as:

$$\begin{aligned} &\textit{minimise } f(x) \\ &s.\ t. \quad h(x) = a \\ &\qquad\ \ g(x) \le 0 \\ &\qquad\ \ x \in \mathbb{R}^n \end{aligned} \quad (1)$$

where $f(x)$ is an objective function, $h(x)$ represents equality and $g(x)$ inequality constraints, and x is a vector with n real variables. The objective function and constraints are defined in the following sections.

3.1.1.1. Objective function. The objective function Z represents the total system costs over the life cycle of each power technology over the planning period and is to be minimised as follows:

$$\boldsymbol{Z = min \sum_{g\in G} \cdot \sum_{t\in T} E_{g,t} \cdot LCOE_{g,t}} \quad (2)$$

where $E_{g,t}$ is electricity generated by technology g in year t, while $LCOE_{g,t}$ is the levelised cost of electricity for technology g in year t. $E_{g,t}$ is a function of two types of variables, $Var_{g,t}^{new}$ and $Var_{g,t}^{phaseout}$, that represent respectively the new-build capacity online in a given year and the existing capacity awaiting phase-out. For simplicity, these are included as part of the total installed capacity ($P_{g,t}^{total}$) function as shown below:

$$E_{g,t} = 8760 \cdot CF_{g,t} \cdot P_{g,t}^{total} \quad (3)$$

where $CF_{g,t}$ is the capacity factor of a technology in year t and 8760 is the total number of hours in a year. The total installed capacity of technology g in year t, $P_{g,t}^{total}$, is defined as:

$$P_{g,t}^{total} = \begin{cases} P_{g,init}^{total} + B_{g,t}^{plan} + Var_{g,t}^{new} - D_{g,t}^{total} - Var_{g,t}^{phaseout}, & \text{if } t-1 < t_0 \\ P_{g,t-1}^{total} + B_{g,t}^{plan} + Var_{g,t}^{new} - D_{g,t}^{total} - Var_{g,t}^{phaseout}, & \text{if } t-1 \ge t_0 \end{cases} \quad (4)$$

As can be seen in Eq. (4), $P_{g,t}^{total}$ is made up of the following:

- initial existing capacity ($P_{g,init}^{total}$) or the capacity in the previous year ($P_{g,t-1}^{total}$);
- a new-build capacity ($B_{g,t}^{plan}$) under construction;
- a new-build capacity ($Var_{g,t}^{new}$) determined by the model (main decision variable); and
- total decommissioned ($D_{g,t}^{total}$) and phase-out capacities ($Var_{g,t}^{phaseout}$).

$Var_{g,t}^{phaseout}$ is a decision variable considered for technologies like coal that will eventually be phased out. The decision variables are all in the domain of positive real numbers.

The total decommissioned capacity ($D_{g,t}^{total}$) constitutes old plants that are planned to be decommissioned ($D_{g,t}^{plan}$) and new-build capacity that has reached the end of its lifespan within the modelling period ($Var_{g,t-\tau_g}^{new}$), where τ_g represents the lifespan of technology g:

$$D_{g,t}^{total} = D_{g,t}^{plan} + Var_{g,t-\tau_g}^{new} \quad (5)$$

$LCOE_{g,t}$ is defined as the sum of levelised and annualised investment costs ($f_{g,t}^{inv}$), fixed and variable operating and maintenance costs (O&M) ($f_{g,t}^{OM}$ and $v_{g,t}^{OM}$, respectively), fuel costs ($v_{g,t}^{fuel}$) and carbon tax ($v_{g,t}^{carbon}$):

$$LCOE_{g,t} = f_{g,t}^{inv} + f_{g,t}^{OM} + v_{g,t}^{OM} + v_{g,t}^{fuel} + v_{g,t}^{carbon} \quad (6)$$

The levelised and annualised investment cost is defined as follows:

$$f_{g,t}^{inv} = \frac{I_{g,t0}^{capital}}{8.76 \cdot CF_{g,t}} \cdot \frac{r_g}{1+(1+r_g)^{-\tau_g}} \cdot \left(1 + \lambda_g^{learning}\left(\left(\frac{W_{g,t}}{W_{g,t0}}\right)^{log_2(1-b_g)} - 1\right)\right) \quad (7)$$

The investment cost of a technology in a particular year is estimated taking into account its initial capital cost ($I_{g,t0}^{capital}$) which is annualised considering a discount rate (r_g) and technology lifespan (τ_g). The capacity factor ($CF_{g,t}$) and 8.76 convert the annual investment cost to levelised cost of electricity from $/kW-yr to $/MWh. The cost must also be adjusted through time based on a learning rate (b_g) for that particular technology. The learning rate $\lambda_g^{learning}$ is a binary parameter, denoting if a technology has a learning rate (1) or not (0). The application of the learning rate is based on the global cumulative installed capacity of the technology at the initial modelling time ($W_{g,t0}$) and the global installed capacity of the technology in year t ($W_{g,t}$).

O&M fixed costs are defined as follows:

$$f_{g,t}^{OM} = \frac{I_{g,t0}^{capital} \cdot S_g}{8.76 \cdot CF_{g,t}} \cdot \left(1 + \lambda_g^{learning}\left(\left(\frac{W_{g,t}}{W_{g,t0}}\right)^{log_2(1-b_g)} - 1\right)\right) \quad (8)$$

where S_g is a fraction of investment costs used to estimate O&M fixed costs. Fuel costs are equal to:

$$v_{g,t}^{fuel} = \frac{3600 \cdot C_{g,t}^{fuel}}{cv_g \cdot eff_g} \quad (9)$$

where 3600 is a factor to convert MJ to MWh; $C_{g,t}^{fuel}$ is the cost of fuel per unit of mass or volume, cv_g is the calorific value of the fuel for technology g in MJ per unit of mass or volume; and eff_g is the fuel efficiency of the technology. $C_{g,t}^{fuel}$ and cv_g are parameters expressed in different units depending on the type of fuel; for example, for coal, natural gas and diesel, the units are tonnes, Nm^3, and billion barrels (bbl), respectively.

Carbon costs are estimated taking into account carbon tax per tonne of CO_2 emitted (${CO_2}_t^{tax}$), the carbon emission factor (${CO_2}_g^{emi}$), the power plant efficiency and a factor 3.6 to convert MJ to kWh, as shown below:

$$v_{g,t}^{carbon} = \frac{3.6 \cdot {CO_2}_t^{tax} \cdot {CO_2}_g^{emi}}{eff_g} \quad (10)$$

3.1.1.2. Energy balance. The power demand is estimated at the consumer side (E_t^{demand}); therefore, the energy loss in the grid (S_t^{loss}) is included in the estimates of the total energy demand at the supply side ($E_t^{demand}(1 + S_t^{loss})$). Total energy demand must be equal to or lower than the electricity supply, as follows:

$$\sum_{g\in G} E_{g,t} \ge E_t^{demand}(1 + S_t^{loss}) \ \forall\ t \in T \quad (11)$$

3.1.1.3. Non-negative total capacity. For each technology, the total capacity in each year must be non-negative. This constraint is essential; otherwise, if more economical technologies are available, the model can set a phase-out capacity exceeding the sum of the other capacity variables in Eq. (4), creating an illogical condition. This constraint is defined as follows:

$$P_{g,t}^{total} \ge 0 \quad \forall\ g \in G, \forall\ t \in T \quad (12)$$

3.1.1.4. New-build capacity. In each year the total electricity demand must be satisfied by the supply. When the current installed capacity cannot fulfil the demand, the model evaluates the available technologies to decide the new-build capacity. $\phi_g^{phaseout}$ is a binary parameter that indicates if a technology is going to be phased-out and, if so, that particular technology cannot be eligible for new-build capacity. For the rest of the technologies, the new-build capacity must be equal to or lower than the sum of maximum annual new-build capacity (N_g^{max}), total decommissioning capacity and a phase-out quota capacity ($PO_{g,t}^{quota}$), as follows:

$$Var_{g,t}^{new} \leq \begin{cases} N_g^{max} + D_{g,t}^{total} + PO_{g,t}^{quota}, & \text{if } \phi_g^{phaseout} = 0\ \forall\ g \in G, \forall\ t \in T \\ 0, & \text{if } \phi_g^{phaseout} = 1\ \forall\ g \in G, \forall\ t \in T \end{cases} \tag{13}$$

The phase-out quota capacity $PO_{g,t}^{quota}$ represents the capacity of technology g with a share (q) of the total phase-out electricity in a particular year. The share q ensures that the PSE model does not select only the most economical options to replace the phased-out power plants. In other words, q ensures that more than one power option is invested in, thereby guaranteeing some supply diversity. The phase-out quota is defined by the following equation:

$$PO_{g,t}^{quota} = \frac{q \cdot \sum_{g \in G} Var_{g,t}^{phaseout} \cdot CF_{g,t}}{CF_{g,t}} \tag{14}$$

