Renewable energy and energy conservation area policy (REECAP) framework: A novel methodology for bottom-up and top-down principles integration

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A B S T R A C T

Climate change mitigation strategies are multifaceted and require collaboration among a range of stakeholder groups. The objective of this paper was to develop an overarching Renewable Energy and Energy Conservation Area Policy (REECAP) framework. The framework was developed based on a comprehensive literature review, in which seven principles for Renewable Energy and Energy Conservation Policies were identified. The paper also includes a case study to demonstrate an application of the REECAP framework. The novelty of the framework stems from its integration of carbon-energy-cash flows among different decision-making spheres, scales and area specific characteristics. The framework provides a mathematical understanding of how energy strategies can be transformed and optimised in a cost-effective manner by integrating stakeholders under a shared vision.

1. Introduction

Climate change mitigation strategies are promoting a fundamental and rapid transition towards renewable energy economies [1]. In accordance with the 21st United Nations Climate Conference (COP21) in Paris in 2015, zero carbon emission goals by 2060–2080 are required to achieve a global warming ceiling of 1.5 °C increase in the global average temperature in relation to pre-industrial levels. Nonetheless, the speed of such transition will depend upon how effective and far-reaching government interventions are in the energy market [1]. Such interventions will need to focus on the interplay among different stakeholder groups who influence the investment and implementation of renewable energy and energy conservation strategies, as these two strategy groups are identified as the most suitable options to meet climate change mitigation objectives [2].

Renewable energy governance is essential to coordinate governmental policies on carbon reduction targets, the energy sector, and area specific initiatives on renewable energy and energy conservation for residential, commercial, industrial and rural developments. Considering the multiple outcomes required to satisfy the needs of different stakeholder groups, the conceptualisation of directives to instruct the investment and implementation of renewable energy and energy conservation strategies is a complex, yet critical, exercise. This requires consistency among policies, guidelines, technical reports, rebate schemes, and area specific conditions.

As pointed out by Beck and Martinot [3], there are several policies which influence the outcomes of renewable energy strategies and initiatives, including: (i) renewable energy promotion policies; (ii) emission reduction policies; (iii) transport and biofuel policies; (iv) electric power restructuring policies; (v) distributed generation policies; and (vi) rural electrification policies. Renewable energy promotion policies (e.g. rebates) have been implemented by several governments [4]. Nevertheless, the multifaceted nature of renewable energy strategies leads to many uncertainties concerning how achievable carbon reduction targets are.

A discrepancy between intended and achieved outcomes in relation to renewable energy strategies may exist due to the misalignment of governmental policies with market and site conditions [5]. This limitation stems from the lack of comprehensive evaluation methods for heterogeneous conditions [4], as well as the general inexistence of dynamic instruments to analyse the economic feasibility of renewable energy strategies during different implementation stages. For instance,

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policies on energy efficiency retrofit for the residential sector at times disregard cost-effectiveness analyses [6]. Nevertheless, renewable energy adoption requires not only favourable policy instruments and technological innovation [2], but also a dynamic intervention of local actors [7]. Therefore, improvements to the underlying methodology and scientific robustness of datasets and indicators are required to provide useful and timely information for the renewable energy market [8].

Comprehensive instruments to guide renewable energy and energy conservation area policy will be essential to guarantee a sustainable and reliable governance of future clean or low carbon energy strategies. Several studies have focused on dynamic pricing of the energy grid (e.g., peer-to-peer electricity trading [9], location marginal pricing [10], smart grid review [11], energy transition for utilities [12], load forecasting [13], information technology for smart grids [14], integration of distributed generation [15], etc.) and the energy transactions among generators, retailers, consumers and prosumers (e.g., federated power plants [16], virtual currency for smart grids [17], distributed resources and demand integration [18], energy sharing in prosumer communities [19], community based markets [20], electricity aggregators [21], etc.). Nonetheless, there is a lack of instruments to guide the alignment between greenhouse gas (GHG) emission reduction policies and cost-effective capital expenditure in the energy sector including generation, storage and demand management initiatives in centralised, semi-centralised and decentralised grids. Therefore, the development of instruments to understand the viability of area specific renewable energy and energy conservation policies is important to achieve carbon reduction targets in a cost-effective manner for investors and government agencies.

The objective of this paper was to develop an overarching Renewable Energy and Energy Conservation Area Policy (REECAP) framework. The purpose of the framework is to provide guidance into the most cost-effective combination of initiatives in the renewable energy and energy conservation portfolio to achieve carbon reduction targets considering area specific goals and characteristics.

2. Framework development

The REECAP framework is based on seven key principles developed considering a range of elements identified in the literature review described in the supplementary material (S-A). This original concept draws from important aspects outlined in the literature. In addition, it provides a comprehensive understanding of the core elements to transform the energy market, and the interplay among key stakeholders and drivers to develop renewable energy and energy conservation strategies. Therefore, the framework development is focused on the main decision-making spheres among stakeholder groups involved in the renewable energy and energy conservation transition, namely: (i) carbon mitigation policy; (ii) energy regulation; (iii) energy transaction; and (iv) area specific investment. The REECAP framework concept is illustrated in Fig. 1.

By consolidating the key principles into a single innovative framework, the focus of the REECAP framework is to achieve GHG emission reduction targets in the most cost-effective and equitable manner for all stakeholders considering a portfolio of renewable energy and energy efficient initiatives. As a result, this provides an underpinning to transform the energy market, and the interplay among key stakeholders and drivers to develop renewable energy and energy conservation strategies. Therefore, the framework development is focused on the main decision-making spheres among stakeholder groups involved in the renewable energy and energy conservation transition, namely: (i) carbon mitigation policy; (ii) energy regulation; (iii) energy transaction; and (iv) area specific investment. The REECAP framework concept is illustrated in Fig. 1.

Detailed data enables the assessment of energy policy outcomes [23]. Thus, renewable energy and energy conservation policies and strategies and related programs must be underpinned by detailed databases (e.g. actual or modelled big data) on the performance of proposed initiatives in order to determine required funds to achieve set carbon reduction targets or vice versa. For instance, power plant data must become available as open data including generation and efficiency parameters to facilitate transparency and reproducibility of energy models [24].

At a policy level, the proposed framework defines the following key variables: (i) the carbon reduction target and associated timeframe; (ii) the amount of available renewable energy and energy efficiency (conservation) funds; and (iii) the deployment scale of renewable energy initiatives expressed as the total quantum of systems based on the average performance of systems (i.e. “equivalent standard” system). The balance among the aforementioned variables is also a function of the available level of subsidy per system (e.g. renewable energy and energy conservation upfront credits entitlement ($ per system)), which will vary depending on market conditions (e.g. proposed initiatives acceptance, efficiency, cost and affordability).

As a key performance indicator (KPI) of carbon mitigation policies, the amount of funding per GHG reduction unit (e.g. $ per kilogram of carbon dioxide equivalent) is fundamental to benchmark and compare the cost-effectiveness of different strategies. This KPI is applicable to different lifecycle stages of renewable energy strategies, and may be
Fig. 2. REECAP framework carbon, energy and cash flows.
utilised across a portfolio of asset (supply) and non-asset (demand) based initiatives. Price for GHG emissions is a classic and sound approach to address externalities, which underpins incentives for GHG reduction and minimisation of GHG abatement costs [25].

2.2. Energy transaction and regulation

The close interconnection between ‘Energy transaction’ and ‘Energy regulation’ as intermediate stakeholder groups is critical for enabling energy exchange functions. Henceforth, energy supply and demand will undergo a significant transformation with the acceleration of the energy market transition towards renewable energy [2]. As part of this transition, energy transaction is one of the main areas of interest, which will require open market conditions to facilitate diffused and centralised renewable energy trading via a dynamic pricing principle. Such conditions will be achieved only with tailored controlling instruments for energy market regulation.

