Applied Energy 210 (2018) 409–419

Contents lists available at ScienceDirect

Applied Energy

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

Role of financial mechanisms for accelerating the rate of water and energy efficiency retrofits in Australian public buildings: Hybrid Bayesian Network and System Dynamics modelling approach

Edoardo Bertone[a,*], Oz Sahin[a], Rodney A. Stewart[a], Patrick X.W. Zou[b], Morshed Alam[b], Keith Hampson[c], Evan Blair[d]

[a] Griffith School of Engineering and Cities Research Institute, Griffith University, Parklands Drive, Southport, Queensland 4222, Australia
[b] Centre for Sustainable Infrastructure and Department of Civil and Construction Engineering, Faculty of Science, Engineering and Technology, Swinburne University of Technology, Hawthorn, Victoria 3122, Australia
[c] Sustainable Built Environment National Research Centre, Curtin University, Perth, Western Australia 6102, Australia
[d] Queensland Department of Housing and Public Works, Brisbane, Queensland 4000, Australia

HIGHLIGHTS

- Retrofitting rate of public buildings constrained by lack of financing schemes.
- We modelled potential retrofitting rate of Australian public buildings.
- We ran scenarios considering different financing and procurement methods.
- We coupled Bayesian Networks and System Dynamics modelling.
- A proper financing mechanism would remarkably boost the retrofitting sector.

ARTICLE INFO

Keywords:
Bayesian Networks
Building retrofitting
Green buildings
System Dynamics
Water-energy nexus

ABSTRACT

In Australia, the government spending on public buildings' energy and water consumption is considerable; however the building energy and water retrofit market potential has been diminished by a number of barriers, especially financial. In contrast, in other advanced economies there are several reported financing strategies that have been shown to accelerate retrofit projects implementation. In this study, a coupled Bayesian Network – System Dynamics model was developed with the core aim to assess the likely influence of those novel financing options and procurement procedures on public building retrofit outcomes scenarios in the Australian context. A particular case-study focusing on Australian public hospitals was showcased as an example in this paper. Stakeholder engagement was utilised to estimate likely preferences and to conceptualise causal relationships of model parameters. The scenario modelling showed that a revolving loan fund supporting an energy performance contracting procurement procedure was preferred. Subsequently, the specific features of this preferred framework were optimised to yield the greatest number of viable retrofit projects over the long term. The results indicated that such a financing scheme would lead to substantial abatement of energy and water consumption, as well as carbon emissions. The strategic scenario analysis approach developed herein provides evidence-based support to policy-makers advocating novel financing and procurement models for addressing a government's sustainability agenda in a financially responsible and net-positive manner.

1. Introduction

1.1. Contextual background

Government buildings are responsible for a large proportion of water and energy consumption; the potential savings which could be accrued through a widespread installation of water and energy efficient devices would be significant; however a number of implementation barriers, even more impeding than in the residential sector, currently hinder the establishment of a robust, effective retrofitting industry.

* Corresponding author.
E-mail address: edoardo.bertone@griffithuni.edu.au (E. Bertone).

http://dx.doi.org/10.1016/j.apenergy.2017.08.054
Received 23 December 2016; Received in revised form 21 June 2017; Accepted 9 August 2017
Available online 14 August 2017
0306-2619/

Such barriers were previously identified [1,2], and include the lack of initial capital investment [3] that is essential to cover the retrofit projects' high upfront cost [4]. This underlines the importance of having financial and procurement mechanisms in place in order to facilitate access to the capital needed to fund the project. Successful examples showcased in the United States, United Kingdom and Germany make use of innovative approaches such as revolving loan funds (RLF) and energy service companies (ESCOs) to facilitate the procurement process, to name a few [1]. What is evident from the reported international case studies is that each country context is very different and it is important to be able to model and simulate the effects of such policies in a different place (country) based on local technological, climate, social, economic and political factors. Hence the purpose of this study was to simulate the costs and benefits of the introduction of a number of accessible financial mechanisms and procurement models for government building water and energy efficiency retrofit projects in Australia.

The forecasting model would have to go beyond simulating the payback period for energy and water saving alternatives for a certain building and portfolio of buildings since the aforementioned financial and procurement barriers often block the commencement of retrofit projects in the government sector. Therefore, the model must be able to integrate traditional technical and economic indicators with less tangible financial, political and procurement alternatives in order to fully understand the likely take-up of retrofit projects over time for various proposed strategies. Additionally, the forecasting model needs to simulate the best decision for each individual building, while concurrently optimising the best funding scheme at a national level considering the overall expected retrofitting uptake. Importantly, the modelling framework will have to holistically account for all the challenging aspects of the water-energy-climate nexus involved in such a system, so that all the costs and benefits are comprehensively quantified, since typically water efficiency and the water-energy nexus are overlooked in policy-making [1,5]. Fortunately, modelling techniques are available to handle complex scenario forecasting problems with uncertainty and time-based parameter interdependency, including general data-driven models, water/energy simulation models, Bayesian Networks, Agent-Based Models, System Dynamic models, or combinations of them.

1.2. Previous water and energy-efficiency models

Data-driven models have been extensively applied in the energy sector for a range of purposes including costs reduction and energy optimisation, provided that enough data is available. As an example, Rieger, Thummert [6], based on a comprehensive dataset including more than 200 German households, developed a data-driven model and ran several simulations in order to estimate the potential cost-savings of different demand-response strategies, concluding that a two-part tariff (i.e. with a consumption-based component) would lead to at least 5% cost saving and a 14% reduction in peak demand. Fang and Lahdelma [7] also combined two data-driven models (namely, multiple linear regression and SARIMA) to predict district heat demand based on both weather and social input factors, in order to optimise the operations planning of district heating systems. Also in this case, a large amount of historical data is required. Walter and Sohn [8] used a database containing data for energy use, building features and equipment for almost 900,000 US buildings, to develop a multivariate regression model able to estimate the likely energy savings due to a particular energy retrofit. Regression analysis was also used in Lam, Hui [9] to quantify the importance of a number of input parameters in affecting energy consumption in Hong Kong high-rise buildings, and such models could potentially be used to estimate the expected change in consumption based on a retrofit (i.e. variations in some of the input parameters' value); a survey of Hong Kong commercial buildings was the foundation to develop the model. A very similar approach was subsequently used to predict building energy use in different Chinese climate zones [10]. A difference of less than 10% was found between statistical and energy model prediction accuracy. A more complex model, based on genetic algorithms was developed by Siddharth, Ramakrishna [11]; this model was able to identify critical input factors for building energy consumption, and could estimate energy and monetary savings resulting from a number of energy conservation measures. Several different energy-efficient options can be also assessed for a specific building through multi-objective optimisation, such as in Diakaki, Grigoroudis [12]. Another example of regression modelling is given by Guerra Santin, Itard [13], who used data for 15,000 homes in the Netherlands to understand the importance of, in particular, occupants behaviour in affecting energy use for heating, concluding it does partially influence energy consumption. Although related to water heating too, this study was focused on energy consumption while water efficiency is not considered. As a matter of fact, one of the main current gaps in the retrofitting industry is the lack of awareness, and interest, in water retrofitting [1] and of the potential combined savings due to the nexus between water and energy. As a result, modelling of water-efficient technologies is not as common as for energy retrofits.

In the Australian context, Beal, Bertone [14] modelled the estimated water, and energy, savings of water-efficiency devices for residential households, such as tap aerators and efficient shower heads. Talebpour, Sahin [15] investigated the performance of residential rain water tanks with an empirical approach based on water, energy, socio-economic and stock inventory data for a number of houses in South-East Queensland. Kenway, Scheidegger [16] developed a static mathematical model to simulate household water use and analyse different scenarios incorporating technical and behavioural changes, with the scenarios combining both strategies predicting much larger water-related energy savings than technical improvements alone. Vieira, Humphrys [17] used the software EnergyPlus to understand and quantify the effects of site-specific features on the performance on domestic water heating systems. Gurung, Stewart [18] analysed and modelled a number of water savings technologies and quantified the mutual benefits for householders and water utilities.