3.1.1.5. Phase-out of plants. Whether a technology has been selected to be phased-out is denoted by a binary parameter $\phi_g^{phaseout}$ (=1). If not, the phase-out capacity decision variable ($Var_{g,t}^{phaseout}$) must be equal to zero. Technologies that are to be phased out are assigned a phase-out starting year ($t_g^{phaseout_{start}}$). Before that year, the phase-out capacity decision variable must be zero, otherwise the capacity must be equal to or lower than a maximum annual phase-out capacity (PO_g^{max}) for a particular technology, as follows:

$$Var_{g,t}^{phaseout} \leq \begin{cases} 0, & \text{if } \phi_g^{phaseout} = 0 \quad \forall\ g \in G, \forall\ t \in T \\ 0, & \text{if } \phi_g^{phaseout} = 1 \text{ and } t \leq t_g^{phaseout_{start}} \quad \forall\ g \in G \\ PO_g^{max}, & \text{if } \phi_g^{phaseout} = 1 \text{ and } t > t_g^{phaseout_{start}} \quad \forall\ g \in G \end{cases} \tag{15}$$

3.1.1.6. Hydropower capacity retention. A binary parameter κ_g^{hydro} indicates whether a technology is a hydropower option. This is necessary to account for the unique system benefits of hydropower options, such as flexibility, reliability, security and in-built storage capacity. Due to these benefits, it is assumed that system operators with existing hydropower capacity would not wish to lose that capacity. Therefore, the new-build capacity of hydropower must be equal to or higher than the total decommissioning capacity, so that the total hydropower capacity remains constant or increases:

$$Var_{g,t}^{new} \geq D_{g,t}^{total}, \quad \text{if } \kappa_g^{hydro} = 1 \quad \forall\ g \in G, \forall\ t \in T \tag{16}$$

3.1.1.7. Non-conventional renewable electricity. Many countries have implemented policy frameworks to enable corporate sourcing of renewables, such as quota support schemes and green certificates [39,40]. Examples of such countries in Europe include the Netherlands, Norway, Sweden and the UK and in South America, Argentina, Brazil, Chile and Mexico. Australia, China, India and the US also have such policy frameworks in place. To reflect this in the model, non-conventional renewable electricity (NCRE) is defined to include all renewable options except large hydropower plants. A minimum quota ($Q_t^{NCRE_{min}}$) for the electricity supplied by NCRE options is set to increase with time. A binary parameter (γ_g^{NCRE}) has been established so that the model can identify the NCRE options as follows:

$$\sum_{g \in G} \gamma_g^{NCRE} \cdot E_{g,t} \geq Q_t^{NCRE_{min}} \sum_{g \in G} E_{g,t} \quad \forall\ t \in T \tag{17}$$

The minimum quota ($Q_t^{NCRE_{min}}$) increases through time linearly; therefore, $S^{NCRE_{min}}$ represents the quota share at a target year ($t^{NCRE_{min}}$), usually set in energy policies, while $S_{t0}^{NCRE_{min}}$ is the quota at the starting year. After the target year, the quota remains constant as defined below:

$$Q_t^{NCRE_{min}} = \begin{cases} \frac{S^{NCRE_{min}} - S_{t0}^{NCRE_{min}}}{t^{NCRE_{min}}} \cdot t + S_{t0}^{NCRE_{min}}, & \text{if } t_0 \leq t \leq t^{NCRE_{min}} \\ S^{NCRE_{min}}, & \text{if } t^{NCRE_{min}} < t \leq t_{end} \end{cases} \tag{18}$$

3.1.1.8. Maximum energy share of a technology in the production mix. A constraint is defined to allow specific technologies to be set a quota ($Q_{g,t}^{techmax}$) of electricity that ensures an electricity production equal to or lower than the quota ($S_g^{techmaxEnd}$) in the last year of the planning horizon. The constraint starts in a predefined year ($t_g^{techmaxInit}$) where the existing quota ($Q_{g,t}^{techmax}$) of the technology is set at 100%, after which point the quota decreases linearly through the years until reaching the target quota ($S_g^{techmaxEnd}$). The technologies achieving their maximum possible quota in any given year can be identified by the model due to a binary parameter ($\omega_g^{techmax}$) equal to 1. The constraints are defined as follows:

$$E_{g,t} \geq Q_{g,t}^{techmax} \sum_{g \in G} E_{g,t}, \text{ if } \omega_g^{techmax} = 1 \quad \forall\ g \in G, \forall\ t \in T \tag{19}$$

$$Q_{g,t}^{techmax} = \frac{1 - S_g^{techmaxEnd}}{t_g^{techmaxInit} - t_{end}} \cdot (t - t_{end}) + S_g^{techmaxEnd}, \text{ if } t \geq t_g^{techmaxInit} \tag{20}$$

3.1.2. Economic dispatch model

The PowerGAMA model has been implemented within FuturES to run economic dispatch for scenarios from the PSE model, focusing on the implementation of storage strategies to enable high penetration of renewables.

Storage values have been estimated as follows:

$$v_{i,h} = v_{i,0} \cdot \hat{v}_{\cdot i,f} \cdot \hat{v}_{\cdot i,h} \quad \forall\ i \in G_S, \forall\ h \in [0. .8760], \forall\ f \in [0\%. .100\%] \tag{21}$$

where $v_{i,h}$ is the storage value of a technology with storage capacity i at hour h. It depends on a base storage value $v_{i,0}$, relative storage value related to the filling level of the storage $\hat{v}_{\cdot i,f}$, and a relative storage value which relates to time of the year; f is the filling level and varies according to the optimal dispatch. The base storage value is a parameter set by the modeller based on a tuning process [11]. The filling level and time-related storage values are specific to local conditions and are discussed in the next section.

4. FuturES application: Electricity scenarios for Chile

As mentioned earlier, application of the FuturES framework is illustrated through the case of Chile. This section provides motivation for the study, followed by the input data used in the modelling.

Chile accounts for only 0.22% of global GHG emissions [41]. Despite that, the country has been shown to be very vulnerable to the effects of climate change [42]. In an attempt to mitigate these effects, Chile has committed to reducing GHG emissions by ratifying the Paris agreement on climate change [43]. One of the priority sectors identified for reduction of emissions is electricity generation.

More than half of Chilean electricity is supplied by fossil-fuel sources, with the rest being from renewables (Fig. 2). Among the latter, hydropower has the highest share (35%). Over the past few years, Chile has started deploying significant solar PV and wind capacity, with the latter doubling each year since 2014 [44]. This has been possible owing to technology cost reductions, the successful implementation of public policies in the sector and the outstanding resource availability in some areas of the country [40,45,46]. The new energy policy sets two targets for the penetration of renewables in the electricity system: 60% by 2035 and 70% by 2050 [47]. However, a recent study has estimated that renewable sources will have a contribution of about 75% by 2030 [48], suggesting that both targets can be met much sooner than envisaged by the policy. Therefore, the government is considering increasing the 2050 target to 90% or even to 100% [49].

For that reason, the FuturES framework models two main scenarios

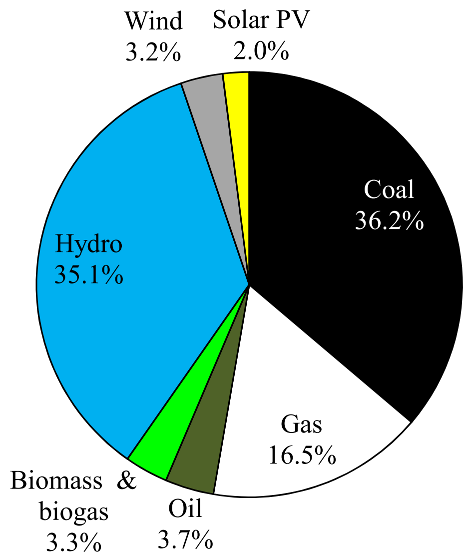

Fig. 2. Contribution of different sources to the total generation of electricity in Chile in 2015 [44].

for the year 2050: Business as usual (BAU) and Renewable energy (RE). The former considers both the fossil and renewable options in the mix while the latter aims to phase out fossil fuels and maximise the contribution of renewables. Each scenario has two sub-scenarios, differing by the total capacity of different technologies deployed. The inventory data and assumptions are presented below, together with a description of how the scenarios have been developed.