In the framework, the effectiveness of the electricity grid operation is a function of the compliance level with desired standards of service to customers, and the reduction of lifecycle costs. The energy transmission and distribution functions of electricity grids act as an intermediate connection between the intended outcomes of carbon policies and the actual results of renewable energy and/or energy efficiency measures in residential, commercial and industrial development sites. Thus, the implementation and success of policies are largely influenced by the readiness of these spheres, which are divided into energy sector (institutions responsible for the generation, transmission, distribution and retail of energy) and energy regulator (institutions in charge of guaranteeing the overall economic and environmental sustainability of the energy market by setting rules and controlling measures for stakeholders).

The REECAP framework takes into account the impact of GHG mitigation initiatives on the potential reduction of peak-hour power load and the associated reduction in capital investments for the electricity grid. The key variables of the framework related to energy transaction and regulation are: (i) the carbon intensity of the energy matrix (transaction) and related controlling instruments to meet strategic directives (regulation), e.g. carbon reduction targets; and (ii) the energy tariff (transaction) and related controlling instruments for economic feasibility, equitable pricing and affordability (regulation). Based on the energy matrix carbon intensity, renewable energy or energy efficiency credits are calculated (refer to Section 2.4). Furthermore, peak-hour power credit units are calculated considering the peak-hour power reduction and associated deferral of energy grid augmentation investments (refer to Section 2.4).

Traditionally, network capital investments are equivalent to 45% of costs incurred by energy retailers [26], with a direct impact on electricity prices passed on to consumers. An increase in peak-hour electricity consumption of customers is likely to lead to network augmentation requirements if demand management solutions are not effective [27]. Therefore, peak-hour power demand is a significant driver for network costs, in particular for the distribution network due to its capital intensive nature to provide peak-hour energy supply even when the average consumption pattern of customers is low [27].

The wholesale electricity cost (e.g. electricity generation prices depending on the energy market supply-demand balance) is also a critical variable for electricity costs, which usually contributes to an additional 45% of costs for retailers [26]. Wholesale cost analyses (e.g. dynamic pricing of wholesale electricity costs) will depend significantly upon the regional energy market structure, infrastructure type and availability (e.g. smart-metering deployment coverage), available electricity tariff plans (e.g. prosumer ability to freely trade energy among different producers and consumers connected to the energy grid), etc.

Significant changes in the business model are likely to take place towards mixed (centralised and decentralised) electricity generation and distribution, and decarbonisation of the energy matrix. The energy consumption from the grid may increase significantly with the renewable energy transition and associated increase in the energy market share related to the electrification of the transport and heating sectors [28,29]. Moreover, its operation will be potentially optimised with the use of renewable energy due to a reduction in the peak energy consumption, which in turn leads to likely deferrals or avoidance of capital expenditures associated with peak-hour driven grid upgrades.

2.3. Area specific initiatives

Depending on the implementation quality and scale of area specific initiatives (e.g. small-scale solar and heat pump water heaters, efficient heating and cooling systems or photovoltaic arrays, and large-scale solar and wind farms, hydropower, tidal and geothermal energy, etc.), renewable energy and energy efficiency strategies may succeed or fail. As a result, area policies must be adopted to coordinate investments in renewable energy and energy conservation at different scales underpinned by a shared vision and in alignment with strategic policies at local, state and national levels. The assessment of area specific conditions is fundamental to quantify the efficiency and effectiveness of adopted initiatives. Thus, a feasibility analysis of renewable energy and energy efficient systems must be based on detailed area specific information to enable a thorough options analysis of initiatives. The higher the efficiency of adopted systems is, the higher the financial returns for the government (taxpayers) and private investors (households, entrepreneurs, etc.).

From an area specific investment viewpoint, the framework analyses the most suitable system among different initiatives/technologies to obtain the largest amount of renewable energy or energy efficiency subsidy, which increases with both an increase in the carbon mitigation and peak-hour energy generation reduction achieved by systems. The investment feasibility of different systems depends on several factors, including the system characteristics and operation and financial incentive benefits. The key variables related to the system characteristics are: (i) output capacity, (ii) average efficiency, (iii) lifespan, and (iv) operation time. In regard to the operation of systems, the identified key performance indicators are: (i) lifecycle renewable energy generation or energy savings (kWh/system); and (ii) average power reduction during peak-hours (kVA/system).

The financial incentives and feasibility of proposed systems depend on a combination of factors, including external factors (e.g. energy tariff, renewable energy credit, and peak-hour reduction power credit) and internal factors (e.g. lifecycle renewable energy generation or energy consumption reduction, output energy or energy consumption reduction at peak-hours, capital cost, maintenance cost, and decommissioning cost). The key performance indicator used for the financial assessment of renewable energy and energy efficient systems is the Internal Rate of Return (IRR). The calculation of financial incentives and feasibility of renewable energy and energy efficient systems is described in Section 2.4.

2.4. Equitable carbon approach

The widespread use of renewable energy is indisputably the trend for the energy market, namely the renewable energy transition. This transition will be largely influenced by the effectiveness of associated political, financial and technological instruments, and its success will be measured in financial terms. In this context, governments, generators, retailers, regulators and consumers of energy are key players in the creation of a win-win pathway towards an economic feasible renewable energy market in which exists financial benefits and responsibilities for all stakeholders involved.

Among key financial barriers, the large initial capital cost of initiatives is usually the main impediment for the adoption of renewable energy and energy efficient systems. In an attempt to compensate such economic disadvantage, many renewable energy policy schemes include
tax credits and/or financial incentives [3]. Such measures are usually related to large-scale policies, which typically do not identify area specific conditions. As a result, subsidies may be allocated to systems at sites with limited suitability for renewable energy generation (e.g. rooftop solar systems on sites with large trees), which in turn undermines carbon reduction targets and the financial feasibility of carbon policies.

The REECAP framework is based on an equitable carbon price approach, as financial benefits for all stakeholders are clearly defined and distributed on a common basis (i.e. fund per equivalent carbon reduction unit). In total, two financial instruments underpin the calculation of subsidies within the framework, namely: a unitary carbon price principle and a maximum IRR for initiatives. Thus, the more carbon reduction a system promotes, the more subsidies it will be entitled to. However, if excessive returns occur due to changes in the market condition (e.g. reduction of upfront or operation costs), surplus financial returns must be returned to the renewable energy fund to promote an equitable distribution of funds and further investments in renewable energy and energy conservation measures. This approach can be applied to a range of scales and carbon policy timeframes. Moreover, the renewable energy generation or energy saving potential of initiatives must be based on technical specifications, area specific conditions and user behaviour, rather than generic assumptions. As a result, sites and technologies with higher energy efficiency or renewable energy generation potential will be prioritised, which in turn provides benefits at micro- and macro-economic levels.