More detailed, building-specific computer models typically would not allow for a large scale feasibility assessment of a retrofitting policy, however to overcome this it is possible to follow the methodology proposed by Dascalaki and Santamouris [19]. They ran an energy model on ten buildings only, however, since each of these was representative of a particular office building type, it can be assumed that the model would yield similar outputs for other buildings within the same category; thus the outcomes were extrapolated to estimate the energy saving potential of a number of retrofitting actions for the whole office stock. Another study focusing on a particular category of public buildings was undertaken in Beusker, Stoy [20], where data for over 100 schools and sport facilities in Germany were used as input for a regression model able to estimate energy consumption for heating. Similarly to Dascalaki and Santamouris [19], energy models were used in Saari, Kalamees [21] to estimate the financial viability of different options (e.g. solar collectors, heat pumps) for new detached houses in Finland, providing the payback period as output.

In terms of financial modelling, in their integrated retrofitting optimisation tool Rysanek and Choudhary [22] incorporated a cost and savings analysis using net present value, also accounting for the uncertainty associated with factors such as engineering performance and energy price. Interestingly, other studies found that the energy savings for solar retrofitting options are typically overestimated [23]. A similar approach, using NPV to find the optimal retrofitting option and accounting for uncertainty in energy price, was used in Kumbaroğlu and Madlener [24]. An "augmented" NPV method, using the capital asset pricing model, is instead proposed in Menassa [25], in order to allow the decision maker to assess and prioritise different retrofitting options over time.

Based on the available literature herein discussed, there are a number of gaps and limitations which need to be addressed. It can be noticed, first of all, that there are no studies that could quantify both the potential water and energy savings for specific technologies, as well as incorporate their financial and procurement viability at a national scale. This is due to limitations of the most common modelling approaches. The most typically deployed models are often deterministic/mathematical models that can simulate energy and/or water use of a specific building; this implies that such calculations are difficult to be performed over a national scale by considering the full building stock. Empirical models similarly, require a large amount of data. Both these approaches, additionally, struggle to handle or properly quantify uncertainty, as well as to deal with missing and/or qualitative data (e.g. householder behaviour). Finally, as already mentioned, the financial component is often modelled separately. However, there are modelling approaches which can help address such limitations. Coupling Bayesian Networks (BN) with System Dynamics (SD) modelling methodologies can reveal richer findings in situations where it is necessary to link strategic parameters related to policy (e.g. financing model, procurement, etc.) with the more practical technical and economic modelling aspects. Benefits relate to handling of uncertainty, probability, preferences, and time-dependent interactions, among others, as detailed in the next sections.

1.3. Benefits of a coupled Bayesian Network – System Dynamics model

A modelling methodology which can potentially overcome data limitation, as well as include qualitative input data and uncertainty in the overall assessment, is given by BN, acknowledged as being one of the most effective and useful modelling frameworks in the field of probabilistic knowledge representation and reasoning [26]. BN allows incorporating not only real numerical data, but also experts' qualitative inputs; this is crucial for retrofitting-related issues, since it has been shown that unrecorded socio-economic factors such as tenants' habits play a major role in affecting the potential of retrofitting technologies, and community engagement as well as policy incentives are deemed essential for triggering energy-saving behaviours [27]. BN also explicitly deals with uncertainty; considering that the optimisation of retrofitting options is a highly multidisciplinary and uncertain modelling problem [22], BN provides a suitable means to overcome these complications. Additionally, the computational time of a BN simulation is considerably shorter than for some process-based models [28] due to the conditional independence attribute of the nodes, meaning that the value (state) of a variable (node) is computed based on the state of parents nodes only, thus making the calculations simpler and faster [29].

An example of BN application in the field of energy efficiency is given by Cai, Liu [26] who combined two different Bayesian Networks in order to predict the probability of failure of ground-source heat pumps, for improved diagnostics. Similarly, in order to deal with large scale assessment of feasibility of building retrofit options, Heo, Choudhary [30] used relatively simple and quick normative energy models coupled with a Bayesian calibration approach in order to account for the uncertainty of a number of parameters and thus allowing to explicitly assess the risks associated with different retrofit options.

SD on the other hand is a modelling methodology which enables to understand and model complex systems in order to improve policy- and decision-making [31]; SD has been extensively applied for several decades to guide policy-makers in several fields including the water and energy sectors [32,33]. Although it cannot explicitly deal with uncertainty such as BN, it can instead model nonlinear system behaviours over time including feedback loops. Combining BN and SD has been previously proposed by the authors as part of the "ARID" (Accessible, Robust, Integrated and Dynamic) framework [34] and it proved to be beneficial, as it allows for combining the advantages of the two separate modelling approaches and at the same time neutralising the respective limitations. Such hybrid BN-SD approach has been successfully applied by the authors in water-related projects [35].

1.4. Research aim and objectives

The overarching aim of this study was to identify the effects of different financing mechanisms on the uptake of water and energy retrofitting projects for Australian public buildings.

Firstly, given the aforementioned benefits and previous applications of BN, it was decided to build a BN which can estimate the willingness to retrofit of a given Australian public building, based on its current efficiency, location, and other contextual factors such as financial mechanisms in place (if any). It would also make use of available water and energy data, as well as the findings of the first part of this project [1] in terms of current barriers and best examples for the retrofitting industry. Although it is not possible to accurately model energy and water use for each individual public building since they differ from each other, such buildings can be grouped together based on a number of common features; in such a way, it is possible to investigate the behaviour of each building group and identify optimal retrofitting actions for each of these building types [19].

Secondly, a System Dynamics (SD) model was developed in order to (1) optimise the features (e.g. loan duration, initial funding amount, interest rates) of the most cost-effective financing schemes; and (2) estimate, over the long-term, the expected monetary (in terms of water and energy use reduction) and carbon savings resulting from the potential implementation of such financial schemes. Outputs of the BNs (e.g. number of buildings per unit of time willing to retrofit) were fed to the SD as part of the ARID framework in order to take advantage of respective benefits of these two separate models.

The combined outputs of such hybrid BN-SD model were used for scenario analysis and to quantify water, energy and carbon savings originating from different retrofit options and financing schemes considered.

The following sections describe the data collection and analysis activities, the development of the two models, and the discussion of the results.

2. Materials and methods

2.1. Data collection

Data for public buildings location, size, and energy consumption were collected from a range of publicly available sources [36–40]. In particular, the data presented in one of these documents [40] were in turn collected from other several studies, statistically analysed and validated. Although the reported data are predominately based on a larger category of commercial buildings, it is possible to extract data for the public category only. For instance, the energy use calculated for hospitals can be broken down into private and public categories based on information available online [38]. As described in a later section, it was possible to notice that hospitals are responsible for the larger portion of energy consumption amongst public building categories, hence the modelling efforts focused on this particular type of building in order to demonstrate the proposed modelling approach. However the modelling framework can be easily re-applied to other less water and energy intensive public building categories if required.

Regarding water consumption, a limited amount of data was available. For instance, some general water consumption and water intensity data was available for Victorian hospitals through the Victoria State Government website [41]. Trends were evident in the water data such as that metropolitan hospitals tend to be more water efficient with an average consumption of 1.5 kL/m^2 per annum, compared to 1.7 kL/m^2 per annum for regional hospitals. Moreover, there was a trend of reduced water consumption in hospitals (up to 30%) in the last 10 years. Finally, from a number of different sources retrieved it was determined that toilet flushing was the highest water use in public buildings (up to 50%), while taps, showers and toilets combined together accounted for up to 80% of the total water use [42].

