Retrofitting Public buildings for Water and Energy Efficiency: Finance Mechanism and Case Study

(Progress Report No. 3 for Project Steering Group)

Research Team

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EXECUTIVE SUMMARY

In Australia, governments occupy over 25% of the commercial building stock with associated water and energy costs estimated to be over $1 billion per year. Building retrofit projects could reduce the spending of the governments in water and energy; however, existing buildings continue to be retrofitted at a very low rate of about 3% per year. Despite some progress, many governments are failing to meet their targets, due to a number of reasons such as unsuitable contracting models and the low priority given to this issue, as well as lack of available funding.

Focusing on the financing side, the main barriers encountered by the stakeholders willing to retrofit are: the high upfront cost and long payback periods, the split incentive issue (i.e. owner paying for an upgrade whose benefits are accrued by the tenants), and in general the difficulty in accessing finance. It is therefore important to identify successful financing schemes for building water and energy retrofits at an international level, and evaluate their potential in the Australian context.

In order to identify the barriers and best international practices, a thorough review of the available literature (including grey literature) was performed. The results were described and discussed in previous progress reports. In order to assess the viability of the selected financial mechanisms in the Australian context, a number of modelling activities were undertaken. First, a Bayesian Network (BN) model was developed in order to estimate the willingness of public buildings to retrofit by considering both technical, numerical variables (e.g. calculated energy/water savings, payback period) and more qualitative parameters (e.g. financial, implementation attractiveness) quantified through experts' consultation. Different initial conditions were considered (e.g. financial/retrofit options); data about the public building stock, including current energy and water efficiency, were collected from a number of sources. At this stage of the research, we have focused mainly on hospitals, as a case study, since they represent the category of public buildings responsible for the highest energy and water use. Following the identification of the best financing schemes (i.e. yielding the highest willingness to retrofit) through the BN, a long-term prediction of the number of completed retrofits, energy, water and carbon savings, was conducted by developing a second holistic model, System Dynamics (SD) model. The model was run with different initial features of the financial scheme (e.g. different initial budget, interest rates, loan duration). All these activities were described in the previous progress report, and partially illustrated here.

Using the current limited available data, the models were run to test a number of case study scenarios by considering different hypothetical hospital sizes, locations, and efficiency. It was noticed how large hospitals in regional areas have a lower attractiveness in absence of financing mechanisms given the higher upfront project and procurement costs. However, assuming a

revolving loan fund is in place, the retrofitting attractiveness sharply increases for both regional and metropolitan hospitals, with larger ones also being more attractive than smaller ones.

Subsequently, the SD model was refined and then used to propose different funding budgets based on hospitals size (and thus expected retrofit costs). Hospitals were divided into 4 size categories and funding amounts optimised to achieve a reasonable amount of retrofitting projects funded and implemented. Preliminary results show, that with a relatively small investment (i.e. $75 million), large savings (over $800 million in ten years) are achievable.

Future work would focus on improving the preliminary models by (1) refining their structure with further experts' consultation and (2) collecting better data, as well as reapplying the model to other building's categories such as schools, and universities buildings.

Contents

1. Introduction

The needs

The built environment accounts for half of the total energy consumption and greenhouse gases emissions in the developed countries, and a fifth of the world's total energy consumption (IEA, 2011). As inefficient energy and water equipment largely contributes to achieving these high levels, buildings represent the most effective target for energy and water conservation (Power and Zulauf, 2011); in fact, it was estimated that 41% of the possible global energy savings potential by 2035 is related to the building sector (IEA, 2012). It has been demonstrated how energy/water savings can be achieved by retrofitting buildings since three decades ago (Goldman et al., 1988), and more recently it was demonstrated how reductions of 30-40% in energy and water consumption are often achievable in buildings (Willis et al., 2011).

A specific building sector where considerable energy and water savings could be achieved is the public building sector (Ardente et al., 2011; Ascione et al., 2015; Chidiac et al., 2011; Mahlia et al., 2011; Xu et al., 2015). For instance, in Australia, governments occupy over 25% of the commercial building stock. The majority of public buildings (e.g., offices, schools, libraries, and hospitals, as well as galleries and museums) are existing stock that were designed and constructed often with insufficient consideration for energy and water efficiency, and the associated life cycle costs. As a consequence, it was estimated that for the State of New South Wales in Australia, up to AUD$99 million in total economic activity could be realised by 2020 with the building energy efficiency market (Ernst and Young, 2010). Retrofit projects could reduce the spending of Australian Governments in water and energy use associated with their building stock, which has been estimated to be over $1 billion per year (ANAO, 2009). Driving an efficiency agenda is particularly important, when also considering that it has been estimated that energy consumption in Australia could increase by up to 5% due to the effects of climate change (Guan, 2012).

A study by the US Department of Energy estimated that the local economic activity generated from energy efficiency investments is more than twice the value of the initial investment (NREL, 1995). However, existing buildings continue to be retrofitted at a very low rate of about 3% per year in both the EU and US (Zhivov, 2013). One of the negative consequences of delaying the refurbishment of water/energy-inefficient public buildings is also the loss of productivity due to a poorer indoor environment, which in the US was estimated to cost as much as US$22.8 billion per year (Milton et al., 2000). Despite some progress, many governments are failing to meet their targets, due to a number of reasons such as unsuitable contracting models and low priority given to this issue (Ryan and Murray-Leach, 2011).

During the first phase of this project, a number of financial and implementation barriers, and international financial best practices for water and energy retrofits, were identified and described

in the Progress Report #1. For a thorough list of barriers and best practices, the reader can refer to such report.

Some barriers

Lack of initial capital investment (Rhoads, 2010) and high upfront cost (USDE, 2012) were identified as being a main limitation since usually, consumers in every sector of the economy emphasise initial costs rather than operating costs in their decision, eventually choosing energy-inefficient systems (Hirst, 1991). The high initial capital investment, the long payback period and the often unclear division of benefits among stakeholders pose limitation to the expansion of the retrofitting market (Kong et al., 2012; Rhoads, 2010). A long payback period is particularly an issue when a split incentive situation is in place and the tenants have a short lease, and thus they would only partially benefit of the retrofit.

It was also concluded that there are a number of other monetary benefits which are typically disregarded: for instance, not only energy and water savings, but also the added value of the property should be considered (Popescu et al., 2012), as well as reduced insurance premiums (Young et al., 2012). Limited data is available to factor in this benefit; nevertheless, a number of studies in the US and Europe confirmed how the market values of the retrofitted buildings increased by 13.5% for green buildings compared to non-green (Pivo and Fisher, 2009) and up to 6.6% for buildings with high energy-efficiency labels (Brounen et al., 2009). Also, the increased property value is an immediate investment return and should be regarded as such by the stakeholders.