As part of the REECAP framework, the integration of bottom-up and top-down drivers for renewable energy and energy conservation deployment is proposed taking into account carbon mitigation policies, energy transaction and regulation, and area specific investment factors as described in Sections 2.1, 2.2 and 2.3, respectively. These factors are integrated into the calculation of financial incentives as outlined in Eqs. (1)–(3).

\[
P_{\text{TCO2}} = \left( S_{\text{Pr}} \times S_{\text{E}} \times S_{\text{Lpr}} \times S_{\text{Oh}} \right) \times \left( T_{\text{CO2}} \times \left[ 1 + T_{\text{Lyr}} \right] \right) \times \frac{P_{\text{CO2}}}{P_{\text{CO2}}} \tag{1a}
\]

\[
C_{\text{RE}} = \left( S_{\text{Pr}} \times S_{\text{E}} \times S_{\text{Lpr}} \times S_{\text{Oh}} \right) \times \left( T_{\text{CO2}} \times \left[ 1 + T_{\text{Lyr}} \right] \right) \times \frac{P_{\text{CO2}}}{P_{\text{CO2}}} \tag{1b}
\]

where: \( P_{\text{TCO2}} \) is the policy carbon reduction target (kgCO2e); \( S_{\text{Pr}} \) is the initiative power output or savings (kW/system); \( S_{\text{E}} \) is the area specific power output or savings efficiency (%); \( S_{\text{Lpr}} \) is the lowest lifespan between the area specific initiative or the carbon policy (years); \( S_{\text{Oh}} \) is the area specific initiative annual operation time (hours/year); \( C_{\text{RE}} \) is the area specific credit related to renewable energy incentives ($/system); \( T_{\text{CO2}} \) is the energy grid carbon intensity (kgCO2e/kWh); \( T_{\text{Lyr}} \) is the energy grid transmission loss (%); \( P_{\text{CO2}} \) is the carbon policy fund ($).

\[
C_{\text{PH}} = C_{\text{RE}} \times \frac{T_{\text{CO2}}}{P_{\text{CO2}}} \tag{2a}
\]

\[
C_{\text{PH}} = \left( S_{\text{Pr}} \times S_{\text{E}} \right) \times T_{\text{CO2}} \tag{2b}
\]

where: \( C_{\text{PH}} \) is the area specific credit related to peak-energy reduction incentives ($/system); \( C_{\text{RE}} \) is the area specific credit related to renewable energy or energy efficiency incentives ($/system); \( T_{\text{CO2}} \) is the energy grid total cost deferral associated with peak-hour power reduction ($); \( P_{\text{CO2}} \) is the policy carbon fund ($); \( S_{\text{Pr}} \) is the initiative power output or savings (kW/system); \( S_{\text{E}} \) is the area specific power output or savings efficiency (%); \( S_{\text{Oh}} \) is the initiative power factor (kW/kVA); \( T_{\text{CO2}} \) is the energy grid unit cost deferral associated with peak-hour power reduction ($/kVA). \( I = C_{\text{RE}} + C_{\text{PH}} \). (3a)

\[
I = S_{\text{Pr}} \times S_{\text{E}} \times \left( S_{\text{Lpr}} \times S_{\text{Oh}} \right) \times \left( \frac{P_{\text{CO2}}}{P_{\text{CO2}}} \right) \times \left( 1 + \frac{T_{\text{CO2}}}{P_{\text{CO2}}} \right) \times \left[ \frac{T_{\text{CO2}}}{S_{\text{PF}}} \right] \tag{3b}
\]

\[
I = S_{\text{Pr}} \times S_{\text{E}} \times \left( \frac{P_{\text{CO2}}}{P_{\text{CO2}}} \right) \times \left( 1 + \frac{T_{\text{CO2}}}{P_{\text{CO2}}} \right) \times \left( \frac{T_{\text{CO2}}}{S_{\text{PF}}} \right) \tag{3c}
\]

where: \( I \) is the area specific total amount of financial incentives ($/system); \( C_{\text{RE}} \) is the area specific credit related to renewable energy or energy efficiency incentives ($/system); \( C_{\text{PH}} \) is the area specific credit related to peak-energy reduction incentives ($/system); \( S_{\text{Pr}} \) is the initiative power output or savings (kW/system); \( S_{\text{E}} \) is the area specific power output or savings efficiency (%); \( S_{\text{Lpr}} \) is the lowest lifespan between the area specific initiative or the carbon policy (years); \( S_{\text{Oh}} \) is the area specific initiative annual operation time (hours/year); \( T_{\text{CO2}} \) is the energy grid carbon intensity (kgCO2e/kWh); \( T_{\text{Lyr}} \) is the energy grid transmission loss (%); \( P_{\text{CO2}} \) is the policy carbon fund ($); \( T_{\text{CO2}} \) is the energy grid total cost deferral associated with peak-hour power reduction ($); \( T_{\text{CO2}} \) is the energy grid unit cost deferral associated with peak-hour power reduction ($/kVA); \( S_{\text{PF}} \) is the initiative power factor (kW/kVA).

The inputs of the REECAP framework can be isolated to determine the balance among area specific, energy grid or policy variables. For example, by isolating the policy carbon reduction target as the dependent variable (Eq. (1a)), the characteristics of area specific initiatives (e.g. performance and efficiency), energy grids (e.g. carbon intensity and transmission losses) and available carbon policy funds can be utilised to calculate the carbon mitigation potential of initiatives. In this case, Eq. (1a) is utilised to calculate the carbon reduction potential of a strategy based on the minimum carbon reduction capacity of initiatives (minimum performance benchmark) and associated renewable energy credits, as well as the energy grid characteristics (carbon intensity and transmission losses) and the total available revenue (carbon policy fund reserve).

By defining the energy grid characteristics and policy variables at a point in time, the area specific renewable energy credit of an initiative can be calculated using Eq. (1b). For instances in which a sensitivity analysis of initiatives is undertaken considering fixed carbon reduction targets and funds, the latter step may be preceded by the carbon reduction target calculation (Eq. (1a)). Moreover, the energy grid characteristics are likely to be dynamic due to a decrease in the carbon intensity and transmission losses with an increase in the penetration of distributed renewable energy initiatives and energy efficiency measures.

Investments in renewable energy are also expected to lead to peak-hour energy reduction in the energy grid, which in turn promote a deferral of capital expenditure related to grid augmentation works. The financial gains arising from the deferral of capital expenditures by energy retailers and other grid operators may be directed to increase subsidies of area specific renewable energy initiatives as per Eq. (2a).

The simplicity of this equation reveals that, from an energy grid perspective, area specific credits related to peak-energy reduction are a direct function of the total capital expenditure deferral and the renewable energy credit. In cases in which the total cost savings estimate associated with the deferral of augmentations of the energy grid is not available, the peak-energy reduction credit may be estimated based on both the performance of renewable energy and energy conservation initiatives (i.e. power output, efficiency and power factor), and an estimated average energy grid unit cost deferral as per calculations using Eq. (2b).

The total amount of financial incentives for area specific renewable energy and energy conservation initiatives is calculated considering both carbon reduction targets (i.e. renewable energy and energy conservation incentives), and improvements in the energy transaction (i.e. energy grid characteristics and area specific conditions). As a result, subsidies may be allocated to systems at sites with limited suitability for renewable energy generation (e.g. rooftop solar systems on sites with large trees), which in turn undermines carbon reduction targets and the financial feasibility of carbon policies.
peak-energy reduction incentives). These variables are integrated using Eq. (3a), which can be expanded into Eqs. (3b) and (3c) for calculations taking into account the capital expenditure deferral gain as a total ($) or as a unit ($/kVA), respectively. As a result, Eqs. (3b) and (3c) provide an integration of top-down (e.g. carbon mitigation targets) and bottom-up (e.g. area specific system characteristics) variables for an equitable decision-making process. This approach is applicable to a range of strategic and tactical objectives related to renewable energy and energy efficient initiatives deployment.

Lifecycle principles are also embedded into the framework. In Eqs. (3a) and (3b), the lowest lifespan between the area specific system and the carbon policy is used to define the lifecycle supply cost or energy savings of area specific initiatives in relation to the carbon policy timeframe. This variable directly influences the total amount of incentives. In addition, the IRR of proposed initiatives based on capital, operation and maintenance, and decommissioning costs, as well as financial credits (subsidies) and gains (cost savings), provides guidance to policymakers, regulators and/or investors on the feasibility of area specific initiatives from high (strategic) and/or detailed (tactical) levels. Landau and Landau [30] explain that data driven decision-making enables policies to be tested and, ultimately, promotes an automated model for decision-making. Thus, data driven decision-making is an important instrument to narrow the gap between expected and achieved outcomes. As a result, the accuracy (statistical confidence) of the REECAP framework increases with the size of databases (records) on the performance of initiatives (e.g. big data use) utilised to calculate the area specific performance of initiatives. However, big data needs to be organised and simplified for use, which can be accomplished using machine-learning techniques (e.g. Artificial Neural Networks (ANN), Bayesian Networks (BN), etc.). Such techniques enable evidence-based analyses of initiatives considering non-specific rules (combination of a myriad of variables) for area specific investments.