4.1. Electricity technologies and resources

Eleven electricity-generating options have been considered as part of this work. These have been selected by considering the current options (in the baseline year 2015), as well as technologies that are not yet part of the national power system but have high potential for future deployment, such as CSP with energy storage and geothermal [50]. The technologies are divided into different categories (Fig. 3), based on whether they are conventional (fossil fuels and hydro), non-conventional (all renewables except hydro) and/or able to store energy. Depending on the type of technology, the constraints described in Sections 3.1.1.5–3.1.1.8 may apply.

4.1.1. Technical and economic parameters for the PSE model

The main technical and economic parameters and assumptions for each technology are presented in Tables 1 and 2. Note that all costs are in US$. An inflation rate has not been included in the analysis and, therefore, all the costs are based on the base year 2015. Considering that Chile has historically maintained inflation to a level that has allowed price stability, this assumption should not affect the results over the planning horizon [51].

The maximum annual new-build capacity (N_g^{max}) has been calculated considering the current technical potential for each technology, along with the historical trend of investment (see Fig. S1 and Table S1 in the Supporting Information (SI)). Based on the historical investment trends, rates of investment can be estimated directly from real-life outcomes in different periods. This is particularly useful because such rates reflect underlying aspects that cannot be quantified easily, such as the difficulty in obtaining environmental permits for new hydropower installations due to their historically low social acceptability.

In Chile, hydropower reservoirs and run-of-river have both had a constant increase in capacity of 171 MW/yr between 1990 and 2017 (Fig. S1). Coal power has had steady investment between 2008 and 2018 of 348 MW/yr. Oil power had a short period of high investment between 2004 and 2010 at a rate of 270 MW/yr, while gas power increased at a rate of 347 MW/yr from 1995 to 2008. Finally, renewable options have had a high increase in investment between 2013 and 2017 at a rate of 869 MW/yr, mostly for solar PV and wind power. Based on these values, conservative assumptions have been made for the maximum annual new-build capacities (N_g^{max}) which are shown in Table 1. However, for solar PV, CSP and wind, which have high future potential (Table S1) but uncertain maximum sustainable growth rates, the maximum annual new-build capacities have been varied between 260 MW and 750 MW, as discussed further in Section 4.2.1.

Regarding other parameters in Table 1, the total initial installed capacity has been estimated based on all operating power plants in 2015. The technology lifespan has been defined for each technology based on literature [52,53]. The capacity factors of the technologies in 2015 have been obtained from records of the system operation in that year and the capacity factor by 2050 is an output value from the simulation (Fig. 1). The year of decommissioning of current power plants has been estimated based on the starting year of operation and the lifespan of each power plant, the latter of which is based on 2015. Similarly, current plants which are under construction have been included in the model [52,53]. Tables S2 and S3 in the SI provide a breakdown of the capacity undergoing decommissioning or construction in each year for which data are available.

The data for investment, fixed and variable costs, as well as the learning rates and global cumulative installed capacity trend (Fig. S2) for wind, solar PV and CSP have been obtained from literature. The following assumptions have been made:

- The Chilean energy authority has set a carbon tax of $5/t CO_2. Based on literature [54,55], this tax is assumed to increase to $10/t CO_2 from 2030 onwards.
- To estimate annualised investment costs, a discount rate of 7% is assumed [56,57].
- Fuel costs have been obtained from US data based on their Free On Board (FOB) price [58]. The Cost, Insurance and Freight (CIF) costs have been estimated to reflect the fuel costs in Chile in any given year (Fig. S3).
- Since biomass prices depend on the local market, the biomass costs have been estimated on the basis of biomass production, processing and transport costs in Chile [59]; these costs are assumed to remain constant throughout the assessment period.
- The potential for biogas power has been estimated based on the

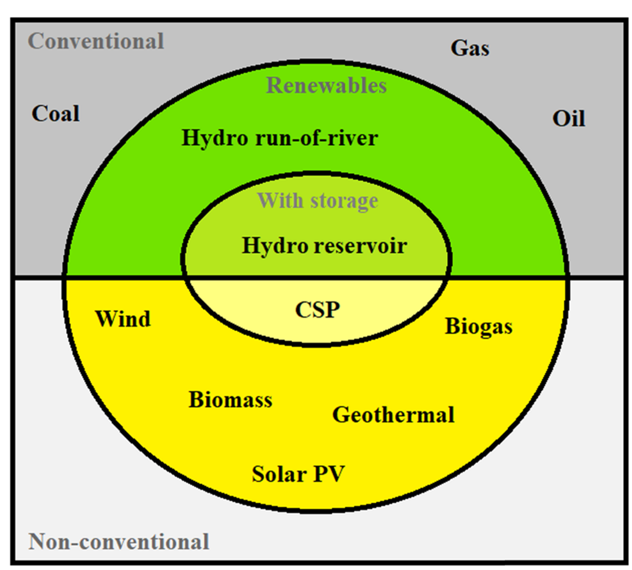

Fig. 3. Classification of technologies considered in the study (CSP: concentrating solar power).

Table 1
Technical parameters considered for the power system expansion (PSE) model [52,53,62–64].

Parameters	Technology									
	Coal	Gas	Oil	Biomass	Biogas	Run-of-river	Reservoir	Wind	Solar PV	CSP	Geothermal
Maximum new-build capacity (MW/yr)	260	260	260	100	25	60	60	260–750	260–750	260–750	150
Initial installed capacity (MW)	4179	3722	3836	408	47	2726	3714	890	509	0	0
Current electricity share[a]	36.2%	16.5%	3.7%	3.0%	0.3%	17.7%	17.4%	3.2%	2.0%	–	–
Lifespan (yr)	38	35	35	40	20	80	80	25	20	25	25
Current capacity factor[a]	0.79	0.41	0.09	0.67	0.62	0.6	0.43	0.28	0.25	0.35	0.6
Maximum capacity factor[b]	0.8	0.8	0.8	0.8	0.8	0.6	0.43	0.32	0.25	0.35	0.8
Efficiency[a]	36%	46%	42%	18%	32%						
Carbon emissions (kg.CO_2/MJ)	98	62	89	–	–						
Calorific value (unit)	29,290 (MJ/t)	1055 (MJ/Nm^3)	6120 (MJ/bbl)	18,100 (MJ/t)	–						

[a] Data for 2015.
[b] The maximum capacity factor (CF) for PV, wind, reservoir and run-of-river reflect the annual capacity factor for each technology in 2015 [63]. The CF for CSP is from literature [64].

biogas production capacity of existing landfill sites (Table S3), yielding a relatively low maximum of 1 GW. Therefore, a low annual new-build capacity has been assumed of 25 MW/yr and zero fuel cost has been considered for this technology since the biogas is produced in landfill from waste. Other sources of biogas are not considered due to a lack of data.

4.1.2. Technical and economic parameters for the ED model

The main assumptions considered for the ED model are shown in Table 3. The relative storage values are presented in Figs. 4 and 5 and the hourly profiles for hydropower, wind and solar power can be found in Figs. S4–S6 in the SI. Merit order is established according to the technologies' marginal costs, which comprise variable and fuel costs as well as carbon tax. As can be seen in Table 3, most renewable options have low or zero marginal costs, due to low variable costs (for the latter, see Table 2).

The selected base storage values for the two technologies with storage (reservoir and CSP) are also given in Table 3, along with the assumed storage capacity and the initial filling levels. To determine the opportunity cost of using a unit of stored energy at the present time (rather than in the future), a shadow price of the storage in reservoirs and CSP can be estimated [60]. However, this is very challenging [61]. Therefore, a simple method for estimation of shadow price has been used based on storage value of reservoir hydropower and CSP, focusing on using the storage as efficiently as possible.

As Chile has large reservoir capacity at low prices, this technology is used as backup for the variable renewable options (wind and solar PV).

Table 3
Input data assumed for the economic dispatch model [52,53].

Technology	Merit order[a] ($/MWh)	Base storage value ($/MWh)	Storage capacity (h)	Initial filling level
Coal[b]	44			
Gas[b]	91			
Oil[b]	175			
Biomass[c]	75			
Biogas[c]	15			
Run-of-river[c]	3			
Reservoir	–	20	1670	35%
Wind[c]	0			
Solar PV[c]	0			
CSP	–	46	17	40%
Geothermal[c]	2			

[a] Marginal costs: Variable costs + fuel costs + CO_2 tax.
[b] Marginal cost estimated from variable costs assumed constant between 2015 and 2050 (see Table 2). Fuel costs in 2050 estimated from fuel cost trends (see Table S3 and Eq. (9)) and carbon tax in 2050 of \$10/t CO_2 (see Table 2 and Eq. (10)).
[c] Marginal costs estimated from variable costs assumed constant over the period 2015–2050 (see Table 2). Biomass fuel costs also assumed constant over the period (see Section 4.1.1).