The best funding scheme example in Australia is provided by the energy upgrade financing – based Melbourne's "1200 Buildings", which however resulted in limited acceleration of the retrofitting rate, and surveys showed how often the reason of undertaking retrofit was due to necessity (e.g. broken asset), more than seeing an opportunity. Internationally, it seems that the most successful financing mechanism is given by the revolving loan fund (RLF) system. This mechanism, combined with energy savings companies (ESCOs), was successful in particular in several US states, and it seems and ideal option for Australia too, in order to more spontaneously trigger interest in this market and create more job opportunities. However, it was also concluded that, following Germany and UK's examples, a combination of different financing options would be more suitable for the "perfect policy" and water should be clearly included in these considerations, as rarely the water-energy nexus has been taken into consideration.

Building on these findings, Progress Report #2 described how such recommendations were numerically verified for the Australian context. Data was collected from a number of sources, in order to better understand the current public building stock size, geographical distribution, and their energy and water consumptions. Next, a preliminary Bayesian Network model was developed in order to estimate the willingness to retrofit of a building based on the technical (numerically quantifiable) and financial/implementation attractiveness (quantified through experts opinion elicitation) of different retrofit options under different financing scenarios. Finally, a preliminary System Dynamics 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 funding schemes.

This Progress Report adds the description of a number of model refinements undertaken, and the results calculated by the model when applied to a number of case studies.

2. Data collection and analysis for case study

Data for public buildings location, size, and energy consumption was collected from the report prepared by Pitt&Sherry entitled "Baseline Energy Consumption and Greenhouse Gas Emissions in Commercial Buildings in Australia" (pitt&sherry, 2012). In this report, data were collected from several sources (including input from BIS Shrapnel and Exergy Pty Ltd) and statistically analysed and validated. Although they provide data for the 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 by considering that, in Australia, 753 hospitals are public, and the remaining 573 are private (http://www.aihw.gov.au/haag09-10/number-of-hospitals/). Also, data are provided for 2009 and projections to 2020 are also calculated. Thus, through interpolation, we estimated the 2015 energy consumption. Future work will focus on collecting more recent and accurate data.

In Figure 1, it is possible to observe the estimated total annual energy consumption for different categories of buildings. It can be noticed how hospitals accounted 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. TAFE and VET accounted for a total of 2.7 PJ. Given these figures, at this stage of the research the team has, for now, focused on the hospital category only.

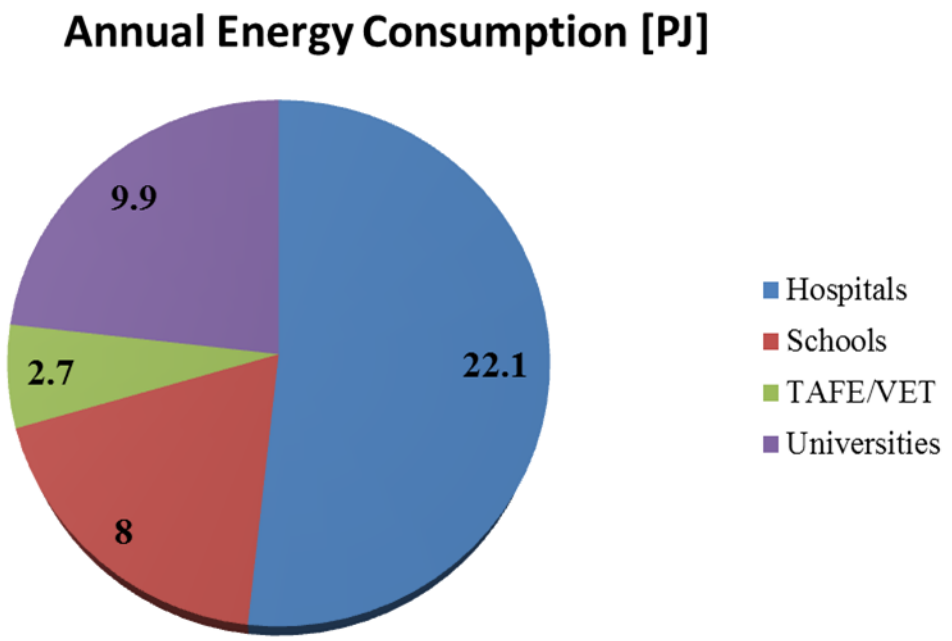

Figure 1 – 2015 annual energy consumption for different building categories [PJ]

In Figure 2, 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.

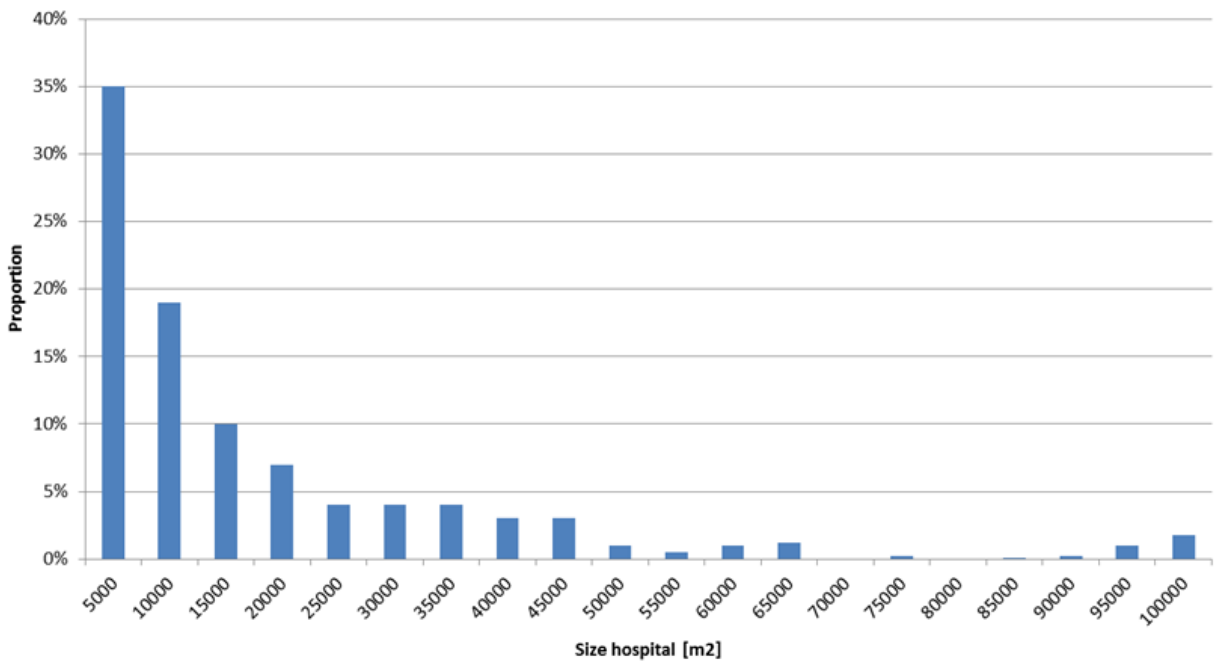

Figure 2 – Australian hospitals grouped by total area

Figure 3 illustrates the energy efficiency of hospitals based on their location. Generally, hospitals in metropolitan areas have better 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 2,000 MJ/m^2, while Hobart has the most energy efficient hospitals, with an average annual consumption of 1,322 MJ/m^2 – 36% less than regional NT. Sydney, Melbourne and Brisbane hospitals have on an average a similar efficiency of about 1,500 MJ/m^2.