3. Framework demonstration

As part of this demonstration, the seven key principles of the REECAP framework are applied to an options analysis addressing water heating systems in a case study of single detached dwellings in Brisbane, Australia. Note all financial analyses in this case study refer to Australian dollar currency (AUDS), which was equal to approximately US$ 0.65 in May 2020. This demonstration encompassed a single example among a range of applications of the REECAP framework.

3.1. Renewable energy and energy efficiency portfolio application

The framework demonstration was focused on water heating systems, which comprises a considerable proportion of energy end-uses in residential buildings. For instance, taking into account the total residential energy demand, water heating accounts for 14%–26% in temperate and cold climates [31,32] and up to 50% in warmer climates (e.g. Australia [33]).

Solar and heat pump water heaters were the selected technologies for the renewable energy and energy efficiency portfolio application due to their widespread use for carbon mitigation of residential water heating systems [34,35]. On the one hand, the distributed implementation of small-scale solar systems installed on rooftops of buildings is considerably important for renewable energy transition strategies in urban areas [36]. The installation of heat pumps has been a long-standing energy efficiency measure in buildings [37,38]. Note energy efficiency measures provide an immediate and permanent decrease in energy consumption and associated carbon emissions [39], and hence are optimal options for demand side energy management strategies [40].

3.2. Decision-making integration

The integration of decision-making is paramount for the success of renewable energy and energy efficiency measures and associated carbon reduction targets. Firstly, a clear understanding of aims and requirements of each stakeholder group must be acquired, followed by a thorough assessment of potential pros and cons from the interplay among their requirements, e.g. carbon policy planning horizon and incentives, rebate calculation method, peak-hour and tariffs, on-site system lifespan and costs, etc. These requirements must be integrated to achieve win-win outcomes among stakeholder groups. The following sections describe the adopted assumptions for each stakeholder group in this case study.

3.2.1. Carbon mitigation policy

In order to achieve carbon reduction targets of 26%–28% below 2005 levels by 2030 [41], the Australian government has set financial incentives for large-scale and small-scale renewable energy initiatives. Such incentives are provided as renewable energy certificates, which are upfront incentives calculated based on the estimated lifecycle energy generation or displacement potential normalised considering a 1 MWh basis. The price of a Small-scale Technology Certificate (STC) price is capped at a maximum of $40/MWh.

The adopted energy policy assumptions for the framework demonstration are summarised as follows:

- **Policy horizon**: Life cycle analysis of 10 years, i.e. from 2020 to 2030 aligned with the Australian renewable energy target; and
- **Carbon incentive**: Amount of available funding per carbon reduction unit (renewable energy credit unit) equal to $40 per MWh in accordance with the maximum STC price.

3.2.2. Energy regulation

As part of the Small-scale Renewable Energy Scheme (SRES), the Renewable Energy Regulator specifies eligible solar and heat pump water heaters with their respective number of STCs per bioclimatic zone across Australia. For cities located within Zone 3 (e.g. Brisbane, Sydney, Adelaide, Perth, etc.), the respective amount of STCs for heat pump water heaters [42] and solar water heater with hot water tank capacity equal or less than 700 L [43] are 27.5 and 32.3 on average, with medians of 27.0 ($1080) and 34.0 ($1360). Fig. 3 illustrates the distribution of systems for different credit ranges.

The determination of STCs without a thorough site-specific analysis may lead to significant overestimation of solar and heat pump performance. In Section 3.3, a detailed analysis of solar and heat pump water heaters performance is provided based on ANN models to demonstrate the use of detailed data analytics utilising practical techniques. In Section 3.6, the STCs calculation is compared considering two analytical methods, namely: (i) fixed performance analysis, and (ii) detailed data analytics. The adopted energy regulation assumptions for the framework demonstration are summarised as follows:

![Fig. 3. Distribution of solar and heat pump water heaters for different small-scale technology certificate ranges.](image-url)
3.2.3. Energy transaction

Among key energy transaction parameters, the peak-hour (4pm–8pm) consumption and energy tariff have a considerable impact on the energy grid operation and upgrade requirements. The Australian Energy Market Commission suggests that an increase of 5 kW at peak-hour is associated with approximately $1000 in additional network costs [27]. This estimate was used to derive an average infrastructure cost reduction unit of $200 per peak-hour power (kVA) assuming a neutral power factor.

The electricity tariff assumption was adopted based on single rate residential tariffs of major energy retailers in Queensland (e.g. Origin, AGL, and Energy Australia). Tariff details were obtained from the Australian Government website ‘Energy Made Easy’ in March 2020 [44] as summarised in Table 1.

The carbon intensity of the Australian electricity grid was reviewed to provide information on carbon mitigation estimates of the assessed systems. Fig. 4 illustrates the average carbon intensity of the Australian electricity grid at a state level between 1990 and 2017 in accordance with the National Greenhouse Accounts Factors 2019 [45].

The carbon intensity of the electricity grid in Queensland decreased from 0.94 to 0.80 kgCO₂-e per kWh between 1990 and 2017 [45]. Between 2006 and 2017, the average carbon intensity of the electricity grid in Queensland (0.84 kgCO₂-e per kWh) trended slightly under the Australian national average (0.87 kgCO₂-e per kWh); nonetheless, in 2017, the Queensland and national averages were the same (0.80 kgCO₂-e per kWh). The adopted energy transaction assumptions for the framework demonstration are summarised as follows:

- Peak-hour: From 4pm to 8pm;
- Peak-hour power cost: The amount of available funding per peak-hour reduction unit (peak-hour power credit unit) was $200 per kVA applicable from 4pm to 8pm;
- Electricity tariff: An average tariff of $0.30 per kWh was adopted (Table 1);
- Electricity carbon intensity: An average carbon intensity of 0.80 kgCO₂-e per kWh was utilised (Fig. 4).

3.2.4. Site-specific implementation

The site-specific implementation assumptions included two key aspects for the financial feasibility of systems, including: the system lifespan, and system operation and maintenance costs.

The lifespan of solar water heaters was reported as 20 years [32,46]. For heat pumps, the literature reports systems operating over 30 years (e.g. McCready [47]) with lifespans for cost benefit analysis ranging from 10 years [32] to 20 years [48]. The most expensive and complex component of heat pumps is the compressor with an expected lifespan of 15–25 years [49]. By adopting a more conservative approach for the cost analysis, the selected lifespan of heat pumps was considered to be 15 years.

The maintenance of heat pumps is recommended every three to five years [49]; hence, an intermediate value was considered for the analysis, i.e. service every four years with an average cost of $200 including minor parts (e.g. sacrificial anode, valves, etc.) and labour (1 h). Major services (e.g. compressor repair) were disregarded from the studied lifespan; however, if such services are required, they are associated with high costs. For solar systems, maintenance was considered to take place on an annual basis due to the need for cleaning dust and debris on solar collectors with a cost of $100 per service ($80 for labour and $20 for minor parts).