A base storage value of \$20/MWh has been selected to ensure the readiness of reservoir power plants when other renewables are not available. Furthermore, the dispatch of coal power can be delayed by the dispatch of reservoir hydropower since coal power has a marginal

Table 2
Economic parameters considered for the power system expansion (PSE) model.[a]

Parameters	Technology										
	Coal	Gas	Oil	Biomass	Biogas	Run-of-river	Reservoir	Wind	Solar PV	CSP	Geothermal
Initial capital cost ($/kW)[b]	3000	1150	1150	3100	3500	4050	2200	1800	1800	9000	7800
Capital cost share for fixed costs[b]	2%	1%	1%	3.5%	3.5%	1%	1%	2%	1.5%	1%	1.5%
Variable costs ($/MWh)[b]	2	3	4	10	15	3	3	0	0	0	2
Learning rate[c]	–	–	–	–	–	–	–	10%	15%	11%	
Discount rate	7%	7%	7%	7%	7%	7%	7%	7%	7%	7%	7%
Carbon emission tax 2015–2029 ($/t.$CO_2$)[d]	5	5	5								
Carbon emission tax 2030–2050 ($/t CO_2)	10	10	10								
Fuel costs (unit)[e]	83.2 ($/t)	7.4 ($/$Nm^3$)	43.4 ($/bbl)	58.9 ($/t)							

[a] All data for 2015.
[b] Source: [65].
[c] Source: [66,67].
[d] Source: [54,55].
[e] Data for coal, gas and oil from [58] and for biomass from [59].

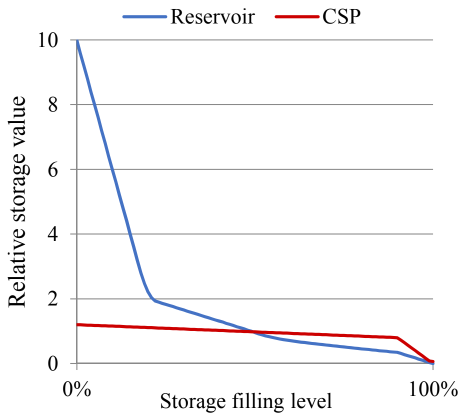

Fig. 4. Relative storage value depending on the storage filling level for hydro and solar CSP (adapted from [11]).

cost of $44/MWh, which is double that of reservoirs. A base storage value of $46/MWh has been assumed for CSP to position its marginal costs above coal's marginal cost and reservoir hydropower's storage value, and also below biomass, gas and oil power marginal costs (Table 3). This is necessary to enable CSP to support peak-load options. Although reservoir and CSP storage values depend on the filling level, the time of the year and/or hour of the day (Eq. (21)), the storage value will vary around the base storage value. Ultimately, the storage value is related to the utility of energy storage to the grid at any given time. For example, CSP can have a storage value of zero between 23:00 and 4:00 and above $70/MWh when its storage filling level is below 60% (Figs. 4 and 5a) [from Eq. (21): 46 × 0.95 × 1.6 = 70]. The lower storage value at night allows CSP to empty the storage, while during the day the storage filling level increases to be available for peak-load times. Similarly, reservoirs increase their storage value in summer when there is lack of precipitation, reaching storage values above $35/MWh when the filling level is below 40% [from Eq. (21): 20 × 1.4 × 1.25 = 35] which eventually can be higher than coal and even CSP.

Different operating modes can be established for CSP with storage; for example, as a base-load or peak-load dispatch mode. As mentioned before, in this study CSP is considered as a peak-load option. This is reflected in Fig. 5a which shows high relative storage values at high solar radiation times of the day and before peak-load hours, after which the relative storage value reduces until reaching zero at night.

The storage values for reservoir hydropower in Fig. 5b are based on the inverse of water inflow records (precipitation) [63]. Therefore, in winter and spring when high precipitation occurs, the relative storage value is low for reservoirs (i.e. stored energy is cheap), leading to hydropower being the first option to be dispatched after wind and solar PV.

4.2. Electricity demand

The annual electricity demand in Chile is expected to increase by 2.2% in the period from 2015 to 2050 [68]. Based on this and a 7% energy loss during transmission [52,53], the average load by 2050 has been estimated at 18,261 MW. Fig. 6 shows the hourly load profile for 2050 which has been developed from historical records of ten years of power dispatch [63] by applying typical hourly load curves to the expected demand in the 2050. Thus, the model assumes that the load profile in Chile does not change significantly over the period of assessment, with the highest loads occurring between 8:00 and 21:00 in the autumn and winter months. The high load during the day is largely due to the mining industry which consumes 54% of electricity and has a constant load during the day [69].

4.2.1. Scenarios – Rationale and constraints

The two future scenarios – BAU and RE – have been defined based on the Chilean energy policy of 2015 which set a minimum target of 70% for the contribution of renewables to the electricity supply in 2050 [47]. BAU has no constraints on the type of technology deployed and, therefore, all 11 options (Table 1) can be chosen by the model. The RE scenario imposes the constraint that 100% of the electricity should be provided by renewable options by 2050. Also, in order to increase the electricity from wind, solar PV and other renewables, the government enacted a quota system with a target of 20% of non-conventional renewable energy electricity by 2025, starting with 10% in 2015 [70]. This constraint has been implemented in all scenarios as shown in Table 4.

The annual new-build capacity limit is a significant parameter that may distinguish the scenarios developed by the model. Since wind and solar PV are becoming more competitive and have high potential, along with CSP, the BAU and RE scenarios are further divided into two subscenarios, based on the cap on the annual new-build capacity for solar PV, CSP and wind power:

(i) one with a low annual new-build capacity limit of 260 MW; and
(ii) another with a high value of 750 MW.

These two values have been obtained after initial testing of different annual new-build capacity values which demonstrated that values below 260 MW and above 750 MW resulted in infeasible scenarios. This is because in the lower range the model does not have enough new-build capacity to meet the future demand. In the higher range, the

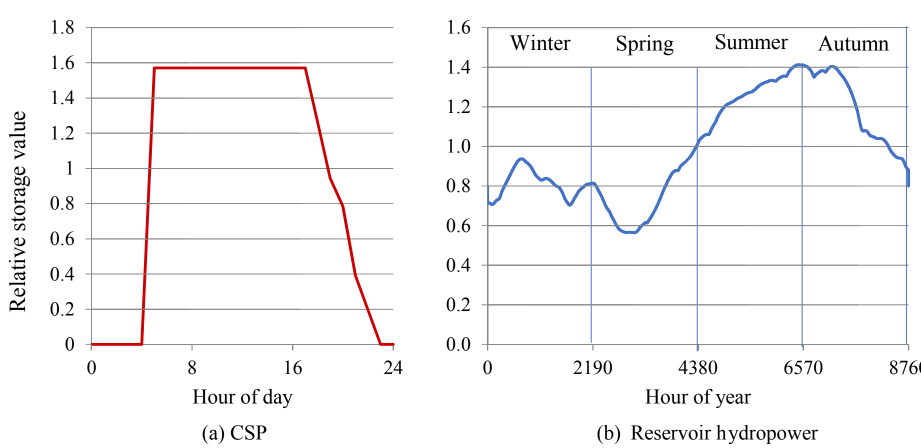

Fig. 5. Relative storage values for concentrating solar power (CSP) and reservoir hydropower depending on time of day (Storage time: CSP: 17 h/yr; Reservoir: 1670 h/yr. Both figures obtained based on criteria in [11]).

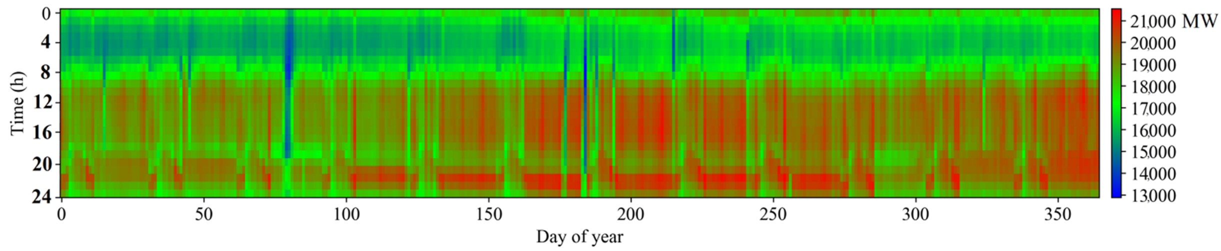

Fig. 6. Load profile (MW) in 2050 estimated based on historical records for an average load of 18,261 MW.

model considers higher investment for solar and wind with large energy spillage and reduced dispatch of the other technologies, which in turn leads the model to look for new-build capacity to meet the demand, until it runs out of new-build capacity after some iterations. Therefore, the four resulting sub-scenarios are referred to as BAU_{260}, BAU_{750}, RE_{260} and RE_{750}. These are summarised in Table 4 with reference to the constraints described in Section 3.1.1.