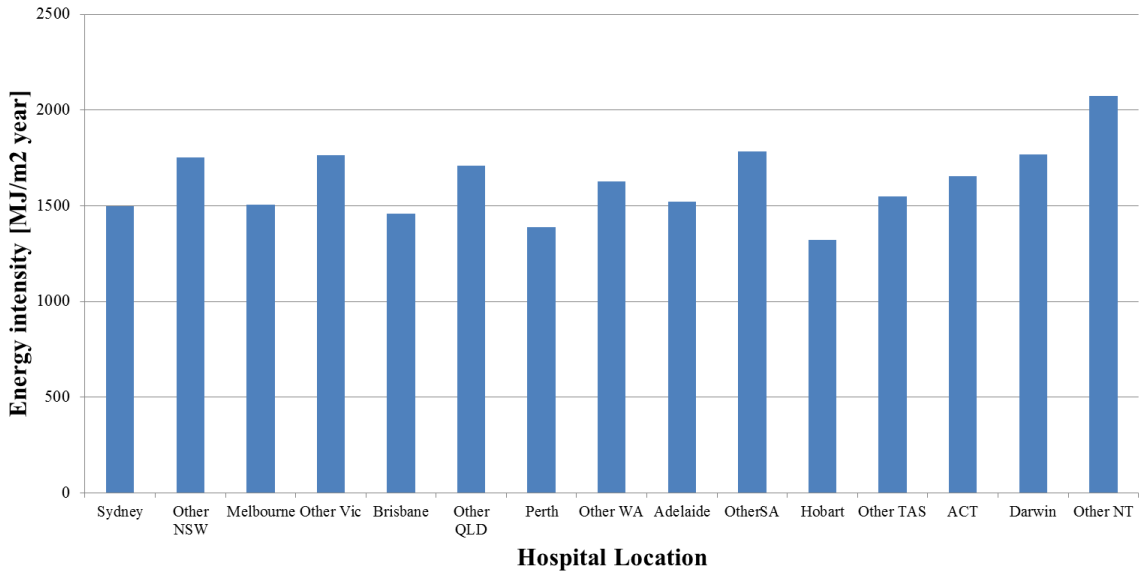

Figure 3 – Australian hospitals grouped by energy intensity

In Figure 4, 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 large amount of total energy consumption in hospitals.

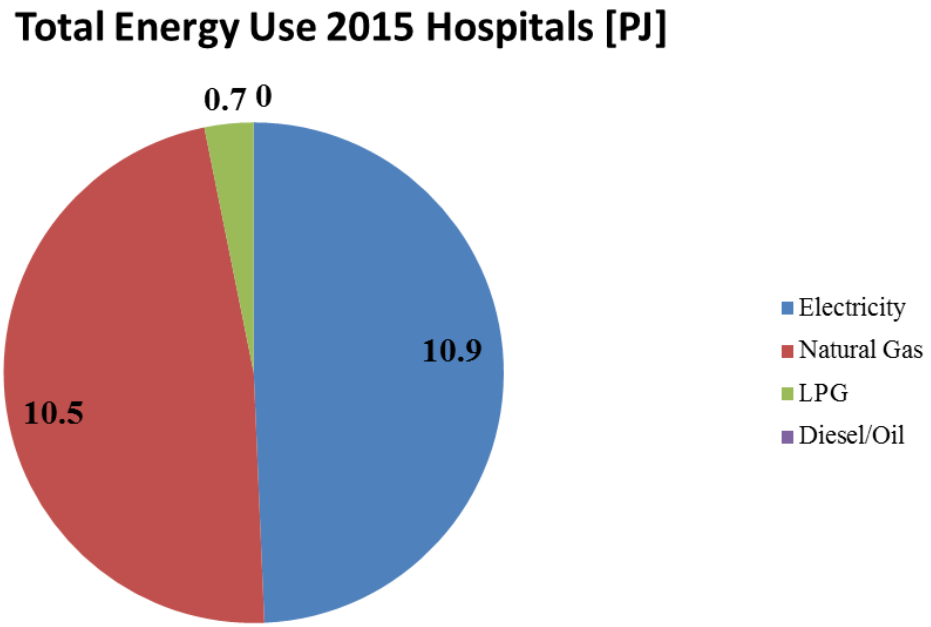

Figure 4 – Australian hospitals: 2015 energy use by type [PJ]

Figures 5 and 6 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 energy use; similarly, space heating is also the main end-use for gas. Interestingly, lightning 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.