The peak-hour energy consumption of systems was converted into apparent power (kVA) based on both the peak-hour period, and their power factor, e.g. 0.8 for heat pumps as described in the literature [50] and 1.0 for solar water heaters with electric heating elements as backup power. The estimated active power (kW) at peak-hours was converted to apparent power (kVA) using Eq. (4).

\[ P_a = \frac{P_R}{PF} \]

where: \( P_a \) is the peak-power as apparent power (kVA); \( P_R \) is the real power (kW); \( PF \) is the power factor (kVA/kVA).

The adopted site-specific implementation assumptions for the framework demonstration are summarised as follows:

- Lifespan: Heat pump and solar systems were considered to operate for 15 and 20 years, respectively;
- Maintenance cost: Heat pump and solar systems maintenance costs were adopted as $200 every four years and $100 per year, respectively; and
- Power factor: Heat pump and solar systems power factors were 0.8 and 1.0, respectively.

3.3. Detailed data analytics

As part of the REECAP framework demonstration, a detailed performance analysis based on site-specific conditions was undertaken using computational models in EnergyPlus 9.2.0 and ANN techniques to estimate the energy consumption of solar, heat pump and electric water heaters in Brisbane, Australia. ANN models were trained and tested considering the specific characteristics of solar, heat pump and electric water heating systems. Trained models were instrumental in undertaking a detailed energy performance analysis of water heating systems in 30 detached dwellings as part of an evidence-based assessment considering

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Electricity tariffs in Brisbane, Australia (March 2020).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy retailer</td>
<td>Tariff name</td>
</tr>
<tr>
<td>Origin</td>
<td>Bill Saver</td>
</tr>
<tr>
<td>AGL</td>
<td>Residential</td>
</tr>
<tr>
<td>AGL</td>
<td>Savers</td>
</tr>
<tr>
<td>Energy Australia</td>
<td>Secure Saver</td>
</tr>
<tr>
<td>Average</td>
<td>–</td>
</tr>
</tbody>
</table>

Source: Australian Government [44].
site-specific characteristics, e.g. dwelling size, roof direction, and shading influence.

3.3.1. Water heaters characteristics

Three water heating technologies were evaluated and compared, including: solar, heat pump, and electric water heaters. Electric systems were used as the baseline scenario for the analysis due to their widespread use associated with low up-front cost, yet high carbon intensity. Solar and heat pump technologies were analysed due to their relevance as initiatives adopted in carbon mitigation policies worldwide to replace electric water heaters. In Table 2, the site-specific characteristics of the water heaters is summarised based on previous studies in Brisbane [51–53].

3.3.2. Artificial neural networks

ANN is an efficient problem-solving technique used for machine learning [54,55] with remarkable information processing capabilities to recognise and learn underlying relations among input and output variables [56,57]. This technique is widely used [58–60] and has extensive application for modelling energy systems [61,62]. For instance, ANN techniques have provided significant improvements in resource and energy forecasting [63–71] and optimisation models [72–74]. It offers large flexibility as an universal nonlinear approximation method [60] – 71 – and optimisation models [72 – 78]; however, they are considerably dependent on input data quality and quantity [56,66,79]. Nonetheless, large volumes of data collected by smart meters within smart grids provide opportunities for the optimisation of ANNs [73].

ANNs were tested in this case study to demonstrate the use of a scalable predictive method with extensive application for a range of detailed analysis. This approach is intrinsically related to two key principles of the REECAP framework, namely ‘strategic scalability’ and ‘detailed analysis of initiatives’. A multi-layer perceptron (MLP) ANN analysis was undertaken to recognise and replicate patterns from computational EnergyPlus (E+) model scenarios of solar, heat pump and electric water heaters under weather conditions for the city of Brisbane, Australia. MLP is among the most used topologies of ANNs [80]. Scenarios were created from the combination of the parameters described in Table 2, with a total sample size of 15,625 electric systems, 78,125 heat pump systems, and 1,584,375 solar systems. For each system type, ANN models were trained and tested with random sub-samples without repetition of 1000 and 333 scenarios, respectively.

By using MLP ANN, the applicability of the modelled information used for training was expanded from the training sample to the population by 15-, 78- and 1584-fold for electric, heat pump and solar water heaters, respectively. This exemplifies the large suitability of ANN models for performance assessment of different technologies. The expansion of renewable energy and energy efficient initiatives in the energy market may create further opportunities for big data collection on the performance of such systems. Such data can be utilised to improve the calibration and respective precision of forecasting models using machine-learning techniques. In this study, modelled and ANN predicted results were significantly correlated as illustrated in Fig. 5.

The correlation between modelled and ANN results for the total energy consumption was stronger than the one for peak energy consumption. Such result is a function of the higher variability of the peak energy consumption in relation to the total energy consumption. The ANN was more precise for electric systems than heat pump and solar systems, as less variables influence the performance of electric systems, resulting in a simpler operation. The distribution of the results from E+ and ANN models are shown in Fig. 6.

Analyses of variance (ANOVA) were undertaken to compare the four training and test sub-samples of each system type. The analyses showed no significant difference for the total and peak energy consumption within groups, i.e. accepted null-hypothesis for the total energy consumption of solar (p > 0.81), heat pump (p > 0.76), and electric (p > 0.96) systems and for the peak energy consumption of solar (p > 0.96), heat pump (p > 0.61), and electric (p > 0.99) systems. The Root Mean Square Error (RMSE), Coefficient of Variation (CV), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) of predicted values of each system type were also calculated. These measures are common performance indicators of energy consumption prediction models [71,75,81] and ANNs [60,80,81]. The calculations of performance measures are described in the following equations (Eqs. (5)–(8)), whereas respective results are summarised in Table 3.

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (E_i - A_i)^2}
\]

\[
CV = \frac{RMSE}{E}
\]

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} |A_i - E_i|
\]

Table 2

<table>
<thead>
<tr>
<th>Parameters ranges of water heating systems.</th>
<th>Systems</th>
<th>Adopted value per energy efficiency class</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solar collector direction</td>
<td>Solar collector tilt angle</td>
<td>Solar collector area</td>
<td>Solar collector efficiency</td>
</tr>
<tr>
<td>Solar</td>
<td>Heat pump</td>
<td>Electric</td>
<td>Lower extreme</td>
</tr>
<tr>
<td>✓</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>✓</td>
<td>–</td>
<td>–</td>
<td>90°</td>
</tr>
<tr>
<td>✓</td>
<td>–</td>
<td>–</td>
<td>13</td>
</tr>
<tr>
<td>✓</td>
<td>–</td>
<td>–</td>
<td>64.0</td>
</tr>
<tr>
<td>✓</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>✓</td>
<td>–</td>
<td>–</td>
<td>630</td>
</tr>
<tr>
<td>✓</td>
<td>–</td>
<td>–</td>
<td>2.4</td>
</tr>
<tr>
<td>✓</td>
<td>–</td>
<td>–</td>
<td>6000</td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>–</td>
<td>80</td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>–</td>
<td>90</td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>–</td>
<td>3.08</td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>–</td>
<td>233</td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>–</td>
<td>50</td>
</tr>
</tbody>
</table>

Note: a - North (N), Northeast (NE), Northwest (NW), East (E), West (W); b - solar collector geometry (i.e. area, tilt and direction) parameters joined into 13 unique combinations; c - solar collector performance (efficiency and dust accumulation) parameters joined into 13 unique combinations.
\begin{align*}
\text{MAPE} &= \frac{1}{N} \sum_{i=1}^{N} \frac{|A_i - E_i|}{|A_i|} \\
(8)
\end{align*}

where: \text{RMSE} is the root mean square error of the sample; \(N\) is the sample size; \(i\) is a record in the sample; \(E_i\) is the estimated value for the ‘i’ record in the sample; \(A_i\) is the actual value for the ‘i’ record in the sample; \(CV\) is the coefficient of variation; \(\bar{E}\) is the mean of actual values in the sample; \(\text{MAE}\) is the mean absolute error; \(\text{MAPE}\) is the mean absolute percentage error.