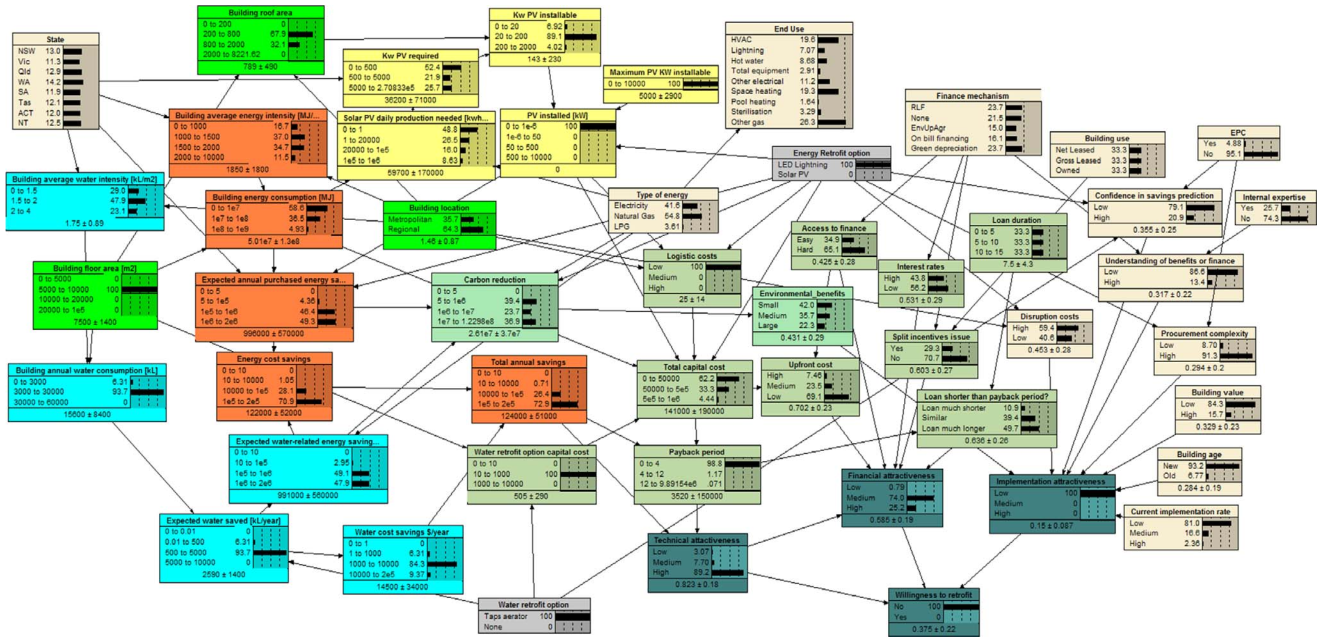

Fig. 1. BN model structure for estimation of "willingness to retrofit".

2.2. Bayesian Network development

Following the identification of the category of public buildings responsible for the highest energy consumption (i.e. hospitals), a BN model was developed in order to numerically quantify the willingness to retrofit a given hospital based on scenarios of:

1. *Financial mechanism in place* (None, RLF, Environmental upgrade agreements, On-bill financing, Green depreciation)
2. *Energy performance contractors* (Yes/No)
3. *Location* (State, Metropolitan/Regional)
4. *Current implementation rate* (High/Low)
5. *Retrofit option* (Energy: Solar PV, LED lights; Water: Taps aerators)

For the purpose of demonstrating the application of the modelling approach, only three retrofitting options were considered in this study. They were selected based on potential savings that they can create, market accessibility, and modelling simplicity. Solar photovoltaic (PV) installation is one of the most common and viable retrofitting options in a country like Australia with high solar irradiation levels [43]. It is a retrofit option that does not deal with "efficiency" per se (i.e. it does not directly imply a reduction in water or energy use), but it is responsible for on-site renewable energy generation and in turn reduced demand for non-renewable energy to be purchased. The second retrofit option was a lightning upgrade since it is well recognised as a low-cost, efficient way to reduce energy costs as demonstrated by previous studies [23]. Regarding water-efficient devices, the study focuses on well recognised least-cost demand management solutions such as tap aerators and shower heads. While reducing shower consumption has a lower impact in public buildings when compared to residential buildings, tap aerators would still provide a very cost-effective means to considerably reduce water and water-related energy consumption [14]. Importantly, the BN was designed to cater for diverse scenarios of different climatic zones within states and territories of Australia; climate has an influence on the building characteristics, the energy behaviour of buildings [19], and the efficiency of considered retrofitting options (e.g. PV panels).

Regarding financial mechanisms, the research team relied on the results of the first stage of this project, reported in Bertone, Sahin [1]. Financial incentives have previously been reported as being important for retrofit projects [44], though this problem has a different research focus and approach. The BN model includes a variable that considers the innovation diffusion rate according to Rogers [45] theory, which suggests that the uptake of a new technology relies not only on external factors (e.g. promotion), but also on internal ones (e.g. current number of adopters). Other similar approaches have been proposed to simulate the uptake of new water/energy technologies, including agent-based modelling [46] and cellar automata-based models (e.g. Kandiah, Berglund [47]).

As previously mentioned, modelling such system is a challenging task since the willingness to retrofit would be dependent not only on numerically quantifiable technical aspects (e.g. water/energy savings, payback period, etc.), but also contextual factors such as available financing mechanisms or building location. Quantifying financial and implementation attractiveness must be performed with a probabilistic approach using experts' judgement whenever data is not collectable, and integrated with the technical calculations. Given these considerations and previously mentioned benefits, the research team decided to develop a BN since this type of model would satisfy all the modelling requirements and overcome the difficulties herein described.

BNs are a type of statistical, probabilistic, acyclical graphical model where variables (called nodes) are connected to each other through causal links. Each node has a number of states (e.g. high/low); with a "conditional probability" assigned to it, which can be derived from different sources (e.g. empirical data, experts' inputs, or outputs of other models). Such probability is called conditional because its value is dependent on the values of the parents' nodes. All the required conditional probabilities for the states of a certain node can be summarised with a conditional probability table (CPT). New information is entered into the BN by substituting the a priori belief with observations or scenarios values for the desired nodes [48]. This mechanism of computing the posterior distribution of a variable when new knowledge is added is called probabilistic inference. Basically, a BN provides a way to automatically apply the Bayes' theorem when complex systems are to be modelled. Through the Bayes theorem, in addition, BN allows for a top-down ("forward inference" – scenario analysis based on pre-set input conditions), as well as a bottom-up ("backwards reasoning" – estimating the inputs leading to a pre-specified output), analysis. Essentially, by building a BN model, it is possible to integrate numerical calculations when data are available (e.g. estimated energy savings based on current consumption and retrofit option) with qualitative information when data are not available (e.g. predicted retrofit uptake based on available financial mechanism besides predicted savings).

Fig. 1 illustrates the structure of the BN model developed for hospital buildings in the locational context of Australia. The model was developed using the software Netica 5.18 32 bit from Norsys Software Corp. The left-hand side of the model contains the nodes that predominately relied on numerical calculations. Predicted water savings for tap aerators were calculated in the light blue (bottom left corner) part of the model. The related energy savings are calculated through the dark orange variables (i.e. second column from the left). The same path is followed by the considered energy-efficient retrofits, namely LED lights and solar PV. For solar PV, additional model input variables are necessary, such as roof area (assumed proportional to the total hospital area) and location (annual solar radiation). These calculations are performed through the yellow variables (top, central) part of the BN. Such numerical calculations are performed through equations, based on current water and energy consumption of hospitals according to the collected data, as well as estimates of water and energy savings achievable through the considered retrofitting technologies based on available literature and basic engineering calculations. All these equations are converted to probability distributions through a Monte Carlo approach. For instance, based on the distribution of the hospital size (see Fig. 4), a number of simulations (i.e. 100,000) are run where a random value for the hospital area is selected every time, leading to a different quantification of savings. However, as these values will be proportional to what is dictated by the frequency distribution of Fig. 4, the resulting probability distribution of the savings will be realistic and reflecting the overall hospitals' characteristics estimated from the available data.

The final output of the technical analysis calculations part of the model is the monetary payback period. Based on the calculated water and energy savings (in case of solar panels, we referred to "purchased" energy savings since, as explained previously, they do not lead to a reduction in consumption, but simply to an increase in produced energy which does not have to be purchased), and on retrofit installation costs, the payback period and thus the technical attractiveness was calculated. Greenhouse gas emission reductions can be calculated based on the emissions per kWh [14].