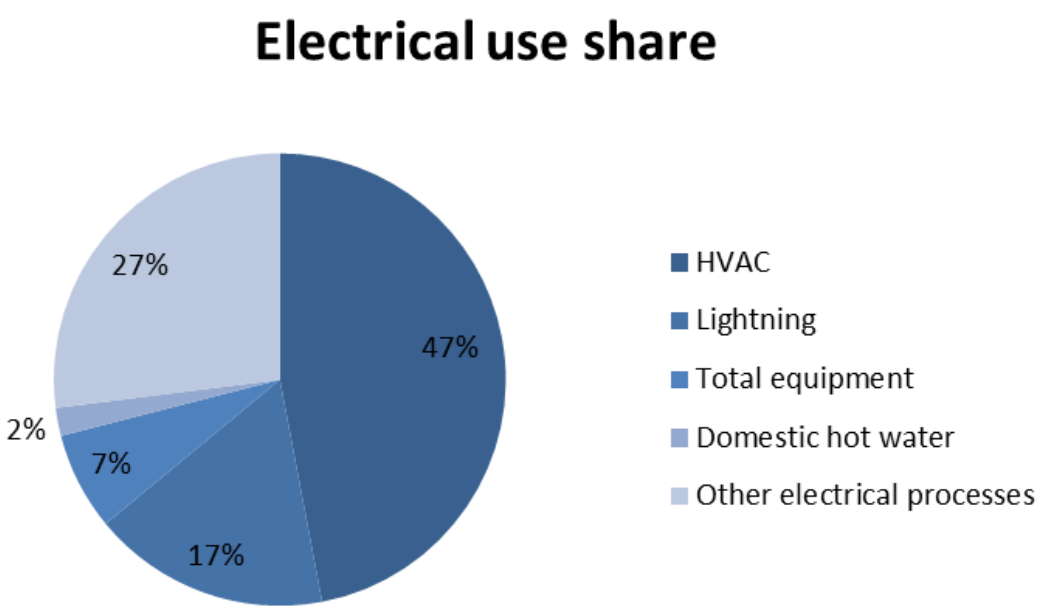

Figure 5 – Electricity end-uses for Australian hospitals, 2015

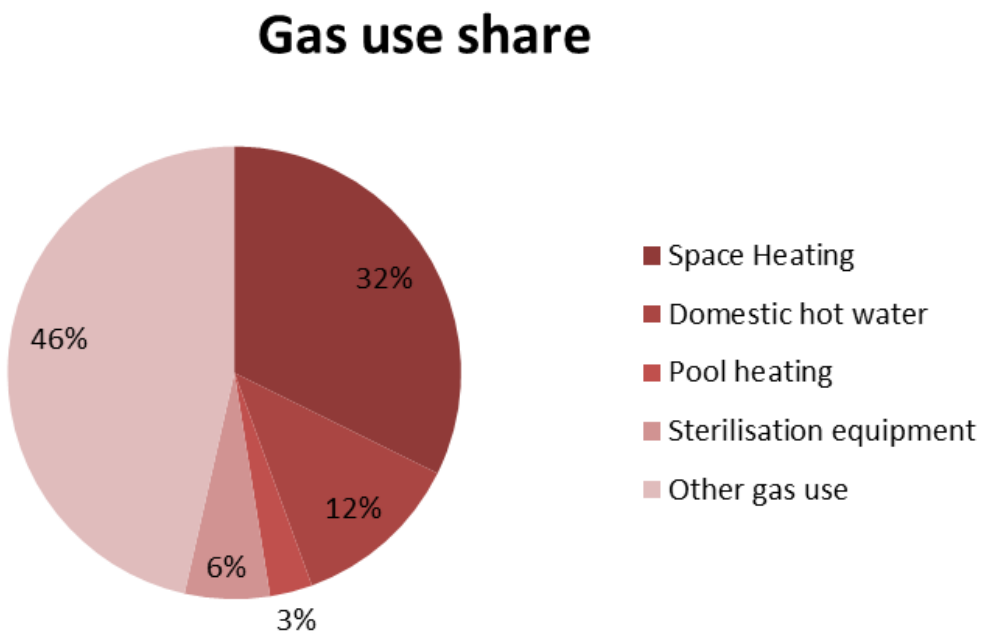

Figure 6 – Gas end-uses for Australian hospitals, 2015

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 (https://www2.health.vic.gov.au/hospitals-and-health-services/planning-infrastructure/sustainability/water/water-consumption). Similarly to energy efficiency, it seems that metropolitan hospitals, despite an high variance in the results, are 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. It can be noticed also a considerable decrease in water consumption (up to 30%) in the last 10 years. Finally, from a number of different sources it was retrieved that the end-use accounting for the highest water use in public buildings is toilets (up to 50%), while taps, showers and toilets together account for up to 80% of the water use (http://dea.org.au/images/uploads/submissions/DEA_Vic_GreenPaperSustHosp.pdf).

3. Bayesian Network model development

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

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

Modelling such variable is a difficult task since the willingness to retrofit would be dependent not only on numerically quantifiable technical aspects (e.g. water/energy savings, payback period), but also contextual factors such as available financing mechanisms, or location of the buildings which can affect its attractiveness for retrofitting companies. 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, the research team decided to develop a BN as such type of model would satisfy all the modelling requirements and overcome the difficulties herein described.

BN models are a powerful tool for risk assessment and management (Fenton and Neil, 2008) especially in interdisciplinary, environmental applications. Their value has been acknowledged in different fields including artificial intelligence (Darwiche, 2009) and probability calculus (Conrady and Jouffe, 2015) due to a number of benefits they provide.

BNs are a type of statistical, probabilistic graphical model; specifically, they are a form of directed acyclic graph, where variables (called nodes) are connected to each other through causal

links. Each node has a number of states (e.g. high/low); each of the states is assigned a conditional probability, which can be derived from different sources (e.g. empirical data, experts' inputs, or outputs of other models). All the required conditional probabilities can be filled through the use of conditional probability tables (CPTs). There is one CPT for each node. "Conditional Probability" means the probability of a child node being in a certain state is conditional upon the influences of its parent nodes. The BN can efficiently express the joint probability distribution of the variables, and when new information is added to the model, the BN is immediately updated to reflect the response of the nodes to the new added knowledge. New information is entered into the BN by substituting the a priori belief with observations (hard or soft evidence) or scenarios values for a number of nodes (Chen and Pollino, 2012). This mechanism of computing the posterior distribution of a variable when new knowledge is added is called probabilistic inference. Basically, a BN is a means of automatically applying 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.

A BN can provide a number of advantages compared to other statistical or process-based models. First, due to its graphical nature, interactions between variables are clearly displayed and users can easily interrogate the reasoning behind the model outputs unlike other "black-box" approaches such as Artificial Neural Networks (ANN) (Chen and Pollino, 2012). However, probably the most important feature of a BN is the ability to integrate several different types of data (numerical and categorical; qualitative and quantitative; empirical data and experts' judgments) and also explicitly deal with uncertainty (Uusitalo, 2007) through the use of probability distributions. These two main advantages make BN an ideal candidate model for a highly uncertain and multifaceted system such as the one of this study (i.e. numerically simulating the water and energy use reductions for a number of retrofit options, as well as qualitatively assess the financial attractiveness of those retrofits, given limited, coarse data available). Additionally, the model simulation is typically very fast compared to some process-based models (Uusitalo, 2007), given the conditional independence attribute of the nodes, implying that the state of a node is conditional on the state of its parents nodes only thus simplifying and expediting the computational process and inferential reasoning (Beaudequin et al., 2016).

Figure 7 illustrates the current structure of the preliminary BN model developed for hospitals. The model was developed using the software Netica 5.18 32bit from Norsys Software Corp. The left-hand side of the model is where all the numerical calculations were performed. Predicted water savings for tap aerators (estimated from data for commercial products available online, and assumptions on the number of taps given the hospital area) are calculated through the light blue variables. The related energy savings are calculated through the dark orange variables. The same path is followed by the considered energy-efficient retrofits, namely LED lights and Solar PV. For solar PV, extra calculations are necessary, based on roof area (assumed proportional to

the total hospital area) and location (which determines the available annual solar radiation). These calculations are performed through the yellow variables part of the BN. All these equations are converted to probability distributions through a Monte Carlo approach. For instance, based on the distribution of the hospital size of Figure 2, a number (100,000) of simulations are run where a different random hospital area value 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 Figure 2, the resulting probability distribution of the savings will be realistic and reflecting the hospitals' characteristics estimated from the available data.