A sensitivity analysis has also been carried out to evaluate the extent to which the technologies with storage (CSP and reservoir hydropower) help to keep electricity costs low while providing flexibility. Therefore, two additional BAU and RE scenarios have been modelled: (i) without CSP; and (ii) without new-build capacity for hydropower (run-of-river and reservoirs).

5. Results and discussion

The following sections discuss the outputs of the FuturES framework applied to the case of Chile. First, the makeup of the optimised scenarios obtained through the modelling is discussed, followed by their feasibility, economic assessment and a sensitivity analysis. Finally, the limitations of the study and recommended future work are outlined.

5.1. Installed capacity, electricity contribution and capacity factors

A summary of the main results of the optimisation model is presented in Table 5 and Fig. 7. These show the estimated installed capacity, capacity factors and electricity generation of different sources taking into account the annual new-build capacity limits of 260 MW (BAU_{260} and RE_{260}) and 750 MW (BAU_{750} and RE_{750}).

It can be seen in Table 5 for BAU_{260} that biogas, wind and geothermal power have higher capacity factors than in RE_{260}. Furthermore, capacity factors are higher in BAU_{260} than in BAU_{750}. These variations can be explained as follows. Reservoir and run-of-river hydropower, wind, solar PV and CSP depend strongly on the resource availability (weather conditions). Therefore, it is expected that the capacity factors of these options should be derived from their local resource availability (Table 1). In BAU_{260}, the installed capacities of these technologies are maximised according to their expected capacity factors. However, in other scenarios it is possible to produce excess energy from these technologies at certain times, leading to energy spillage and, hence, the capacity factors become lower. This is observable, for instance, for wind power in RE_{260} where the capacity factor is 30% instead of 32% (Table 5) due to some of the harvested wind energy exceeding demand at the time of generation.

In BAU_{750} and RE_{750}, the energy spill is even higher. For example, run-of-river has capacity factors of 47% and 49% in BAU_{750} and RE_{750}, respectively, instead of its potential capacity factor of 60%. In the case of wind, BAU_{750} and RE_{750} have a capacity factor of 25%, 7 percentage points below the maximum capacity factor. For both run-of-river and wind, this energy spillage occurs because in these scenarios the installed capacity of solar PV is larger than the demand around midday, leaving the other power options without demand to fulfil. Reservoir and CSP do not show energy spillage in any scenario, since both options store energy to be dispatched later.

In terms of the contribution of different technologies to the electricity mix, it is notable from Fig. 7 that the only fossil fuel option retained in the BAU scenarios by 2050 is coal power, which decreases from 57% at present to 19% in BAU_{260} and 10% in BAU_{750}. This is due to the fact that, even when fossil fuel options are allowed by the constraints in the model, by 2050 gas and oil power are no longer cost competitive against coal and the renewables.

Over the period of 2015 to 2050, the installed capacity of coal increases from 4179 MW to 9876 MW in BAU_{260} and to 6500 MW in BAU_{750} despite its decreasing share in the mix. This is partly due to the doubling of the electricity demand over the same period, but also due to a significant reduction of the capacity factor from 79% to 36% in BAU_{260} and to 28% in BAU_{750}. This is a consequence of the increase in solar PV and wind power, the fluctuations and variability of which force the other technologies to reduce their capacity factors via increased regularity in the ramping up and down of their output.

Solar PV increases its contribution significantly in all the scenarios, from 2% at present to 20–33% in 2050 due to the large Chilean solar resource and rapidly decreasing costs. In each scenario it is the option with the highest contribution by 2050, followed by wind and run-of-river hydropower. The contribution of reservoir power decreases from 17% at present to approximately 14% in all scenarios as the other renewables become more cost competitive. Nevertheless, its overall installed capacity still increases by 60–67% compared to the present, suggesting that hydropower remains competitive and the capacity retention constraint described in Section 3.1.1.6 may not be necessary to ensure continued use of reservoirs.

Geothermal power has a higher contribution in the RE scenarios (9% in RE_{260} and 14% RE_{750}) in order to fill, in part, the electricity generation gap left by fossil fuels after their phasing out. Finally, biogas

Table 4
2050 scenarios and key constraints.

Constraints		Scenarios			
Description	Section describing constraints	BAU_{260}	BAU_{750}	RE_{260}	RE_{750}
Maximum total new-build capacity (MW/yr) for solar PV, CSP & wind	3.1.1.4	260	750	260	750
Fossil-based power phased out by 2050	3.1.1.5	No	No	Yes	Yes
Hydropower options replaced at end of lifetime	3.1.1.6	Yes	Yes	Yes	Yes
Non-conventional renewable electricity quota in the mix in 2015	3.1.1.7	10%	10%	10%	10%
Non-conventional renewable electricity quota in the mix in 2025	3.1.1.7	20%	20%	20%	20%

Table 5
Installed capacity and capacity factors for the technologies in the proposed 2050 scenarios.[a]

Technologies		2015	BAU_{260}	BAU_{750}	RE_{260}	RE_{750}
Coal	Capacity (MW)	4179	9876	6500	–	–
	Capacity factor (%)	79%	36%	28%		
Gas	Capacity (MW)	3722	–	–	–	–
	Capacity factor (%)	41%				
Oil	Capacity (MW)	3836	–	–	–	–
	Capacity factor (%)	9%				
Biomass	Capacity (MW)	408	–	–	4000	4000
	Capacity factor (%)	67%			3%	4%
Biogas	Capacity (MW)	47	635	618	1073	449
	Capacity factor (%)	62%	70%	55%	66%	57%
Run-of-river	Capacity (MW)	2726	5974	5804	6418	5632
	Capacity factor (%)	60%	60%	47%	60%	49%
Reservoir	Capacity (MW)	3714	5928	5931	6212	6092
	Capacity factor (%)	43%	43%	43%	43%	43%
Wind	Capacity (MW)	890	11,741	12,419	12,413	13,081
	Capacity factor (%)	32%	32%	25%	30%	25%
Solar PV	Capacity (MW)	509	14,611	27,702	15,111	25,807
	Capacity factor (%)	25%	25%	22%	25%	23%
Concentrating solar power	Capacity (MW)	–	–	4831	5524	2073
	Capacity factor (%)			35%	35%	35%
Geothermal	Capacity (MW)	–	1215	–	2642	5000
	Capacity factor (%)		67%		59%	53%
Total	Capacity (MW)	20,031	49,980	63,805	53,394	62,134

[a] BAU: Business as usual; RE: Renewable electricity. The subscripts "260" and "750" refer to the annual cap on the new-build capacity in MW for solar PV, concentrating solar power and wind as described in Section 4.2.1.

has the lowest share in the electricity mix (< 4% in all scenarios) due to its low annual new-build capacity.

Overall, BAU_{260} has the lowest total installed capacity of 49,980 MW (Table 5). This is due to the absence of energy spillage, together with the lowest installed capacity of solar PV and wind. By contrast, BAU_{750} has the largest installed capacity of 63,805 MW caused by the high energy spillage of run-of-river, wind and solar PV power and large installed capacity of solar PV, wind and coal power plants. Because the model chooses coal as an economic option together with solar PV, this enables high new-build capacity of both power options, even though the high capacity of solar PV leads to a low capacity factor for coal (28%). While the RE scenarios have lower energy spillage than BAU_{750}, they have total installed capacity in between BAU_{260} and BAU_{750}.

5.2. Scenario feasibility

The PSE model prioritises technologies with low levelised costs of electricity, while the ED model prioritises technologies with low marginal costs (variable costs, fuel costs and carbon tax). After running the two models iteratively (see Fig. 1), it can be seen in Fig. 8 that technologies with low investment costs and low marginal costs (wind, solar PV, run-of-river and reservoirs) are prioritised, while high marginal cost options (oil, gas and biomass) are avoided. For example, oil and gas power have the lowest investment costs (Table 2), but high marginal costs (Table 3). In addition to this, since the ED model considers these options at peak-load times, their capacity factors are lower (Table 5) leading to high LCOE and, consequently, new-build capacity is discouraged by the PSE model. A worse situation is found in the case of biomass power since it has both higher investment and higher fuel costs (Table 2) as a result of the low calorific value of biomass (18,100 MJ/t) and low efficiency (18%) of the power plants.

The installed capacities of CSP are 4831 MW in BAU_{750}, 5524 MW in RE_{260} and 2073 MW in RE_{750}, (Table 5). These allow CSP to attain the maximum capacity factor due to a high availability of solar radiation, with a LCOE of $139/MWh across the scenarios. When solar radiation is low, as in autumn and winter, CSP seldom has excess energy to store and therefore can barely contribute to grid flexibility for BAU_{750}, RE_{260} and RE_{750}. Hence, in those periods, hydropower reservoirs provide the main contribution at peak-load times, supplemented by biomass (except for BAU_{260} which relies mostly on reservoirs).