The right hand-side of the BN model, on the other hand, is predominantly qualitative, and it is where financial and implementation attractiveness was estimated. Firstly, based on the review completed in the first stage of this project [1], a number of variables which, according to the research team, could considerably affect the attractiveness of a retrofit project, were listed and logically connected together based on cause-effect relationships. Hence, for instance, each financing mechanism would affect the variables upfront cost, the interest rates, and loan duration. In addition, other important variables were identified as being: the procurement complexity, the presence of energy (and water) performance contractors, the presence of related expertise within the building/organisation, the building age and value, and the current implementation rate.

As stressed before, no numerical equations can be retrieved to fill in the CPTs of these variables and thus quantify the relationships between parent and child nodes for this part of the BN. Hence these must be qualitatively assessed. The importance of each factor was therefore weighed based on literature, the research team judgement, and industry partners' opinion. In particular, two meetings were organised; one in Brisbane with Queensland Government stakeholders, and one in Perth with Western Australian Government stakeholders.

In complex systems, stakeholders must be involved and consulted to implement initiatives that could affect their interests. Bringing together the key stakeholders is a way of building consensus and has multiple benefits such as: (1) avoiding early-stage conflicts; (2) pushing the process forward against delays; and (3) promoting initiatives which share decision-making responsibility. Therefore, engaging stakeholders throughout the modelling process represents a minor expenditure of resources when compared with the costs of poor performance, or even disaster that typically follows in the wake of failing to consult key stakeholders, and to retrieve their interests and their information [49].

Continuous stakeholder engagement has been previously used by the authors in projects involving BN or SD [50,51] and it is a crucial component of the proposed ARID framework to ensure the development of a robust and reliable model. These meetings were used to elicit expert data (to complement the preliminary input weighting) and to get feedback on the model structure. The model was then refined accordingly; CPTs for these nodes were created based on the simulation results, existing data, and the weight of different input factors provided by the consulted industry and government experts. The model was then validated by running several scenarios and checking for inconsistencies or illogical behaviours.

2.3. System Dynamics model development

BN modelling established a preference for a RLF financial arrangement, as described in the Results section. Subsequently, based on such finding, a SD model was developed to determine the retrofit rate for hospital buildings based on the RLF initial capacity, interest rates, and duration of the available loan. For each of the scenarios considered, the following outputs were calculated: (1) quarterly and total monetary savings from avoided water and energy consumption; (2) quarterly and total avoided carbon emissions; (3) number of hospitals which have completed a retrofit project; and (4) evolving RLF budget. The model was firstly developed in-house by the research team but was later refined after stakeholders' consultation.

The structure of the SD model is illustrated in Fig. 2. The software used for its development was Vensim DSS 6.3 Double Precision, from the Ventana Simulation Environment. The model starts by considering the number of eligible hospitals and the number of hospitals per quarter willing to retrofit. This is dependent on the BN output parameter "*willingness to retrofit*", which is dynamically influenced by other parameters of the SD model, such as interest rates, loan duration, and the current hospital retrofit implementation rate. The *willingness to retrofit*, as well as other BN output variables (e.g. cost and savings of the retrofit project) also depends on the retrofit option considered, as illustrated in Fig. 2. Hence, a SD model was developed which can interactively be adjusted in order to assess different scenarios; in particular: one considering the RLF scheme being set up for solar PV retrofits only, and another one for the LED lights + tap aerators retrofit scenario. A basic step-by-step procedure on how to deploy such two interconnected models would be as follows:

1. Open BN and select background conditions; e.g. (a) a specific state or the whole Australia; (b) the retrofit option to be considered; (c) the size of hospitals to be considered; etc.
2. BN output: willingness to retrofit of a given hospital, and expected average energy and water savings;
3. Open SD and set up background conditions used in the BN (e.g. hospital size);
4. Enter BN outputs in SD (e.g. willingness to retrofit, costs and savings);
5. Optimise the RLF features based on SD outputs.

Based on certain input conditions and BN prediction, a number of hospitals would decide, every quarter, to retrofit; hence, they would apply for a loan from the RLF scheme, based on the estimated project cost (calculated from the BN model). However, the RLF budget will allow for only a limited number of loans per quarter to be approved. Although the RLF budget is going to increase over the long term due to the loan repayments (which are higher than the lent amount due to interest), the RLF initial capital would soon deplete because the loan repayments will slowly increase in number, but will be limited at the very start. Hence, only a portion of the interested hospitals will have a

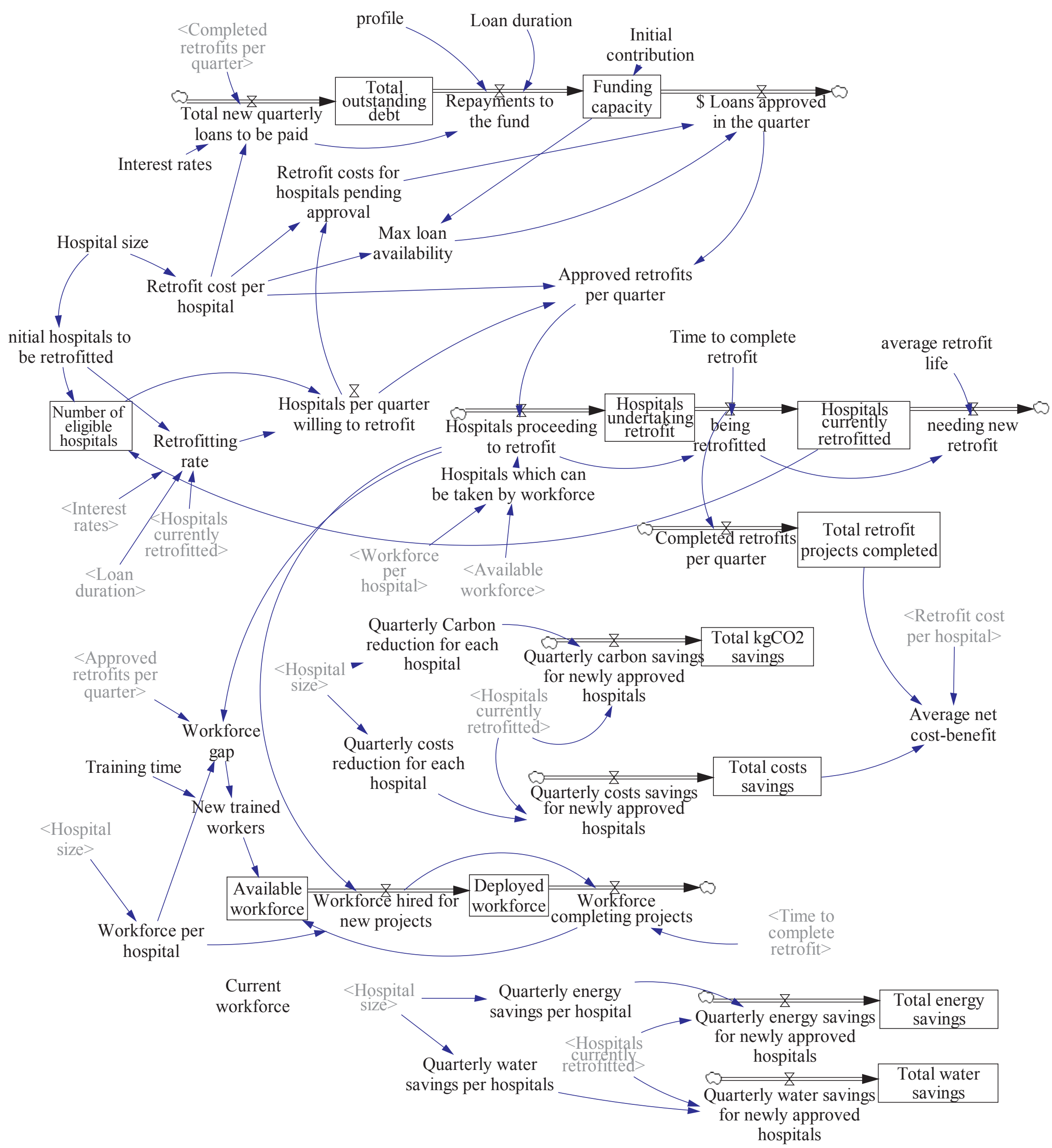

Fig. 2. SD model for revolving loan fund optimisation for retrofit projects.