The final consideration of these technical calculations is the payback period. Based on the calculated water and energy savings (in case of solar panels, we referred to "purchased" energy savings, as the solar panels themselves 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 retrieved online, the payback period and thus the technical attractiveness was calculated.

The right hand-side of the BN model represents instead the more qualitative part, where financial and implementation attractiveness was estimated. Firstly, based on the review summarised in previous progress reports, a number of variables which, according to the research team, can considerably affect the attractiveness of a retrofit project, were listed and logically connected together. Hence, for instance, each finance mechanism will affect the upfront cost, the interest rates, and loan duration (which potentially should match the payback period). 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.

The importance of each factor was weighed based on literature, the research team judgement, and industry partners' opinion (in particular, Mr. Evan Blair). The model was then refined accordingly and conditional probability tables for these nodes created based on the simulations results and the weight of different input factors provided by the consulted industry experts.

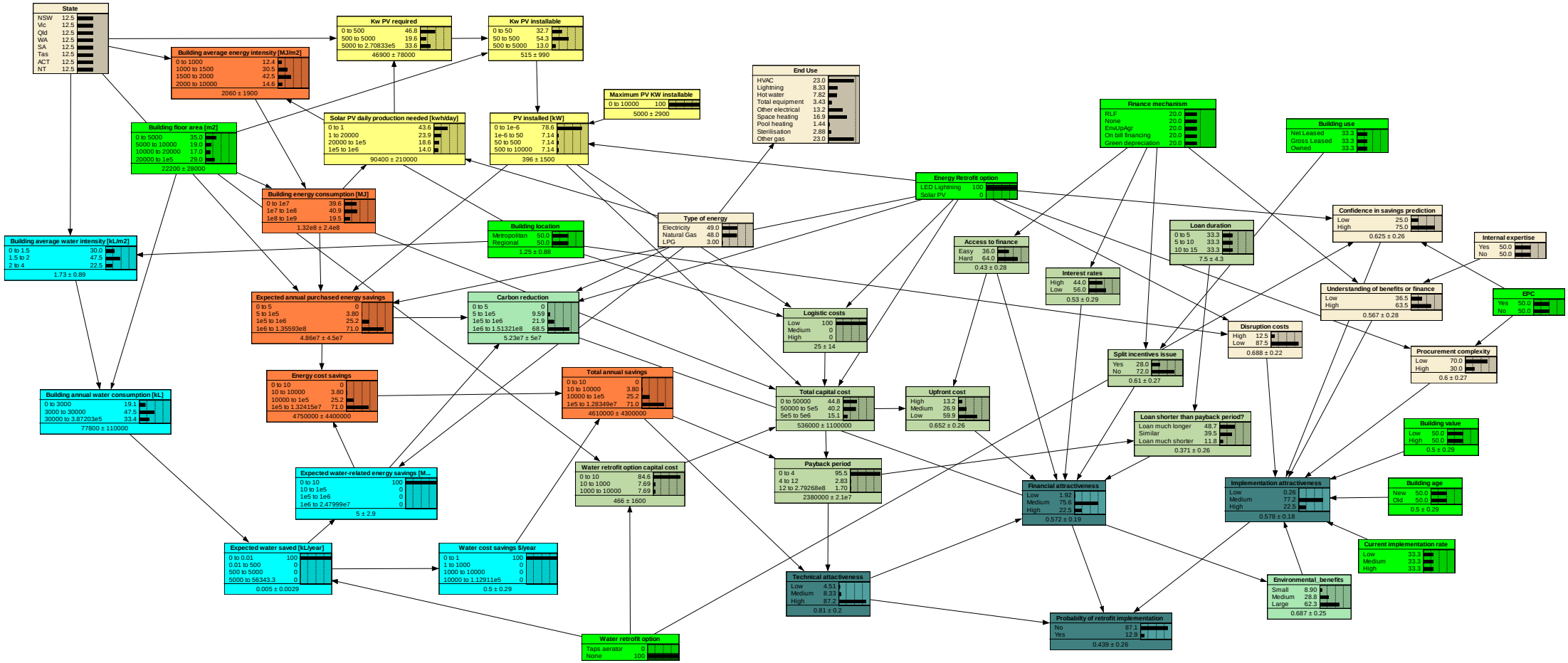

Figure 7 – BN model for hospital's energy and water retrofitting project

4. Bayesian Network modelling results

In Figure 8, the willingness to retrofit calculated with the BN is reported for a number of financial option scenarios, for two retrofit options: the installation of solar panels (blue bars), and a combination of LED lights and taps aerators (red bars).

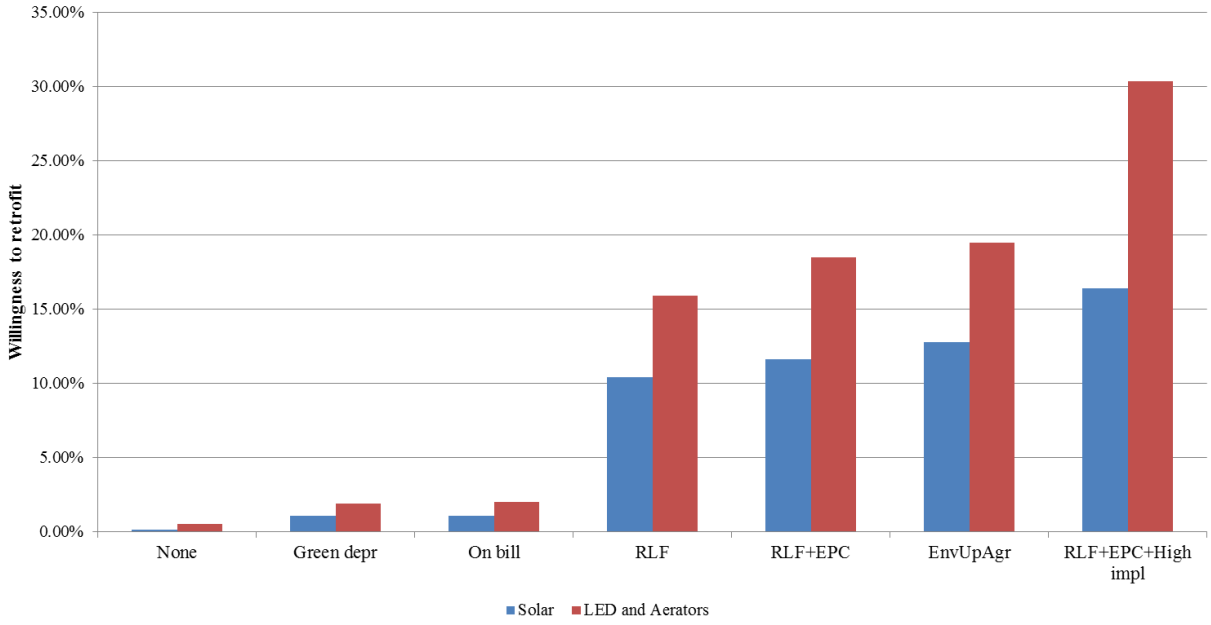

Figure 8 – Willingness to retrofit based on different financial options (output of BN analysis)