Wind and solar PV have the highest contributions to electricity generation in all the scenarios (17–21% in BAU and 20–33% in RE). This is a result of their low capital costs estimated on the basis of their

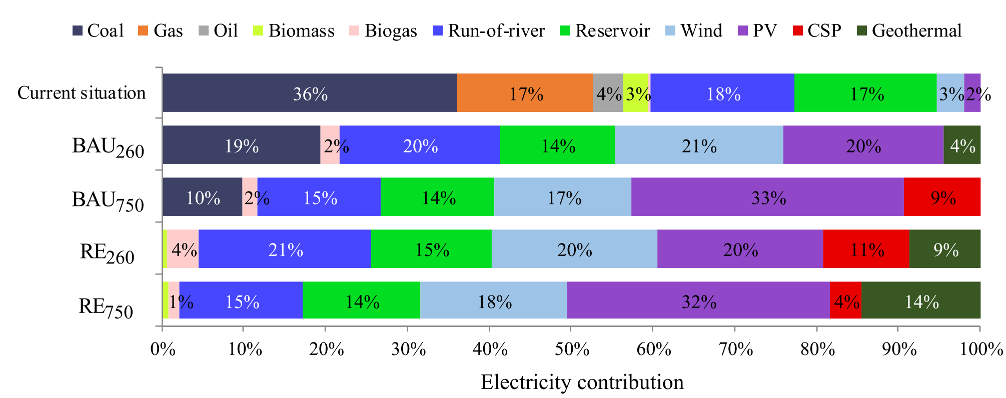

Fig. 7. Contribution of different technologies to electricity generation in the four scenarios [BAU: Business as usual; RE: Renewable electricity. CSP: concentrating solar power. The subscripts "260" and "750" refer to the annual cap on the new-build capacity in MW for solar PV, concentrating solar power and wind.]

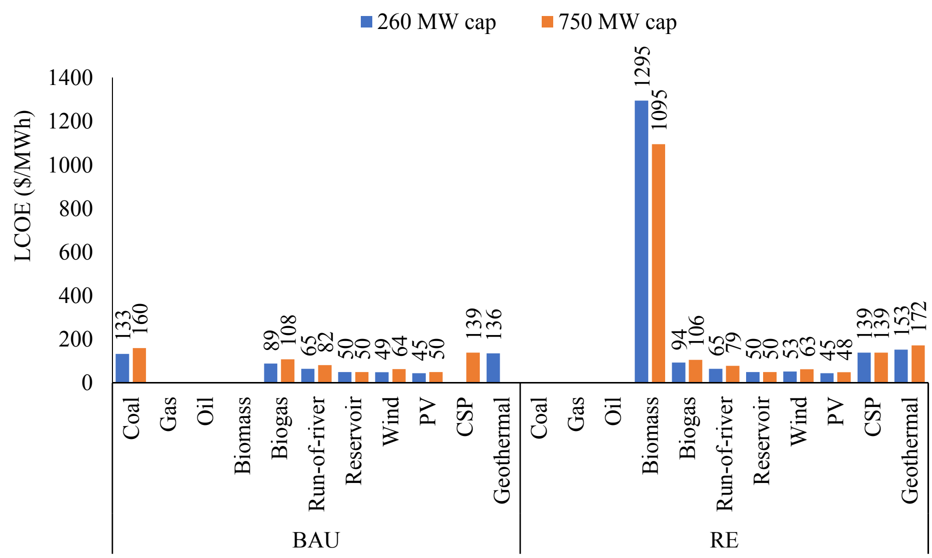

Fig. 8. Levelised cost of electricity (LCOE) in 2050 for different technologies. [BAU: Business as usual; RE; Renewable electricity. The legend refers to the annual cap on the new-build capacity in MW for solar PV, concentrating solar power and wind.]

learning rates, which lead to the 2050 LCOEs of $45–50/MWh for solar PV and $49–63/MWh for wind power. In BAU$_{750}$, wind has its lowest capacity factor of 25%, causing an increase in the LCOE ($64/MWh) due to electricity spillage. Even though higher installed capacities of wind and solar PV lead to the spillage, investments in these two options are prioritised to the detriment of other renewable options due to their very low LCOEs.

As illustrated in Figs. 9 and 10, the higher contribution of hydropower reservoirs in the RE scenarios occurs in autumn when solar radiation is low. Therefore, reservoirs provide seasonal storage and support the fluctuations in solar and wind power, assuming that sufficient water inflow is available. Although hydropower reservoirs have enough storage capacity, their maximum dispatchable load is not usually sufficient to replace the missing solar PV, CSP and wind output during autumn and winter due to the very high installed capacities of those technologies in the RE scenarios. Hence, biomass is dispatched for short periods as the only other flexible non-fossil technology. This low utilisation of the biomass plants leads to very high LCOEs of up to $1295/MWh. Such a high cost would likely not be tolerated by the market without other financing mechanisms in addition to the standard energy market as included in the PSE model. An example would be the inclusion of a capacity market for reserve margin in order to provide a supplementary financing mechanism for technologies that contribute to grid flexibility. Such considerations are outside the scope of this work and could be explored as part of future research.

In summary, it can be seen that all the scenarios are fully feasible in terms of grid stability and electricity supply, including the ones with 100% renewables, demonstrating that it is possible to deploy such systems in the future. The following section discusses the economic feasibility of the scenarios.

5.3. Economic assessment

The optimised LCOEs obtained through the FuturES framework are presented in Fig. 11 for each scenario. As indicated, the two BAU scenarios have the lowest LCOE by 2050 ($72.7/MWh in BAU$_{260}$ and $77.3/MWh in BAU$_{750}$), with up to 6% reduction compared to the current situation ($77.6/MWh). The RE scenarios show LCOEs that are 5–12% ($81.3–86.9/MWh) higher than today's electricity cost and 12–20% higher than in BAU$_{260}$.

Based on the learning rates assumed for solar PV, CSP and wind [66,67], their costs are expected to decrease greatly over the coming decades. Therefore, these options are systematically selected as new-build capacity to meet the demand. As discussed above, biomass power

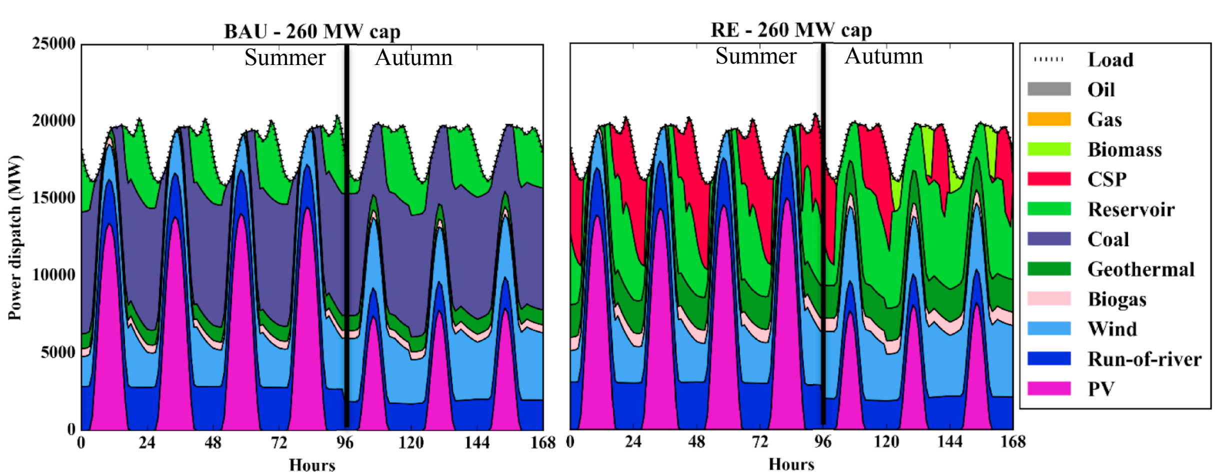

Fig. 9. Load dispatch for a sample of seven days for the BAU and RE scenarios for the annual new-build capacity limit of 260 MW for solar PV, concentrating solar power and wind. [BAU: Business as usual; RE: Renewable electricity. CSP: concentrating solar power.]