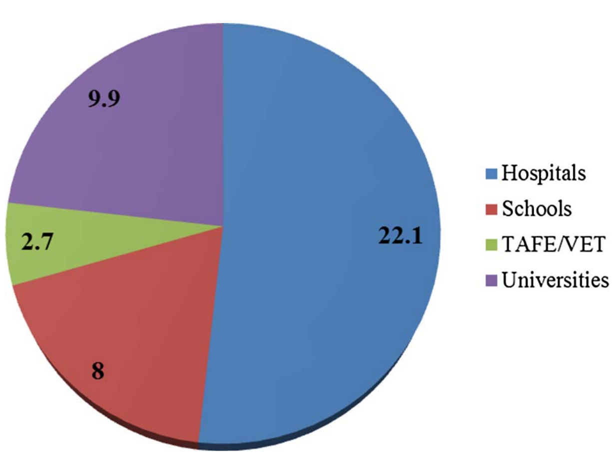

Fig. 3. 2015 annual energy consumption for different building categories [PJ].

retrofitting loan approved in any given quarter, and these could be selected on a case-by-case base according to the savings potential. It could be also possible however, to spread the awarded RLF budget over a longer time or to "top up" such amount after a number of years, at times when it is momentarily almost depleted. These scenarios could be explored through the developed SD: the interactive environment in Vensim in fact allows for dynamically adjusting the RLF features by instantaneously check how a change in one of the inputs (e.g. RLF budget) affects the outputs (e.g. number of retrofitted hospitals over time). Following retrofit project approval, a designated project implementation period has been allocated before the operational phase of the retrofit projects commences and water/energy consumption is reduced each year. Another temporal factor considered by the SD model is the average life of a retrofit project. Any hospital reaching the end of the life of the installed retrofit will go back into the pool of "hospitals to be retrofitted".

Additionally, the bottom part of the model calculates, based on both BN and upper SD model outputs, the savings achieved in terms of

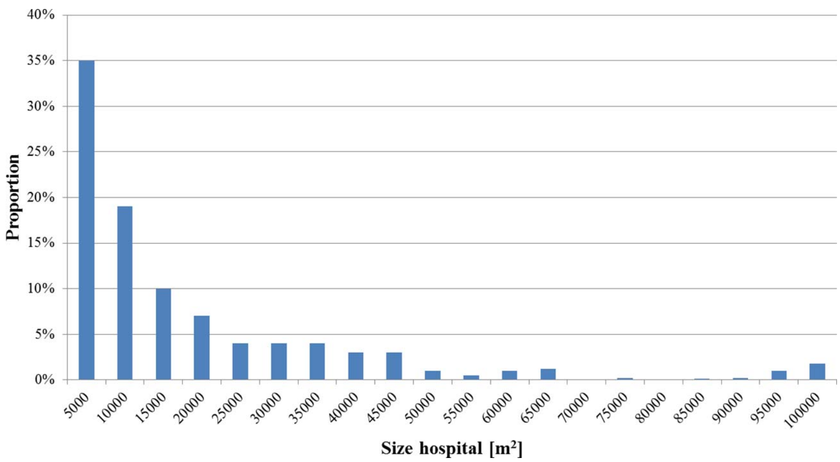

Fig. 4. Australian hospitals grouped by total area.

monetary costs, carbon emission reductions, and water and energy savings. Theoretical performance parameters have been reduced to account for practical issues such as poor installation or maintenance and environmental factors (e.g. dust/shade on PV panels).

The model can also be run considering four different hospital size categories, namely:

1. Small (< 5000 m^2): 464 hospitals;
2. Small-to-medium (between 5000 m^2 and 10,000 m^2): 252 hospitals;
3. Medium-to-large (between 10,000 m^2 and 20,000 m^2): 133 hospitals;
4. Large ($> 20,000$ m^2): 477 hospitals.

These four categories account for different average project costs associated with the size of the retrofit project for a particular hospital and allow for the assessment of alternative funding amounts/mechanisms for these different sized hospitals.

3. Results and discussion

3.1. Data analysis results

In Fig. 3, it is possible to observe the estimated total annual energy consumption for different categories of buildings. It can be noticed how hospitals were responsible for more than half of the total energy consumption of these building categories, accounting for a total of 22.1 PJ. Universities and schools follow with, respectively, 9.9 PJ and 8 PJ. Technical And Further Education (TAFE) and Vocational Education and Training (VET) buildings accounted for a total of 2.7 PJ. Given these figures, the research team decided to focus on hospitals only.

In Fig. 4, the frequency distribution of the size of the Australian hospitals is represented. It can be noticed how more than a third of them has a total area lower than 5000 m^2, and a combined total of over 70% has a total area lower than 20,000 m^2. However, there are also some outliers, with approximately 5% of the hospitals having an area higher than 90,000 m^2.

Fig. 5 illustrates the energy efficiency of hospitals based on their location. Generally, hospitals in metropolitan areas have higher energy efficiency. This might reflect the fact that the implementation of new technologies may be easier and more accessible in these areas rather than in remote regional areas. This factor must be considered in the modelling framework. Overall, the least energy-efficient location is regional Norther Territory (NT) with an annual energy intensity of over 2000 MJ/m^2, while Hobart has the most energy efficient hospitals, with an average annual consumption of 1322 MJ/m^2 – i.e. 36% less than regional NT. Sydney, Melbourne and Brisbane hospitals have on an average a similar efficiency of about 1500 MJ/m^2.

In Fig. 6, a breakdown of the type of energy used by Australian hospitals is presented. It can be seen how electricity (10.9 PJ) and natural gas (10.5 PJ) are the two types of energy sources that account, almost evenly, for the vast majority of energy consumption in hospitals. It is important to underline how in Australia only 13% of the generated electricity comes from renewable sources [52].

Figs. 7 and 8 also show a breakdown of the electricity and gas end-uses in hospitals. Heating, Ventilation and Air Conditioning (HVAC) systems account for a large portion of the energy use; similarly, space heating is also the main end-use for gas. Interestingly, lighting also accounts for a considerable 17% of the electricity use, equivalent to over 1.8 annual PJ. Given the relatively low initial implementation costs of a number of lightning retrofit options when compared to deep retrofits such HVAC systems, this end-use has a lot of potential for energy efficiency optimisation through retrofitting. Finally, a considerable amount of energy (12% of natural gas and 2% of electricity) is used for heating water; the importance of considering the water-energy nexus, and water retrofit measures in order to simultaneously reduce energy use, is evident.

3.2. Bayesian Network modelling results and discussion

The willingness to retrofit (Fig. 9), calculated with the BN is reported for a number of financial option scenarios, for the two retrofit options: (1) the installation of solar PV panels (blue[1] bars); and (2) a combination of LED lights and taps aerators (red bars). Fig. 9 represents an example of a few of the various scenarios that can be assessed through the developed BN.

Expectedly, if no particular financing mechanism is in place which can support the public building owner/manager in overcoming financial barriers, the willingness to retrofit is extremely low despite a potentially high monetary rate of return from the retrofit project. If a *green depreciation* or *on-bill* financing scheme is available, helping to reduce the high upfront costs, the willingness to retrofit increases to meagre 2%. However, RLF and *Environmental Upgrade Agreements* (EnvUpAgr) are the two schemes leading to the highest rates of retrofit willingness. These modelling results confirm qualitative findings in a recent review paper by the authors [1]. In particular, if a RLF is combined with a high current implementation rate (High Impl) and also the presence of energy performance contracts (EPC) which transfer long-term savings risks to contractors, then the willingness increases to 16% for solar PV and 30% for the combination of LED lights and tap aerators. Such a big difference between the two retrofit options is justified by a higher technical attractiveness for the latter one (i.e. LED lights and tap aerators have a rapid payback period due to their limited

[1] For interpretation of color in Figs. 9 and 10, the reader is referred to the web version of this article.