Expectedly, if no particular financing mechanism is in place which can support the stakeholder in overcoming financial barriers, the willingness to retrofit is extremely low despite a potentially high technical attractiveness. If a green depreciation of on-bill financing scheme is available, helping reducing the high upfront costs, the willingness to retrofit increases to about 2%. However, RLF and Environmental Upgrade Agreements are the two schemes leading to the highest values. These modelling results are in line with the results of the review of the previous progress reports. In particular, if a RLF is combined with a high current implementation rate and presence of energy savings performance contractors which take much of the risk associated with predicted savings and overcome the limitation of a potential lack of knowledge of the stakeholders, then the willingness increase to 16% for solar 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 (i.e. LED lights and tap aerators have limited cost and high savings, making the payback period quite short and also increasing the financial attractiveness).

Future work will focus on refining the model by integrating comments and judgements of other industry partners, as well as more reliable data. The model will be also adapted to other categories of public buildings, such as schools and universities. The willingness to retrofit is a

useful relative indicator to compare different scenarios, and it is a critical input for the second developed model, the System Dynamics (SD) model.

5. System Dynamics model development

The second part of the modelling framework seeks to, after having established the best financial mechanism to be a RLF, calculate how many hospitals can in fact retrofit, based on the RLF initial capacity, interest rates, and duration of the conceded loan. For each of the scenarios considered, the following outputs can be 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.

SD is a set of conceptual tools allowing for the understanding of the structure and dynamics of complex systems; SD is also a rigorous modelling method which enables users to build formal computer simulations of such complex systems, and use them to design improved policies and decision-making (Sterman, 2000). SD is a powerful methodology and computer simulation modelling approach, which was originally rooted in the management and engineering sciences (Forrester, 1961). However, the SD approach gradually has evolved and started to be employed in other fields to simulate complex systems behaviour such as in the social, economic, physical, chemical, biological, and ecological systems (Fiddaman, 1997; Ford, 1999; Sahin and Mohamed, 2013; Zhang, 2008).

SD allows for addressing research aspects that BN cannot deal with, such as including time as a variable (as well as feedback loops). The integration of BN and SD, in order to merge the benefits and overcome the limitations of the two models, has been previously performed by the Griffith research team in other projects (Bertone et al., 2016a; Bertone et al., 2016b).

In Figure 9, the structure of the SD model is illustrated. The software used for its development was Vensim DSS 6.3 Double Precision, from the Ventana Simulation Environment. Although the model structure is quite complicated, through Vensim it is possible to create simple graphical interfaces with charts representing outputs and sliders representing input conditions, which the user can modify and in order to instantaneously evaluate the evolution of the output variables of interest.

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 “willingness to retrofit”, which is in turn dynamically changing according to the value of other parameters of the SD model, such as interest rates, loan duration, and current implementation rate (the latter represented by the variable “ hospitals retrofitted”). 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 Figure 9. Hence, two separate SD models were developed: one considering the RLF scheme being set up for solar PV retrofits only, and another one for LED lights + tap aerators retrofit scenario.

Based on these considerations, 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 and by adding a random number to account for variability and uncertainty). However, the RLF budget will allow 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 loan repayments (+interest rates), especially in the first years, the funding budget will soon deplete as the loan repayments will slowly increase in number, but be very limited at the very start. Hence, only a portion of the interested hospitals will have a loan approved and will retrofit. Following the approval, a certain amount of time to undertake the retrofit is considered by the model, before the retrofit is completed and water/energy consumption reduced. Another temporal factor considered by the SD model is the average life of a retrofit. Any hospital reaching the end of the life of the installed retrofit will go back into the pool of "hospitals to be retrofitted".

Finally, the bottom part of the model calculates, based on both BN and upper SD model outputs, the savings achieved both in terms of monetary costs and carbon emission reductions.