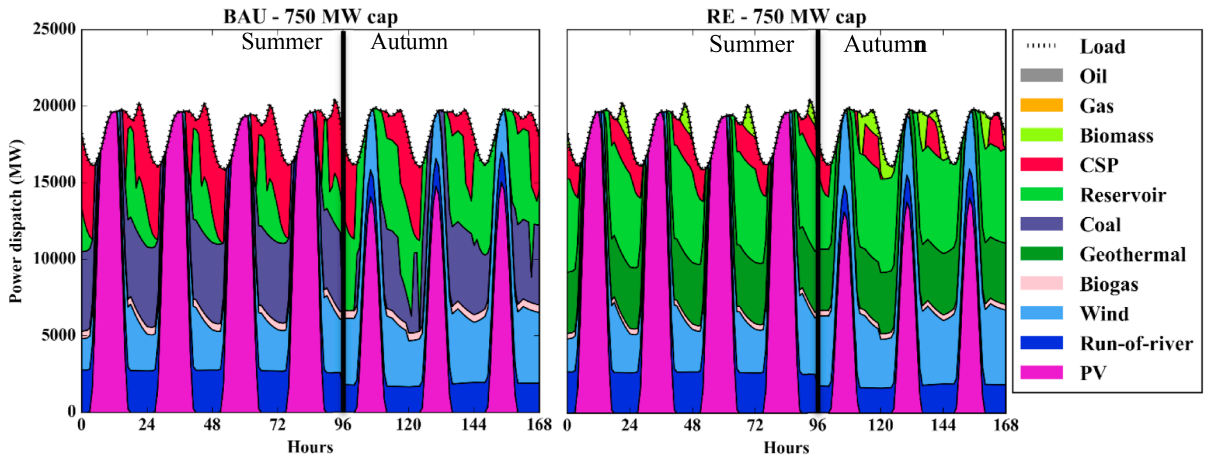

Fig. 10. Load dispatch for a sample of seven days for the BAU and RE scenarios for the annual new-build capacity limit of 750 MW for solar PV, concentrating solar power and wind. [BAU: Business as usual; RE: Renewable electricity. CSP: concentrating solar power.]

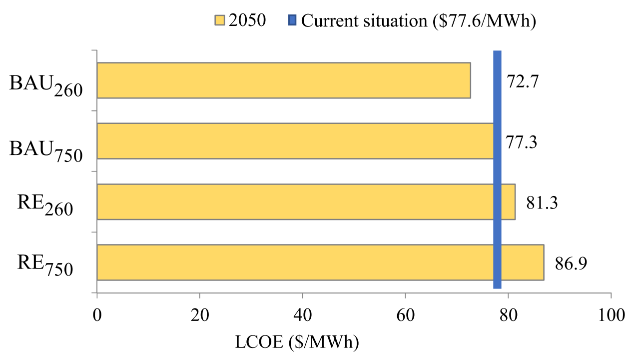

Fig. 11. Estimated levelised cost of electricity in different scenarios compared to the current situation. [BAU: Business as usual; RE; Renewable electricity. The subscripts "260" and "750" refer to the annual cap on the new-build capacity in MW for solar PV, concentrating solar power and wind.]

has been included in both RE scenarios, but the very low capacity factors (3–4%) and therefore high LCOEs have discouraged its investment.

Regarding the total system cost (Fig. 12), the RE scenarios are the most expensive in 2050 with total costs of $356–361 bn, while the BAU scenarios are in the range of $337–338 bn. The higher costs of the RE scenarios are due to higher contributions of biogas and geothermal power as base-load options and the energy spillage from wind and run-of-river. This in turn leads to lower capacity factors (25% for wind and 49% for run-of-river) than their resource availability could support (32% for wind and 60% for run-of-river), as can be observed in Table 5. When RE_{260} is compared with RE_{750}, the higher annual new-build capacity of 750 MW for wind, solar PV and CSP in RE_{750} allows wind and solar PV to have greater installed capacity than in RE_{260}. However, during periods of high resource availability, this high installed capacity causes the generation of wind and solar PV to be greater than the load (demand). Therefore, energy spillage occurs and the capacity factor of other generators, such as run-of-river, is reduced, which leads to RE_{750} having higher overall system costs. These higher costs could potentially be offset if the energy spillage could instead be put to productive use elsewhere in the economy via some form of demand-side management, the consideration of which is beyond the scope of the current study.

Fig. 12 also shows that capital costs contribute the most (67%) to the total system costs in the BAU scenarios, followed by fuel (17%) and fixed costs (13%); carbon tax adds a further 3%. In the RE scenarios, the contribution of the capital costs is even higher (70%) but that of the fuel costs is lower (12%) than in the BAU scenarios; the fixed costs account for 17% of the total.

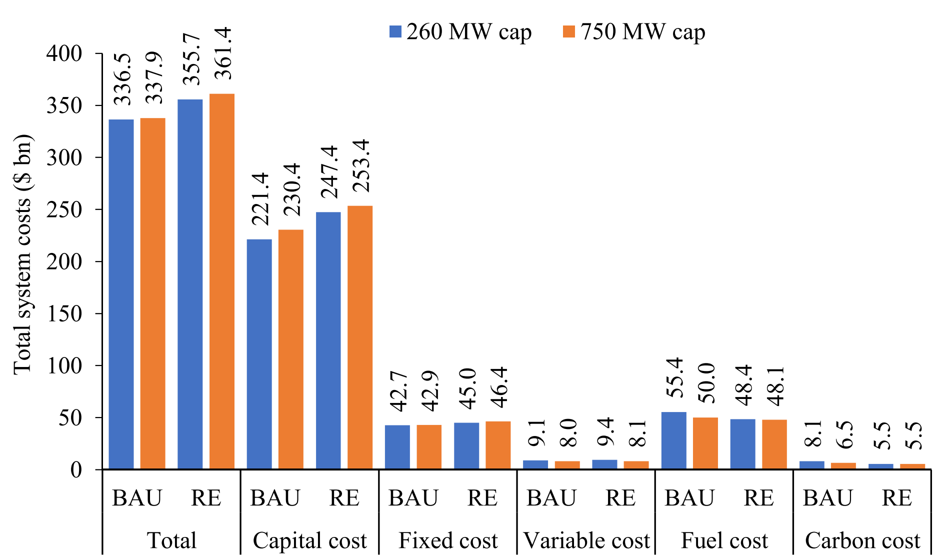

Fig. 12. Total system costs in 2050 and contribution analysis by scenario. [BAU: Business as usual; RE; Renewable electricity. The legend refers to the annual cap on the new-build capacity in MW for solar PV, concentrating solar power and wind.]

In addition to the capital costs, the cumulative investment has also been estimated (Fig. 13). This represents the investment cost of power plants that need to come online in a specific year and is aggregated over the period 2015–2050. This differs from the capital costs which have been estimated considering annualisation of the investment of each technology, taking into account lifespan and discount rate while including both existing and new capacity. As can be seen in Fig. 13, the BAU_{260} and BAU_{750} scenarios have the lowest cumulative investment, estimated at \$123 and \$145 bn, respectively. The latter is close to the investment of \$147 bn needed in RE_{260}, while in RE_{750} the value is slightly higher at \$157 bn.

As illustrated in Fig. 13, the BAU scenarios have lower investment in biogas, biomass and gas power due to their LCOEs being higher than coal, wind, solar PV and run-of-river. However, the RE scenarios exhibit lower investment in biogas due to its low annual new-build capacity and its high LCOE, but also, in coal, gas and oil power due to the fossil fuel power phase-out constraint.

In relation to low and high annual new-build capacity limits (260 or 750 MW), it can be seen that the cumulative investments are larger in scenarios with the higher limit due to the increased investment in solar PV and wind in both the BAU and RE scenarios (Fig. 13). It is also notable that BAU_{750} has lower investment in coal power than BAU_{260} (reducing from \$27 to \$17 bn) due to the model diverting the funding into renewable projects, most of which become cheaper than coal power in future.

Across all scenarios, there is a clear trend of investments led by solar PV (with an average investment over the period of \$31 bn), wind (\$23 bn) and run-of-river (\$20 bn). In the RE scenarios, geothermal power and CSP also have significant contributions (\$34 and \$18 bn, respectively). The average annual investment estimated across all the scenarios is \$4.0 ± 0.4 bn/yr.

5.4. Sensitivity analysis

A sensitivity analysis has been performed to investigate the impacts of storage on the costs by estimating the LCOE of systems without CSP and new hydropower (reservoir and run-of-river) capacity. The results are shown in Fig. 14 which compares the LCOE of the original scenarios with eight new scenarios: $BAU_{260\text{-No CSP}}$, $BAU_{260\text{-No new hydro}}$, $BAU_{750\text{-No CSP}}$, $BAU_{750\text{-No new hydro}}$, $RE_{260\text{-No CSP}}$, $RE_{260\text{-No new hydro}}$, $RE_{750\text{-No CSP}}$ and $RE_{750\text{-No new hydro}}$.