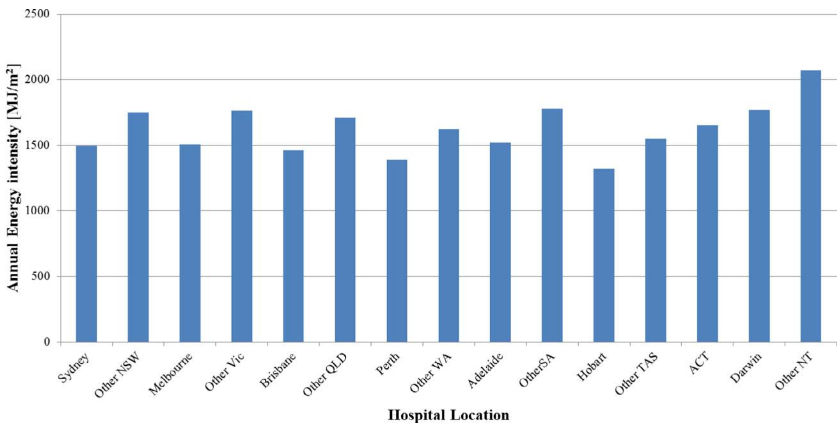

Fig. 5. Australian hospitals grouped by energy intensity.

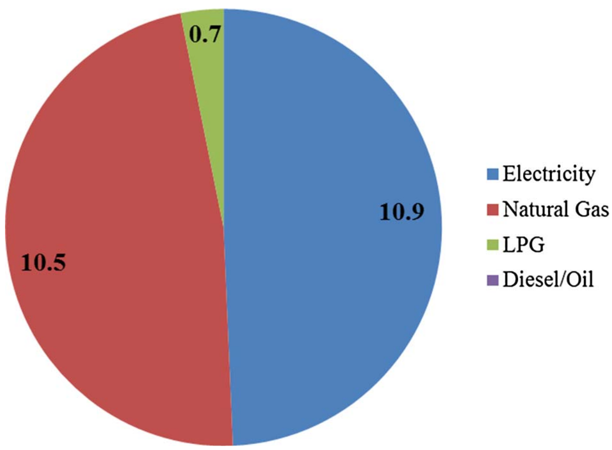

Fig. 6. Australian hospitals' 2015 energy use by type [PJ].

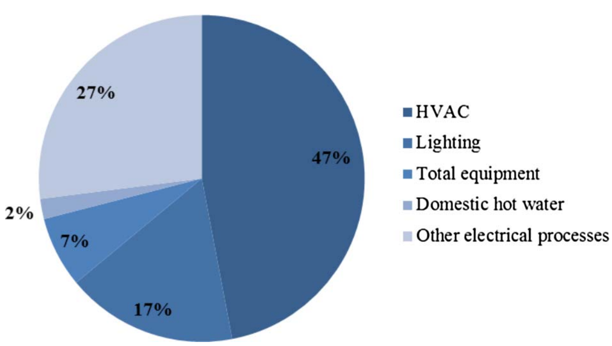

Fig. 7. Electricity end-uses for Australian hospitals, 2015.

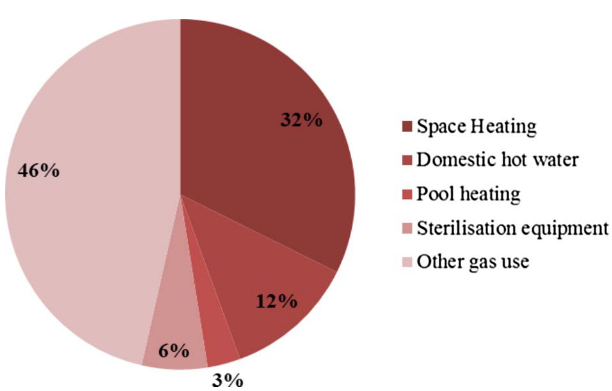

Fig. 8. Gas end-uses for Australian hospitals, 2015.

capital cost and relatively high annual savings).

The willingness to retrofit is a useful relative indicator to compare different scenarios, and it is a critical input for the interconnected SD model. Other critical BN variables which link with the SD model include the cost (mean and standard deviation) of a retrofit project based on different hospital's features (e.g. size, location), as well as the associated predicted annual water and energy savings.

3.3. System Dynamics model results and discussion

Fig. 10 shows the number of hospitals that would be retrofitted with solar PV panels over time, given certain characteristics of the RLF. The base case scenario (blue line) has a RLF with: (1) initial funding budget of AUD$10 million; (2) *low* interest rate (set to 2%); and (3) an average loan duration of 10 years. Three alternative scenarios were examined where the specific RLF features were changed. In the base case scenario, despite a slow initial uptake due to a quick depletion of the RLF funding budget before the repayments can replenish it, a peak number of hospitals (i.e. 60) were retrofitted after about 10 years. The simulations ran for 75 years in order to account for multiple life-cycle of the retrofit option and the associated interdependent, nonlinear effects on the full system modelled. This does not account obviously for new emerging future technologies or changing political/financial environments and thus the policy-maker should focus on the first few years of the simulations based on their own interests.

Three strategies were examined to increase the initial retrofit project loan approval rate: (1) double interest rate to 4% (green line); (2) halve loan duration (purple line); and (3) double initial RLF capital to AUD$20 million (red line). Doubling the interest rate led to an increase in the amount of repayments back to the RLF pool but did not produce any considerable change in trend since higher interest rates reduced the level of the attractiveness of a retrofit project and thus the proponents' willingness to retrofit. Decreasing the loan duration led to an increase in the retrofitting rate, since the repayments would be quicker and the adverse effect on the willingness to retrofit would be more contained than in case of higher interest rates. The best of the three strategies was to double the initial RLF funding pool since greater numbers of retrofit projects could be initially funded without impeding on the monetary attractiveness of the retrofit project. Doubling the initial RLF capital enabled 100 hospitals to retrofitted, instead of 60 for the baseline scenario, in the first 10 years. It should be noted that the RLF capital can be returned to the funding agency with accrued interest after a stipulated period of time (e.g. 25 years).

Fig. 11 shows the same outputs estimated for the second retrofit LED lights and tap aerators option. In this case, a total of 150 hospitals would be retrofitted under the same optimised scenario for the RLF; this is due to the higher willingness to retrofit calculated from the BN, and the lower cost allowing the same funding pool to approve more loans.

The interlinked BN and SD models demonstrated that a RLF coupled

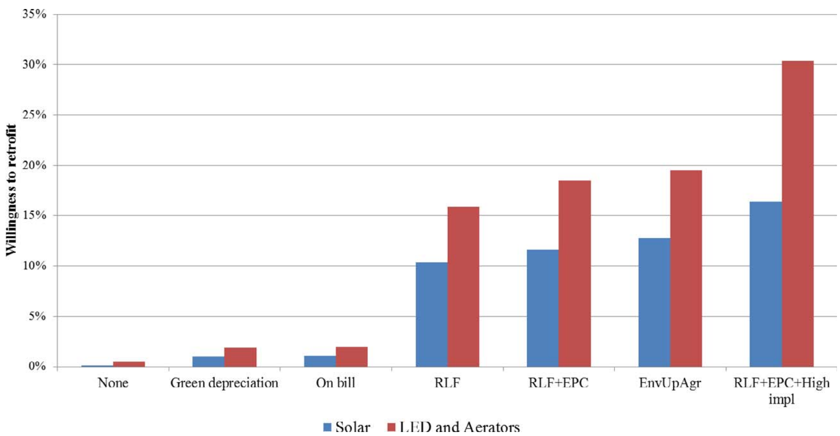

Fig. 9. BN modelling results for willingness to retrofit based on different financial options.

with performance contracting approach showed that the combination of LED lights and tap aerators was preferable to solar PV panels. The RLF scheme had four categories of funding based on the size of the hospital (i.e., each hospital would be able to access only one specific funding scheme based on its size). Table 1 illustrates the results of the optimisation process with the SD model. The common inputs were a low (2%) interest rate and loan duration of 10 years. Although the SD model presents monetary savings based on recent energy prices, both kWh and ML of predicted energy and water saved is also provided in order to free the model from the uncertainty around future energy prices. Different scenarios of potential future energy prices can be incorporated in the SD model, however they were out of the scope of the current study, given the high volatility of the energy price and thus the uncertainty around such projections [24]. Nevertheless, based on current (2016) water and energy prices in different Australian states, from the models it could be estimated that savings in water bills account for only a small portion (7% on an average) of the total costs savings, unlike energy savings which accounts for the remaining 93%. It must be noticed though, that a proportion of the energy savings originated from an expected reduction in water-related energy consumption (i.e. water heating). This outlines the importance of the water-energy nexus and of relatively inexpensive solutions such as tap aerators, traditionally regarded as water-saving devices but that can considerably help decreasing the energy use.