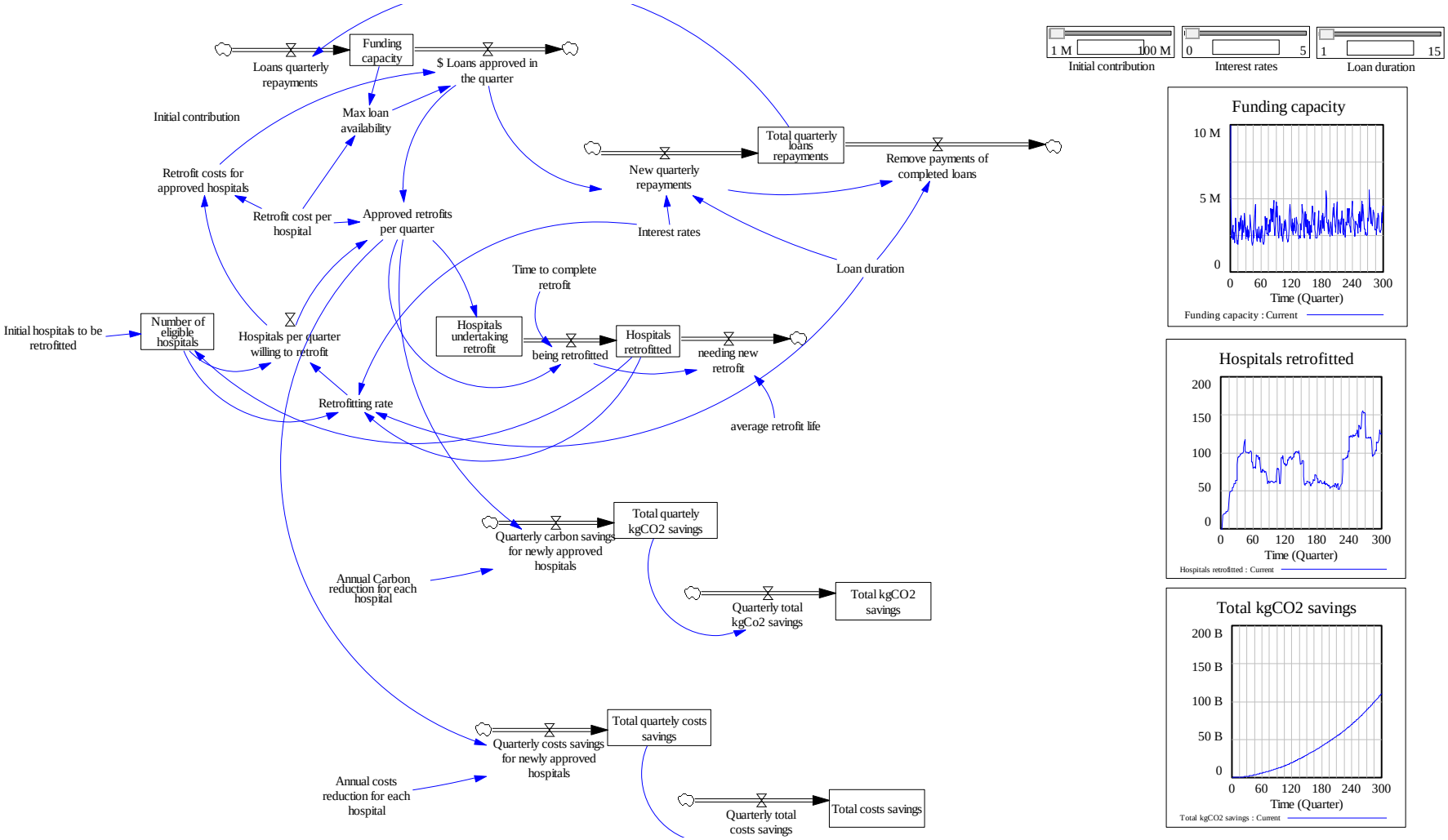

Figure 9 – SD model for Australian hospitals, 201

6. System Dynamics modelling results

Figure 10 shows the number of hospitals that would retrofit with solar panels over time, given certain characteristics of the RLF. The base case scenario has a RLF with: (1) An initial funding budget of $10 million; (2) interest rates of 2%; inflation is not accounted for in the modelling but this scenario wants to represent a condition of "low" interest rates; and (3) an average loan duration of 10 years. Three alternative scenarios are run where the RLF features are changed. In the base case scenario, despite a slow pick up (due to a quick depletion of the funding budget before the repayments can refill it), a peak in retrofitted hospitals of almost 60 is reached after about 10 years, i.e. when some hospitals will start needing a new retrofit.

In order to increase the initial loan approval rate, three different options can be considered. It can be seen that, by doubling the interest rates to 4%, which would lead to an increase in the repayments amount, would actually not produce any considerable change in trend since, as per BN results, an increase in interest rates would decrease the attractiveness and thus the willingness to retrofit. Decreasing the loan duration, instead, had a lower weight in the BN and thus it would in fact lead to an increase in the retrofitting rate. Nevertheless, the optimal solution, but also the most costly, would be to increase the initial funding capacity, as this would not affect the attractiveness of the project. Doubling the initial funding amount to $20 million would lead to 100 hospitals to retrofit in the first 10 years. Despite not being staggering numbers, 20$ million is a relatively small investment; also this figures related to a specific retrofit option only (solar) and a specific category of public buildings only (hospitals).

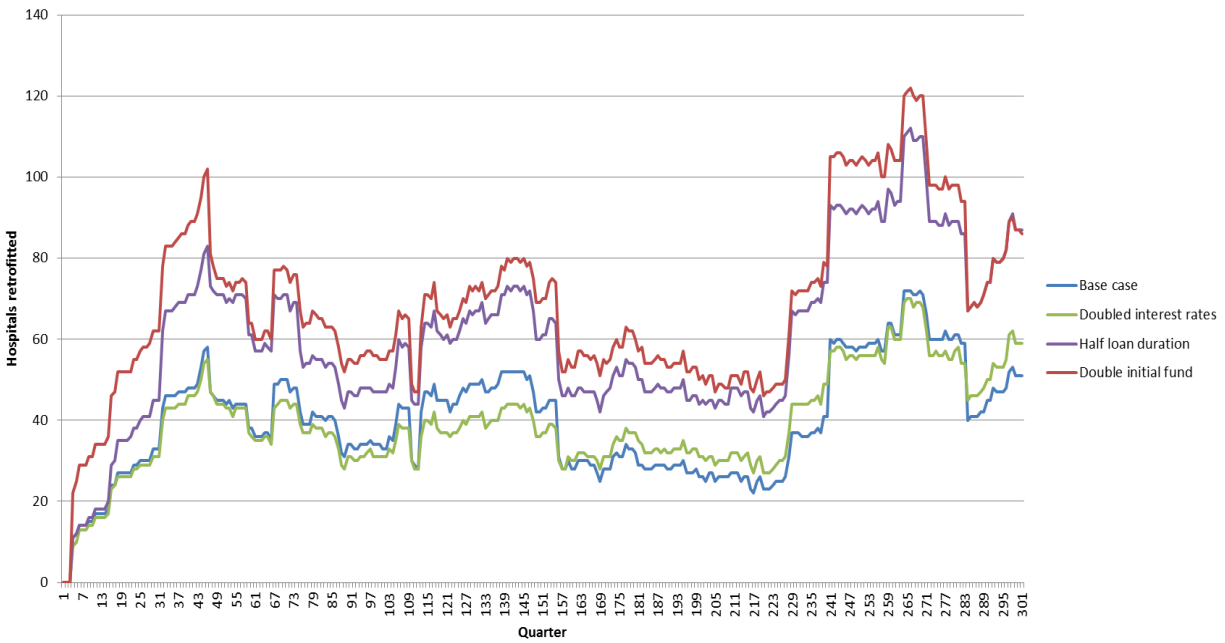

Figure 10 – Hospitals retrofitted with solar panels (SD simulation results)

Figure 11, instead, shows the same outputs estimated for the LED lights + tap aerators option. In this case, the number of hospitals which would retrofit, under the same optimised scenario for the RLF, would be 150; 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.