Acceptable levels of accuracy of models for energy consumption forecasting are usually within a \(CV\) of 20\% (e.g. Kumar et al. [75]). The precision of ANN models for all day energy consumption was within the acceptable accuracy levels. For the peak-hour ANN models, only electric systems were within acceptable levels (i.e. \(CV \leq 13.8\%\)); whereas, the \(CVs\) of both heat pumps and solar ANN models were above 20\%. The level of uncertainty of peak-hour energy consumption forecasts may be reduced by increasing the sample size of solar and heat pump systems; nonetheless, such results were considered acceptable for the analysis taking into account the high accuracy level of ANN models for the total annual energy consumption. The calculated ANN factors are described in detail in the supplementary material (S-B.1).

### 3.3.3. Residential property sample

Detailed energy performance analyses were undertaken for a sample of 30 single detached residential properties located in Brisbane, Australia. A key feature of the method is that site characteristics of properties can be assessed using readily available tools and information. The house sample was selected using aerial photography to identify properties with solar water heaters and their respective characteristics (e.g. solar collector orientation and shading direction). The characteristics of each sampled property are described in Table 4.

The selected properties were characterised using the information available in real estate websites (e.g. number of bedrooms). Moreover, the roof pitch angle of properties was modelled using three dimensional (3D) tools (Fig. 7).

Based on the number of persons and bedrooms in private dwellings published as part of the Census 2016 by the Australian Bureau of Statistics [82], the following dwelling occupancy trend was found for Brisbane (Fig. 8).

In Brisbane, the number of persons per bedroom decreases from 1.4 to 1.0 in properties with 1 and 2 bedrooms, respectively. The occupancy per bedroom reduces even further to approximately 0.8 for 3, 4 and 5 bedrooms properties, and reaches the lowest values for properties with 6 or more bedrooms, i.e. approximately 0.7.

### 3.4. Economic indicators

Investment decisions must be based on economic indicators that can provide a clear comparison for options analysis. Traditional indicators for investment decision include the Net Present Value (NPV) and the Internal Rate of Return (IRR), which are respectively an economic indicator (society’s viewpoint) and a financial indicator (investor’s viewpoint).
viewpoint) of capital investments [83]. IRR is also widely applied as a profitability measure which indicates the discount rate to balance cash inflows and outflows in a NPV analysis [84]. Moreover, IRR has been increasingly used for investment decisions related to renewable energy [85–88], energy efficiency, and carbon mitigation [89]. These two indicators were adopted in the REECAP framework demonstration.

As part of the REECAP framework, the IRR is used not only to indicate the economic feasibility of systems for investors, but also to set maximum return limits to optimise the distribution of subsidies among adopters of renewable energy and energy efficient initiatives. This is necessary as market conditions may change (e.g. economic balance among initiative capital cost, up-front incentives and feed-in tariff for renewable energies); as a result, the return on investment is likely to change. In this demonstration, rebates were limited to a maximum IRR of 20% for the examined water heaters in the studied residential property sample.

The IRR of solar and heat pump systems was calculated considering the initiative upfront cost (i.e. system cost and installation cost), and future cash flows related to maintenance and decommissioning services. As per the report from the Australia Competition and Consumer Commission [90], electricity costs have increased in the period between 2007 and 2017 by 8% per annum versus a Consumer Price Index (CPI) of 2.4%. Between 2018 and 2020, electricity prices have been stable due to an increase in the penetration of renewable energy and the associated increase in competition. On the other hand, with a future decrease in thermal power generation, prices will likely increase due to a reduction in competition [91]. Taking into account the variability in electricity price, an intermediate price trend in the long-term was adopted in the analysis, i.e. 4% per year. The CPI for Brisbane for the last decade (from December 2009 to December 2019) was also considered in the analysis, i.e. 2.1% per year.

3.5. Economic goals

The economic goals of the REECAP framework encompass an equitable carbon price distribution among all stakeholders. As a result, the economic advantages and disadvantages of investments in renewable energy are considered in order to balance financial gains among all stakeholder groups. The equitable price analysis also assists in the selection of profitable investments, as it optimises the choice of systems based on economic indicators (IRR and NPV) and enables the redistribution of incentives considering the overall economic goal.

For carbon mitigation policy stakeholders, the equitable carbon price instrument enables the recovery of renewable energy and energy efficiency funds provided to initiatives with returns in excess to the maximum IRR set in the policy, e.g. an IRR of 20%. Hence, the energy regulator can reallocate recovered funds to new investments in renewable energy and energy efficiency. The financial benefits from the adopted initiatives related to peak-energy reduction are also considered and redistributed from energy transaction stakeholders (e.g. energy retailers) to new investments in renewable energy as directed by the energy regulator. Upfront incentives were calculated for new investments in solar and heat pump water heating systems for each house in the residential property sample described in Section 3.3.3, including: (i) renewable energy and efficiency incentive; and (ii) peak-energy reduction incentive.

3.6. Lifecycle analysis

The lifecycle analysis was underpinned by the economic goals (Section 3.5) and addressed the whole-of-life carbon mitigation potential and cash flows of investments in solar and heat pump water heaters. Electric water heaters were also analysed to provide the baseline for
comparing the economic and carbon reduction advantages associated with solar and heat pump water heaters. A summary of inputs adopted in the analysis is provided in Table 5.

The IRR of solar and heat pump systems was calculated considering the initiative upfront cost (i.e. system cost and installation cost), and future cash flows related to maintenance and decommissioning services. The lifecycle performance of each assessed system is described in the following sections.

### Table 4
Residential property sample characteristics.

<table>
<thead>
<tr>
<th>ID</th>
<th>Suburb</th>
<th>Property characteristics</th>
<th>Solar system characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Price ($’000)$</td>
<td>Land size (m²)</td>
</tr>
<tr>
<td>1</td>
<td>Kangaroo Point</td>
<td>780</td>
<td>556</td>
</tr>
<tr>
<td>2</td>
<td>Herston</td>
<td>1550</td>
<td>420</td>
</tr>
<tr>
<td>3</td>
<td>Auchenflower</td>
<td>1237</td>
<td>809</td>
</tr>
<tr>
<td>4</td>
<td>Spring Hill</td>
<td>985</td>
<td>202</td>
</tr>
<tr>
<td>5</td>
<td>West End</td>
<td>780</td>
<td>304</td>
</tr>
<tr>
<td>6</td>
<td>West End</td>
<td>985</td>
<td>271</td>
</tr>
<tr>
<td>7</td>
<td>Paddington</td>
<td>1962</td>
<td>455</td>
</tr>
<tr>
<td>8</td>
<td>Highgate Hill</td>
<td>780</td>
<td>405</td>
</tr>
<tr>
<td>9</td>
<td>Auchenflower</td>
<td>2550</td>
<td>809</td>
</tr>
<tr>
<td>10</td>
<td>West End</td>
<td>1550</td>
<td>486</td>
</tr>
<tr>
<td>11</td>
<td>Fairfield</td>
<td>780</td>
<td>609</td>
</tr>
<tr>
<td>12</td>
<td>Highgate Hill</td>
<td>1237</td>
<td>541</td>
</tr>
<tr>
<td>13</td>
<td>Milton</td>
<td>780</td>
<td>253</td>
</tr>
<tr>
<td>14</td>
<td>Kangaroo Point</td>
<td>1237</td>
<td>415</td>
</tr>
<tr>
<td>15</td>
<td>New Farm</td>
<td>1550</td>
<td>551</td>
</tr>
<tr>
<td>16</td>
<td>East Brisbane</td>
<td>985</td>
<td>407</td>
</tr>
<tr>
<td>17</td>
<td>Paddington</td>
<td>1237</td>
<td>468</td>
</tr>
<tr>
<td>18</td>
<td>Hamilton</td>
<td>1237</td>
<td>691</td>
</tr>
<tr>
<td>19</td>
<td>East Brisbane</td>
<td>985</td>
<td>405</td>
</tr>
<tr>
<td>20</td>
<td>St Lucia</td>
<td>1550</td>
<td>506</td>
</tr>
<tr>
<td>21</td>
<td>Wooloongabba</td>
<td>780</td>
<td>809</td>
</tr>
<tr>
<td>22</td>
<td>St Lucia</td>
<td>1237</td>
<td>43</td>
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<tr>
<td>23</td>
<td>Auchenflower</td>
<td>1962</td>
<td>647</td>
</tr>
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<td>24</td>
<td>West End</td>
<td>1237</td>
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</tr>
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<td>25</td>
<td>South Brisbane</td>
<td>985</td>
<td>569</td>
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<tr>
<td>26</td>
<td>Bowen Hills</td>
<td>1550</td>
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<tr>
<td>27</td>
<td>Teneriffe</td>
<td>1550</td>
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<td>Highgate Hill</td>
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</tr>
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<td>29</td>
<td>Teneriffe</td>
<td>2550</td>
<td>271</td>
</tr>
<tr>
<td>30</td>
<td>Kangaroo Point</td>
<td>780</td>
<td>405</td>
</tr>
</tbody>
</table>