Since in the base case the BAU_{260} scenario does not have CSP, the results show that there are no differences in the LCOE between this and $BAU_{260\text{-No CSP}}$ scenario. The remaining scenarios without CSP have only marginally lower LCOE than their equivalent base-case scenarios (Fig. 14). This outcome appears counterintuitive since the optimisation model should choose the minimum cost option, and thus the four base-case scenarios should be the cheapest within their respective constraints. This outcome can be explained as follows. In the base-case scenario, CSP has zero marginal cost at peak-load times; hence, the model selects this option in preference to geothermal power, leaving the latter with lower capacity factor. As a consequence, geothermal has higher LCOE than CSP in the presence of CSP. However, when geothermal power is not in competition with CSP, it is dispatched more frequently, attaining a high capacity factor and a lower LCOE than CSP.

While the cost impacts of omitting CSP from the mix are minimal, the effect of omitting new-build hydropower is much more pronounced: the BAU scenarios with no new hydropower have 8–13% higher LCOEs than the base-case scenarios, while the RE scenarios with no new hydro are 13–18% more expensive than their base-case equivalents. The seasonal storage capacity of reservoirs, along with their relatively low investment costs per unit capacity, enable both reservoirs and run-of river to play a critical role in helping to keep the electricity costs low while maintaining flexibility in the system.

5.5. Advantages, limitations and recommendations for future research

This study has been developed based on a simplified representation of complex interactions in power systems with as reasonable as possible considerations of the main aspects that drive the power market. The main advantages of the proposed framework include:

- estimation of investment needed for different power technologies and the whole system up to 2050;
- high penetration of renewables while maintaining the system's flexibility and matching supply and demand; and
- the inclusion of storage with concentrating solar power serving as short-term and hydropower reservoir as long-term storage.

Some of the limitations of this work are that:

- no distance and site-specific differences have been considered between the technological options. In that sense, transmission and distribution power constraints are assumed equal for all 11 technologies;
- although hydropower has been represented by two distinct power options (reservoir and run-of-river), in reality, interactions occur among those two options, such as in serial arrangement of plants with the effect of upstream inflows and water infiltration; these relationships have not been taken into account; and

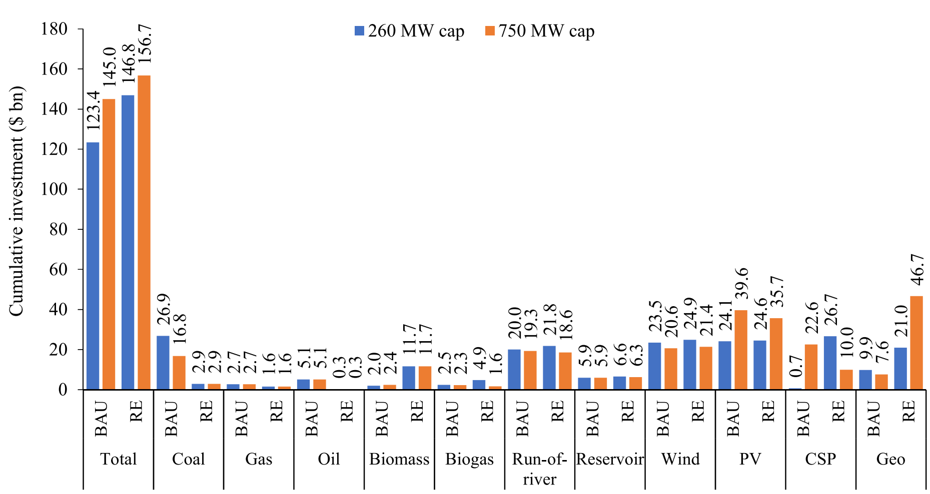

Fig. 13. Total cumulative investment by technology. [BAU: Business as usual; RE; Renewable electricity. The legend refers to the annual cap on the new-build capacity in MW for solar PV, concentrating solar power (CSP) and wind. Geo: geothermal.]

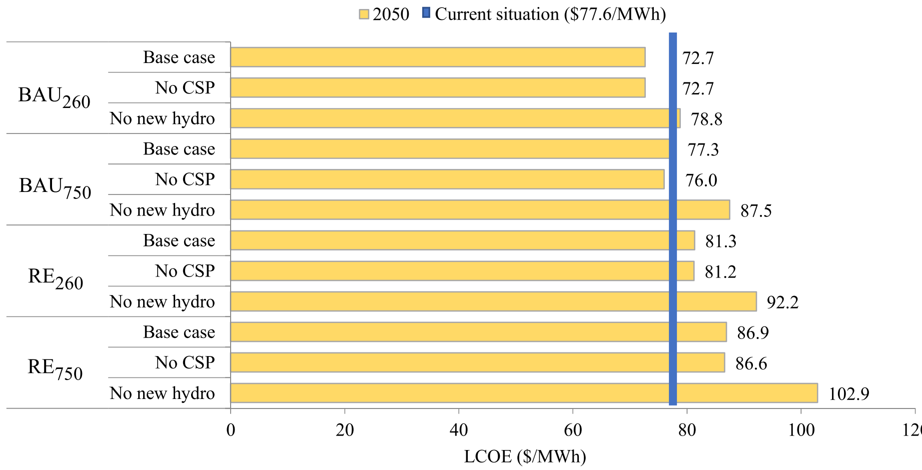

Fig. 14. LCOE of scenarios with sensitivity analysis. [BAU: Business as usual; RE; Renewable electricity. The subscripts "260" and "750" refer to the annual cap on the new-build capacity in MW for solar PV, concentrating solar power (CSP) and wind.]

- inflation has not been considered.

To improve the FuturES framework and its constituent models, future studies in this field should include the following:

- consideration of technological improvements for biomass power to find out if this option can be more competitive as well as its consideration for peak-load dispatch;
- estimation of biogas potential and its production cost, since in this study only landfill gas with zero marginal cost is considered, while the high installed capacity estimated in the RE scenarios would require additional production of biogas;
- evaluation of the effects of including other energy storage systems (e.g. pumped storage and batteries);
- integration of small- and medium-scale distributed energy generation systems into the power system;
- investigation into the effects of climate change on water availability for hydropower generation;
- assessment of alternative uses of energy spillage, such as hydrogen production, water desalination, energy export/import and regional grid integration; and
- estimation of future load profiles taking into account electric vehicles, electrical heating devices and consumer behavioural changes.

6. Conclusions

This paper has presented a new framework for development of cost-optimal electricity systems with high penetration of renewables. The framework enables consideration of different power technologies taking into account their technical and economic characteristics. Some of its key advantages over other frameworks include the ability to consider high penetration of renewables while maintaining the system's flexibility and matching supply with demand as well as the inclusion of short and long-term storage.

The application of the FuturES framework has been illustrated through the development of scenarios for Chile for the year 2050. The results reveal that the cost-optimal Business as usual (BAU) scenarios comprise 81–90% renewables. This is close to the Renewable electricity (RE) scenarios both of which consist of 100% renewables. The RE scenarios show sufficient flexibility in matching demand and supply, despite solar PV and wind power having a combined contribution of around 50%.

Run-of-river hydropower is used as a base-load option in all the scenarios, while coal power provides base-load only in the BAU scenarios. As gas and oil power have high marginal costs, they operate at low capacity factors within the modelled power systems, which leads to higher levelised costs of electricity (LCOE) than for the hydropower options, solar PV and wind. Consequently, no gas or oil capacity is selected by the model in either of the BAU scenarios. Biomass also has high marginal costs and hence very low capacity factors (3–4%). Together with high capital costs, this leads to a LCOE of biomass in excess of $1295/MWh. Thus, this option is only retained in the RE scenarios to substitute for missing solar generation in the winter months.

The BAU scenarios have lower costs than today ($72.7 and $77.3 vs $77.6/MWh), while the RE scenarios are up to 12% more expensive than at present. Compared to BAU, they have 12–20% higher costs. The cumulative investment across the scenarios is between $123 and $157 bn, requiring an annual average investment of $4.0 ± 0.4 bn. Reservoir and run-of-river hydropower are crucial for keeping a low cost of electricity: excluding hydropower increases the costs of the system by 8–18% (up to $102.9/MWh).

If all the costs are considered, the BAU scenarios are the most economical, although this means that the coal power capacity would double. All the scenarios sit within approximately ± 10% of the present system costs.

This paper has demonstrated that the FuturES framework is a powerful tool for providing economic and technical insights into the challenges of achieving cost-efficient power systems with high penetration of renewables. The outputs of the framework can also be used for analysing the environmental and social consequences of the resulting scenarios, helping to identify overall the most sustainable configurations of future electricity systems.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2019.05.006.

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