Smaller hospitals (Category 1) would have lower project costs and thus a small funding capacity would be sufficient to retrofit several of them. However, the same funding capacity might be very limited for larger hospitals requiring expensive, large-scale upgrades. In our simulations, a funding amount of $5M was enough to retrofit a total of 151 small hospitals after 20 quarters or five years, however the same funding pool would only enable the retrofit of six Category 4 hospitals within the same period. Hence we were able to optimise the funding amount for each pool with the SD in order to achieve an acceptable number of retrofitted hospitals (i.e. around 30% across the different categories).

The RLF capital investment of AUD$80M, spread differently across the four size categories, achieved monetary savings in energy and water use of almost five times such capital investment within ten years. An added benefit was that more than 23 million of metric tonnes of emitted carbon dioxide could be avoided; on an annual basis, this would represent more than 1% of the total greenhouse gases emission of the overall Australian electricity sector [53]. Considering that we analyse only one category of public building (i.e. hospitals), and only two simple retrofit options in this study, such figures are promising. Also, almost 2000 GWh in energy savings could be achieved, as well as more than 10,000 ML of water savings. More importantly, each hospital would achieve an average AUD$400,000 positive net return of investment after ten years.

This study was limited in scope to considering only the direct monetary water and energy benefits from retrofit projects. The wider indirect benefits were not examined, including the creation of employment and specialist retrofit industry growth within Australia and potentially export services overseas.

4. Conclusions

A hybrid BN-SD modelling framework was developed to examine the attractiveness and potential benefits of a number of strategies for promoting public building energy and water retrofit projects in Australia. In this current study, the framework was demonstrated for one particular public building category, namely hospitals which are acknowledged as being energy and water intensive. However, the

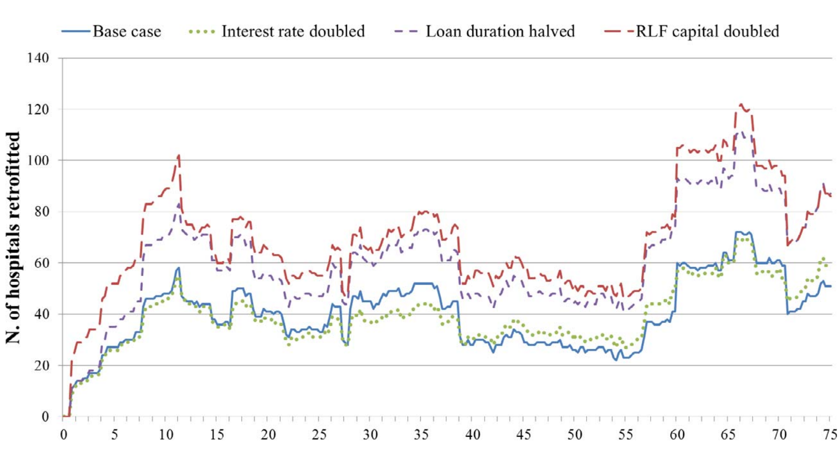

Fig. 10. SD predicted number of hospitals retrofitted with solar PV panels.

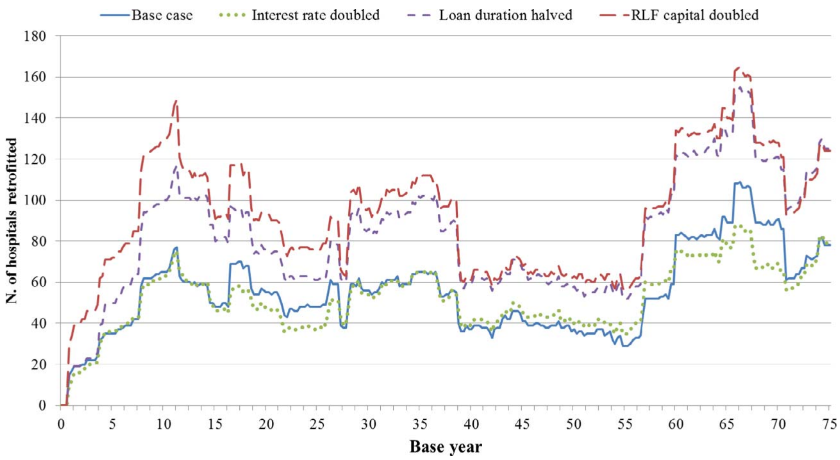

Fig. 11. SD predicted number of hospitals retrofitted with LED lights and tap aerators, SD simulation.

Table 1
Predicted retrofitting projects benefits for different funding pools and overall; case of LED lights and tap aerators.

Hospital size category	1	2	3	4	Total/average
Funding amount proposed [AUD$M]	5	10	15	50	80
Number of retrofitted hospitals after 5 years [No.]	151	71	34	128	384
Number as a % of the category's total [%]	32%	28%	26%	27%	29%
Average net savings per hospital in 10 years [AUD$]	490,000	474,000	345,000	281,000	397,000
Cost savings after 10 years [AUD$M]	132.2	79.3	39.6	128.5	379.6
Total energy savings in 10 years [GWh]	499	363	203	698	1763
Total water savings in 10 years [ML]	1767	1434	1107	6139	10,448
Emission savings after 10 years [MMt CO_2-e]	1.9	5.7	3.8	12.3	23.7

developed models can be easily adapted to other public buildings categories.

Firstly, a BN model was developed to examine the suitability of different financing mechanisms, procurement approaches and contextual factors, based on how they would affect the willingness to retrofit a given hospital. BN modelling identified RLF coupled with ESCO as the optimal financial/procurement strategy for promoting greater rates of public building retrofits, which confirmed the findings of a review completed by the authors [1].

The BN model was linked to a developed SD model that was purposed to quantify how the best-practice strategic options examined (i.e. RLF) influenced energy and water savings of the two explored retrofit solutions (i.e. solar PV panels; LED lights and tap aerators) as well as the associated monetary and carbon emission savings.

The results showed how the RLF capital investment of AUD$80M coupled with an effective procurement approach could deliver significant monetary savings of approximately AUD$400M within ten years. Moreover, carbon emission reductions of over 23.7 million tonnes of CO_2 could be avoided over a ten-year time frame, which would assist the Australian government to achieve stated carbon reduction targets. Additionally, the creation of a growing specialist retrofit industry within Australia would create new employment and promote greater retrofitting rates within other building sectors (e.g. private commercial buildings). Achieved water savings are also important in a scenario where increased climate variability and population growth pose threats to water supply availability. Moreover, the potential of inexpensive water-saving devices (e.g. tap aerators) to remarkably decrease energy consumption through the water-energy nexus (e.g. hot water use reduction) is evident.

Future work will focus on better capturing the wider indirect benefits of retrofit projects (i.e. employment growth), exploring retrofit rates for other public building categories (e.g. schools) as well as other building sectors (e.g. hotels), and the optimisation of a wider range of retrofit opportunities (e.g. efficient air-conditioning systems). Such a comprehensive coupled BN-SD model would assist policy makers to better understand how the best combination of well-formulated strategies and incentives can derive optimal net-positive retrofit project investments over the long term.

Acknowledgements

This research project was supported by the Sustainable Built Environment National Research Centre (SBEnrc) based in Australia. The collaborative industry partners to the project include the Queensland Government (Department of Housing and Public Works), Western Australian Government (Department of Commerce, Building Commission, Sustainable Building and Department of Finance), and Aurecon. Research partners include Swinburne University, Griffith University and Curtin University. We are grateful for the support provided for this project.