**Note:**
- Property price valuation reported in thousands (’000).
- North (N), Northeast (NE), Northwest (NW), East (E), West (W).
3.6.1. Baseline case: electric water heaters

A performance analysis was undertaken to select the most optimised electric systems for the houses in the studied sample taking into consideration different hot water tank sizes (i.e. 90, 250, 315, 450 and 630 L). The upfront electric system cost was estimated based on the price of systems available in the market [93] as described in the supplementary material (S-B.2).

Results showed that 250 L tanks are associated with the lowest annual energy consumption estimates for the sampled houses, ranging from 1689 to 2268 kWh per annum depending on the water consumption pattern. The cost of a 250 L electric system was estimated as $989 including Goods and Service Tax (GST).

3.6.2. Energy efficiency: heat pump systems

Among the sampled houses, the total and peak-hour annual energy consumption of heat pump water heaters ranged from 542 to 1219 kWh and from 136 to 343 kWh, respectively. In relation to electric systems, heat pump systems were associated with a decrease in the total electricity consumption from 735 to 1548 kWh per annum. Average electricity savings varied from 44% to 68% with an increase in the COP from 2.4 to 4.8 and a power factor of 0.8.

Energy saving incentives were proportional to the total and the peak-hour electricity reduction of systems, ranging from $332 to $694. Incentives were mainly related to total energy efficiency credits (88–90%), whereas peak-hour energy reduction credits were equal to 10–12%.

Upfront costs included both the price of systems, from $2432 to $3,909, and installation costs, $480 considering two installers for 3 hours at $80 per hour. Lifecycle costs were also considered with maintenance every 4 years at $200 per service and decommissioning costs of $77 [94].

Investments in heat pump water heaters provided estimated returns, IRRs, between 9% and 14% for the studied houses. Systems with COP of 3.8 had the highest returns among the studied sample.

3.6.3. Renewable energy: solar systems

Solar water heaters had the largest number of variables among the studied systems. The performance of this system type varied considerably depending on site-specific conditions. The total annual energy consumption of solar systems ranged between 351 and 1176 kWh, and the annual peak-hour energy consumption varied between 27 and 117 kWh among the studied houses. As a result, solar systems promoted total annual energy savings varying from 903 to 1582 kWh and peak-hour energy savings between 531 and 735 kWh in relation to electric water heaters.

The upfront cost of studied solar systems was $5882 divided into the system cost ($4922) and installation cost ($960), while their total incentives varied between $434 and $733. Incentives related to renewable energy ranged between 81% and 87% of the total incentives; whereas, peak-hour consumption reduction incentives varied from 13% to 19%.

Incentives calculated using site-specific characteristics were generally lower than the estimates based on SRES incentives for Zone 3 (e.g. Brisbane, Sydney, Adelaide, and Perth), where the latter incentives are mostly from 24 STC credits ($960) to 45 credits ($1800) with a median of 35 credits ($1400). This difference is associated with the detailed analysis of incentives based on site-specific conditions using ANN models, which shows variations in solar systems performance due to site characteristics (e.g. shadowing of collectors, etc.). As a result, incentives are reduced with a reduction in the renewable energy generation potential of sites. Moreover, the calculation of incentives in the case study was focused on carbon policy targets within a set timeframe (i.e. 10 years until 2030) rather than on the lifespan of solar systems (i.e. 20 years). This enables the maximisation of funds to achieve carbon reduction targets within carbon policy timeframes by increasing the total renewable energy capacity within the carbon policy planning horizon.

Notwithstanding the absence of financial incentives beyond the planning horizon, systems with a long lifespan promote extended cost savings for investors.

Lifecycle costs and returns of solar systems were considered throughout the system lifespan, i.e. 20 years. Costs were escalated at 2.1% p.a., including both an average service cost of $100 per year related to solar collectors cleaning and the service of other minor parts, and a decommissioning cost of $296 in 2040 (i.e. $180 in 2016).

Financial returns measured in IRR ranged from 1% to 8% depending on site-specific conditions.
3.6.4. Solar versus heat pump systems

A comparison of solar and heat pump systems was undertaken considering site-specific conditions based on the REECAP framework. Table 6 provides a comparison between the main financial and environmental performance indicators of heat pumps and solar water heaters.

Heat pumps had a higher rate of return than solar systems for the sampled houses due to lower capital investments (lower upfront cost) and market conditions (e.g., moderate increase of electricity tariffs). In terms of absolute lifecycle returns, solar systems were more favourable in 16 houses due to their longer lifespan (20 years) in relation to heat pumps (15 years); yet, in 14 houses, heat pumps showed higher lifecycle returns due to their lower upfront costs in relation to solar systems. Thus, heat pump technology may be more suitable in cases where there are budgetary or site-specific limitations for solar systems, whereas solar water heaters may be preferred among households with higher purchasing power living in larger lot sizes (e.g. low-density residential developments) less impacted by shadowing. On average, solar systems at single detached dwellings promoted slightly higher carbon mitigation (1039 kgCO2e per year) than heat pumps (939 kgCO2e per year).

The analysis undertaken using the REECAP framework also showed that the feasibility of systems (i.e., solar and heat pump water heaters) is highly influenced by long-term market trends. For instance, by increasing electricity price escalation rate from 4% (moderate level) to 8% (high level, solar systems showed higher economic returns for 90% of the studied sample due to its lower electricity consumption. The carbon mitigation policy timeframe also has a significant impact on the feasibility of systems. For example, by modifying the timeframe from 10 years (period between 2020 and 2030) to a period aligned with the lifespan of proposed systems (i.e., 15 years for heat pumps and 20 years for solar systems), the overall IRR of systems increases and the financial returns of solar systems outperform the returns of heat pumps 67% of the times. Notwithstanding the economic benefits for households, the misalignment of the carbon policy timeframe and rebate schemes based on the designed lifecycle of systems reduces the economic efficiency of strategies to achieve carbon mitigation targets as described in Section 3.7. Such analysis provide a comprehensive understanding of how bottom-up (e.g., site-specific characteristics) and top-down (e.g., market trends) factors are integrated in the REECAP framework to provide a holistic understanding of carbon, energy and cash flows for an informed decision-making process including a range of stakeholders (e.g., policy makers, regulators, retailers and consumers) of the energy market, as relevant factors ought to be analysed to dynamically forecast the outcome of initiatives under different contexts [95].

3.7. Strategic scalability

Strategic scalability is the last principle of the REECAP framework, in which all the other principles are combined (e.g. ‘detailed data analytics’ and ‘lifecycle analysis’ principles). This principle enables the REECAP framework to focus on carbon targets using a coordinated allocation of incentives. For instance, the standard calculation of incentives based on STCs is focused on the potential reduction in electricity consumption during the total lifecycle of initiatives; whereas, incentives calculated using the REECAP framework focus on tangible outcomes to achieve the carbon policy objective within a set planning horizon. As a result, the standard calculation of incentives in the case study would assign 27 STCs for solar systems, i.e., 27,000 MWh or 21,600 kgCO2e during the lifecycle of the system; nonetheless, such systems can only achieve 1039 kgCO2e per year on average, i.e. 10,390 kgCO2e during the carbon mitigation policy timeframe. This discrepancy of 52% in the carbon mitigation potential of solar systems is due to the allocation of investments beyond the carbon mitigation policy timeframe, which may jeopardise the ability of governments/institutions to achieve carbon reduction targets.

Another important aspect for the ‘strategic scalability’ of carbon mitigation policies is to concentrate investments on areas with the highest returns on carbon reduction per unit of investment. Despite the similarity of average lifecycle carbon reduction estimates between the detail site-specific analysis using ANN modelling (20,780 kgCO2e in 20 years) and STC credits (21,600 kgCO2e), the use of detail modelling in the REECAP framework enabled incentives to be concentrated in areas/sites with higher carbon reduction potential, rather than applying average assumptions for the studied sample. For instance, if carbon mitigation investments are concentrated in the upper quartile range of houses with the highest carbon reduction potential as part of the REECAP framework, this would promote an increase of 7–21% in the carbon reduction of the studied sample in comparison to the generic approach using STC credits. Therefore, the ‘detail analysis’ principle of the REECAP framework can be used to provide ‘strategic scalability’ through the optimum sequencing of renewable energy and energy efficient initiatives among different sites/areas. As a result, strategies can be scaled up to a larger number of sites, increasing their coverage and, thus, resilience against area specific barriers. Moreover, an increased coverage can offer opportunities to collect more information for detailed analytics (e.g. ANN model training), promoting the continuous improvement of the REECAP framework applications for different deployment areas and scales.

4. Conclusion

The paper provides a novel framework for the development of renewable energy and energy conservation area policies (the REECAP framework). Seven key principles underpin the framework, including: renewable energy and energy conservation portfolio application, decision-making integration, detailed data analytics, economic indicators setting, economic goals setting, lifecycle analysis, and strategic scalability.

The novelty of the framework stems from its entire integration of carbon-energy-cash flows among different decision-making spheres, deployment scales, area specific characteristics, and technological initiatives. In the context of the energy market, the REECAP framework provides a clear and transparent mathematical description of carbon-energy-cash flows applicable to develop renewable energy and energy conservation strategies. The core elements of the REECAP framework are aimed at promoting an optimised allocation of financial resources, which is critical for a more structured and predictable transformation of the energy market.

As part of the framework, carbon mitigation policy, energy regulation, energy transaction, and area specific investment parameters are analysed to estimate ideal levels of carbon incentives to achieve both carbon targets in a cost-effective manner and area specific financial feasibility on investments. To achieve these outcomes, the framework defines the carbon-energy-cash flows at different levels (e.g. building, site, local, regional, state and/or national). This approach enables the optimisation and coordination of investments in renewable energy and energy conservation with a shared vision among different stakeholder groups, which promotes more transparency and strategic alignment in the decision-making process taking into account a portfolio of initiatives.

As outlined in the case study addressing residential water heating systems in Brisbane, Australia, detailed analytics (i.e. machine learning ANN) are used as a key principle of the framework to undertake performance analyses of initiatives considering area specific characteristics and user behaviour parameters. This is important to promote more certainty in achieving carbon policy targets within set timeframes, as well as to provide an efficient and equitable allocation of carbon mitigation funds. Thus, strategies can be scaled up to a larger number of initiatives, increasing their coverage and, thus, resilience against area specific barriers. Moreover, an increased coverage can offer opportunities to collect more information on the performance of initiatives for evidence-based training of models, promoting the continuous
Table 6
Lifecycle analysis performance outcomes of solar and heat pump water heaters.

<table>
<thead>
<tr>
<th>Houses</th>
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<th>Heat pump (HP) systems*</th>
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<td>Carbon mitigation (kgCO2e/year)</td>
<td>Upfront incentive ($)</td>
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Note: * Solar system with lifespan of 20 years; * Heat pump systems with COP of 3.8 and lifespan of 15 years.
improvement of data analytics and prediction models.

The demonstration of the REECAP framework showed how a coordinated approach for renewable energy and energy conservation is applied to prioritise initiatives among different options. It enabled the allocation of funds considering a reduction of funds for least favourable initiatives and an increase in funds for more favourable ones. Moreover, incentives could be adjusted based on fund availability ($40/MWh) and market conditions. As a result, the REECAP framework promoted an increase between 7 and 21% in the carbon reduction performance of dwellings in the studied sample. On average, solar systems at single detached dwellings achieved slightly higher carbon mitigation (1039 kgCO2e per year) than heat pumps (939 kgCO2e per year). The peak-hour energy reduction of heat pump and solar water heaters was equivalent to 0.29 and 0.43 kVA per house on average, respectively. Peak-hour credit arrangements provided 11%–14% of total subsidies for the selected initiatives among studied households, and hence contributed to an increase in the financial returns of selected initiatives for investors.

In the framework, the fund distribution for renewable energy and energy conservation in the energy market is aligned with the planning horizon of strategic policies; therefore, the REECAP framework concentrates resources within a defined carbon policy timeframe. Moreover, the strategic scalability analysis of the REECAP framework provides a dynamic calculation of renewable energy and energy conservation subsidies and an organic response to energy market signals. This, in turn, provides a more comprehensive understanding of the implication of specific area policies in relation to the overarching carbon policy goals at a local, regional or national levels for a logical up-scaling and sequencing of initiatives to meet carbon targets within set budgets and time schedules.

To assess the feasibility of area specific policies, key performance indicators related to environmental (e.g. lifecycle carbon mitigation potential), social (e.g. energy supply resilience) and financial (e.g. internal rate of return on investment) drivers are considered. These indicators provide a tailored methodology for options analyses of initiatives to transform the energy market, including: (i) the comparison of different locations considering one type of initiative/technology; (ii) the comparison of different initiatives/technologies for a single location; (iii) the comparison of a portfolio of initiatives/technologies across different locations; (iv) the analysis of different market conditions and the respective impact on initiatives performance and return on investment; (v) the minimum level of carbon mitigation funds to promote adequate levels of subsidy to transform the energy market of different localities; among other assessments. The flexibility of the framework to create fit-for-purpose strategies on an area specific basis also enables a diverse mix of policy instruments.

Future research directions include, but are not limited to: (i) the development of a repository of evidence-based trained machine learning models to predict the energy performance of different combinations of initiatives and area specific conditions to underpin policy strategies on renewable energy and energy conservation; and (ii) the creation of a web portal for the open and free access of the REECAP framework among different stakeholder groups to promote transparency and clarity on the performance of different initiatives.

CRediT authorship contribution statement

Abel S. Vieira: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. Rodney A. Stewart: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Software, Supervision, Validation. Roberto Lamberts: Conceptualization, Methodology, Resources, Supervision, Validation. Cara D. Beal: Conceptualization, Methodology, Project administration, Resources, Supervision, Validation.

Declaration of competing interest

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

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Appendix A. Supplementary data

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References