References

[1] Bertone E, et al. State-of-the-art review revealing a roadmap for public building water and energy efficiency retrofit projects. Int J Sustain Built Environ 2016;5:526–48.
[2] Alam M et al. Guidelines for building energy efficiency retrofitting. In: Sustainability in public works 2016, Melbourne, Australia; 2016.
[3] Rhoads J. Low carbon retrofit toolkit: a roadmap to success. Accenture; 2010.
[4] USDE. Guidance for the implementation and follow-up of identified energy and water efficiency measures in covered facilities. United States Department of Energy; 2012. p. 49.
[5] GHD. Scoping study to investigate measures for improving the water efficiency of buildings. Prepared by GHD Pty Ltd for the Department of the Environment and Heritage, Australian Government; 2006. p. 191.
[6] Rieger A, et al. Estimating the benefits of cooperation in a residential microgrid: a data-driven approach. Appl Energy 2016;180:130–41.
[7] Fang T, Lahdelma R. Evaluation of a multiple linear regression model and SARIMA model in forecasting heat demand for district heating system. Appl Energy 2016;179:544–52.
[8] Walter T, Sohn MD. A regression-based approach to estimating retrofit savings using the Building Performance Database. Appl Energy 2016;179:996–1005.
[9] Lam JC, Hui SC, Chan AL. Regression analysis of high-rise fully air-conditioned office buildings. Energy Build 1997;26(2):189–97.
[10] Lam JC, et al. Multiple regression models for energy use in air-conditioned office

buildings in different climates. Energy Convers Manage 2010;51(12):2692–7.
[11] Siddharth V, et al. Automatic generation of energy conservation measures in buildings using genetic algorithms. Energy Build 2011;43(10):2718–26.
[12] Diakaki C, et al. A multi-objective decision model for the improvement of energy efficiency in buildings. Energy 2010;35(12):5483–96.
[13] Guerra Santin O, Itard L, Visscher H. The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock. Energy Build 2009;41(11):1223–32.
[14] Beal CD, Bertone E, Stewart RA. Evaluating the energy and carbon reductions resulting from resource-efficient household stock. Energy Build 2012;55:422–32.
[15] Talebpour MR, et al. Evaluating rain tank pump performance at a micro-component level. Altern Water Supply Syst 2014:25.
[16] Kenway SJ, et al. Water-related energy in households: a model designed to understand the current state and simulate possible measures. Energy Build 2013;58:378–89.
[17] Vieira AS et al. Optimising residential water heating system performance to minimise water-energy penalties; 2016.
[18] Gurung TR, et al. Investigating the financial implications and viability of diversified water supply systems in an urban water supply zone. Water Resour Manage 2016;30(11):4037–51.
[19] Dascalaki E, Santamouris M. On the potential of retrofitting scenarios for offices. Build Environ 2002;37(6):557–67.
[20] Beusker E, Stoy C, Pollalis SN. Estimation model and benchmarks for heating energy consumption of schools and sport facilities in Germany. Build Environ 2012;49:324–35.
[21] Saari A, et al. Financial viability of energy-efficiency measures in a new detached house design in Finland. Appl Energy 2012;92:76–83.
[22] Rysanek AM, Choudhary R. Optimum building energy retrofits under technical and economic uncertainty. Energy Build 2013;57:324–37.
[23] Ardente F, et al. Energy and environmental benefits in public buildings as a result of retrofit actions. Renew Sustain Energy Rev 2011;15(1):460–70.
[24] Kumbaroğlu G, Madlener R. Evaluation of economically optimal retrofit investment options for energy savings in buildings. Energy Build 2012;49:327–34.
[25] Menassa CC. Evaluating sustainabile retrofits in existing buildings under uncertainty. Energy Build 2011;43:3576–83.
[26] Cai B, et al. Multi-source information fusion based fault diagnosis of ground-source heat pump using Bayesian network. Appl Energy 2014;114:1–9.
[27] Yang T, Zhang X. Benchmarking the building energy consumption and solar energy trade-offs of residential neighborhoods on Chongming Eco-Island, China. Appl Energy 2016;180:792–9.
[28] Uusitalo L. Advantages and challenges of Bayesian networks in environmental modelling. Ecol Model 2007;203:312–8.
[29] Beaudequin D, et al. Utility of Bayesian networks in QMRA-based evaluation of risk reduction options for recycled water. Sci Total Environ 2016;541:1393–409.
[30] Heo Y, Choudhary R, Augenbroe GA. Calibration of building energy models for retrofit analysis under uncertainty. Energy Build 2012;47:550–60.
[31] Sterman JD. Business dynamics: systems thinking and modeling for a complex world. United States of America: The McGraw-Hill Companies; 2000.
[32] Ford A. System dynamics and the electric power industry. Syst Dynam Rev 1997;13(1):57–85.
[33] Sahin O, Stewart RA, Porter MG. Water security through scarcity pricing and reverse osmosis: a system dynamics approach. J Clean Prod 2015;88:160–71.
[34] Bertone E et al. Modelling with stakeholders: a systems approach for improved environmental decision making under great uncertainty. In: 8th International congress on environmental modelling & software (iEMSs), 2016, Toulouse, France.
[35] Bertone E et al. Bayesian Network and System thinking modelling to manage water quality related health risks from extreme events. In: The 21st international congress on modelling and simulation (MODSIM), Gold Coast, Australia, 29th November; 2015.
[36] ABS. ABS cat. no. 4660.0 – energy, water and environment management, 2008-09; 2010.
[37] AIHW. Australian hospital statistics 2009–10. Health services series no. 40. Cat. no. HSE 107. Canberra: Australian Institute of Health and Welfare; 2011.
[38] AIHW. How many hospitals are there? [2016 8 November].
[39] DRET. Energy use in the Australian Government's operations. Department of Resources Energy and Tourism; 2013.
[40] Pitt & sherry. Baseline energy consumption and greenhouse gas emissions in commercial buildings in Australia. Published by the Department of Climate Change and Energy Efficiency; 2012.
[41] Government VS. Water consumption and benchmarks. Available from: <https://www2.health.vic.gov.au/hospitals-and-health-services/planning-infrastructure/sustainability/water/water-consumption> [2016 8 November 2016].
[42] McGain F, Kayak E. Sustainable hospitals – response to Victorian climate change. Green paper, 2010, Doctors for the Environment Australia. <http://dea.org.au/images/uploads/submissions/DEA_Vic_GreenPaperSustHosp.pdf>.
[43] Nicholls A, Sharma R, Saha TK. Financial and environmental analysis of rooftop photovoltaic installations with battery storage in Australia. Appl Energy 2015;159:252–64.
[44] Zafirakis D, et al. Modeling of financial incentives for investments in energy storage systems that promote the large-scale integration of wind energy. Appl Energy 2013;105:138–54.
[45] Rogers EM. Diffusion of innovations. Simon and Schuster; 2010.
[46] Marquez L et al. Modeling the adoption of energy efficient retrofits by mid-tier commercial buildings. In: 21st International congress on modelling and simulation, 2015, Gold Coast, Australia.
[47] Kandiah VK, Berglund EZ, Binder AR. Cellular automata modeling framework for urban water reuse planning and management. J Water Resour Plan Manage 2016:04016054.
[48] Chen S, Pollino C. Good practice in Bayesian network modelling. Environ Model Softw 2012;37:134–45.
[49] Bryson JM. What to do when stakeholders matter: stakeholder identification and analysis techniques. Publ Manage Rev 2004;6(1):21–53.
[50] Bertone E, et al. Extreme events, water quality and health: a participatory Bayesian risk assessment tool for managers of reservoirs. J Clean Prod 2016;135:657–67.
[51] Sahin O, et al. Paradigm shift to enhanced water supply planning through augmented grids, scarcity pricing and adaptive factory water: a system dynamics approach. Environ Model Softw 2016;75:348–61.
[52] DIIS. Australian energy update 2016. Canberra, Australia: Department of Industry, Innovation and Science; 2016.
[53] CA. Quarterly update of Australia's national greenhouse gas inventory: December 2015. Commonwealth of Australia 2016; 2016.