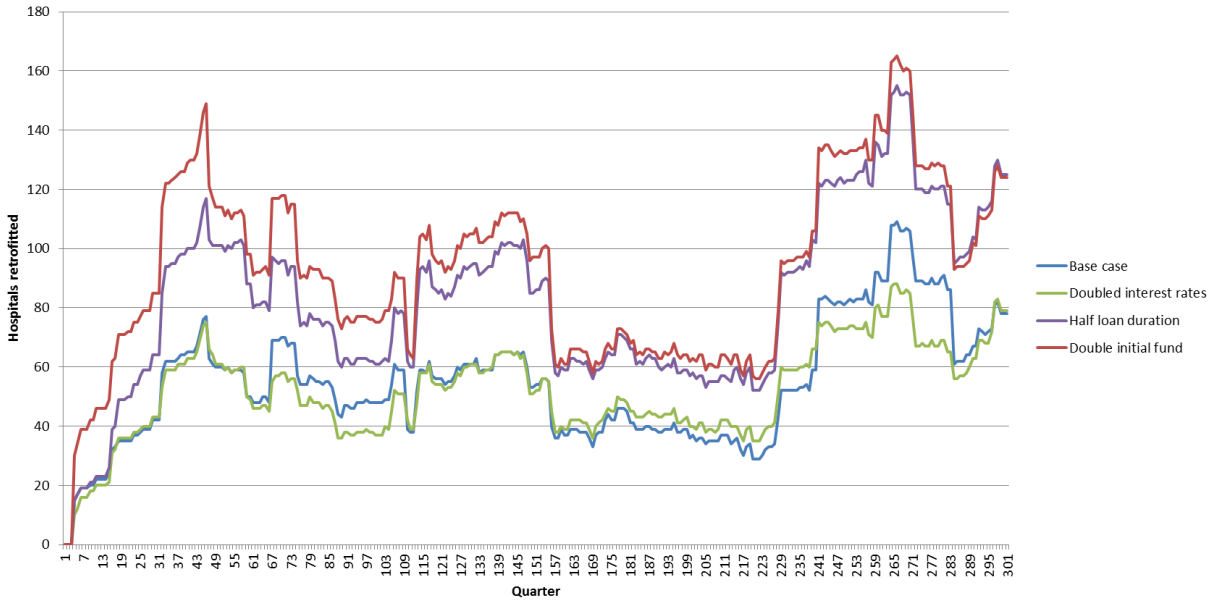

Figure 11 – Hospitals retrofitted with Led lights and tap aerators (SD simulation results)

Figure 12 illustrates, over a 20 year timeframe, what monetary savings would be achieved from avoided purchased energy considering the four scenarios of Figure 11, for solar retrofitting. By optimising the features of the loan, the savings would increase from $324 million to over $674 million, equivalent to $33.7 million per year, given a RLF one-off investment of $20 million.

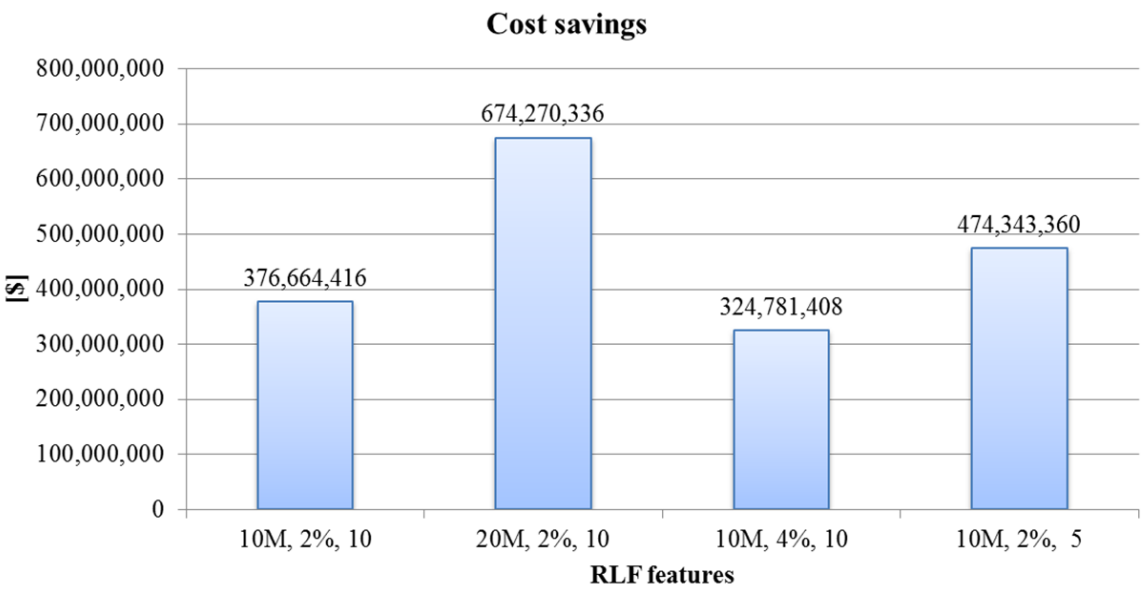

Figure 12 – Predicted cost savings from solar panels retrofits based on SD simulations for RLF

This must be coupled with the expected reduction in greenhouse gas (GHG) emissions of up to over 4 Mton CO_2-e summarised in Figure 14.

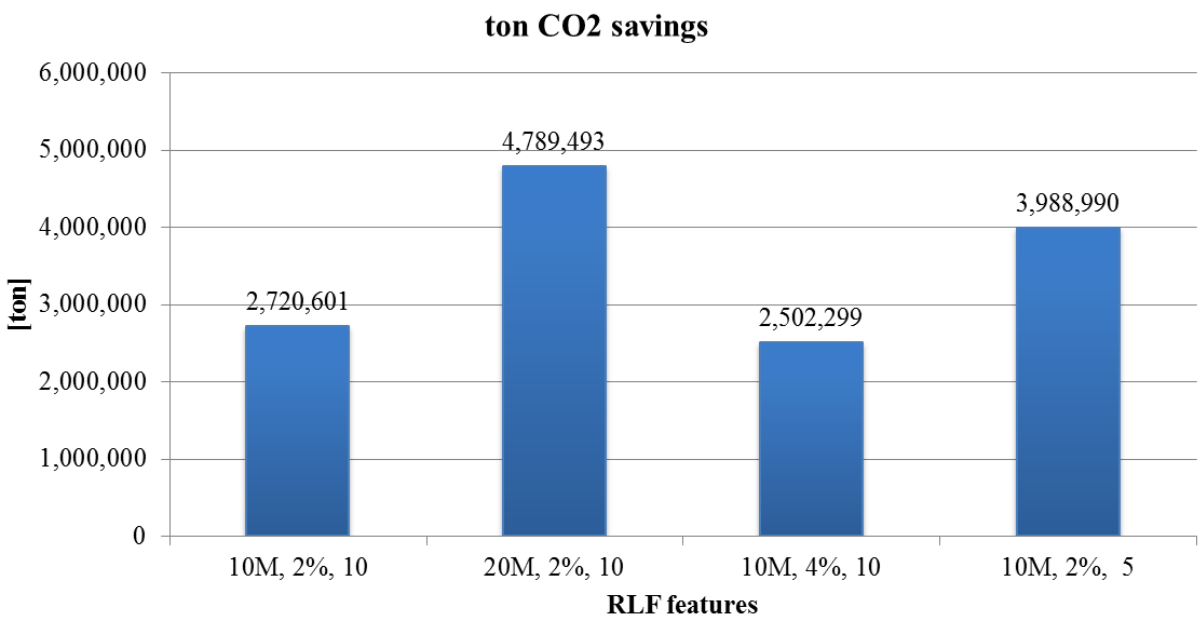

Figure 13 – Predicted carbon savings from solar panels retrofits based on SD simulations for RLF

Similarly, Figures 14 and 15 summarise the same outputs for the LED lights + taps aerators retrofit scenario. In this case the monetary savings would be the result of water and energy consumption reduction. Considering these conditions, savings of over $1 billion and 12 Mton CO_2-e could be achieved over a 20-year period.

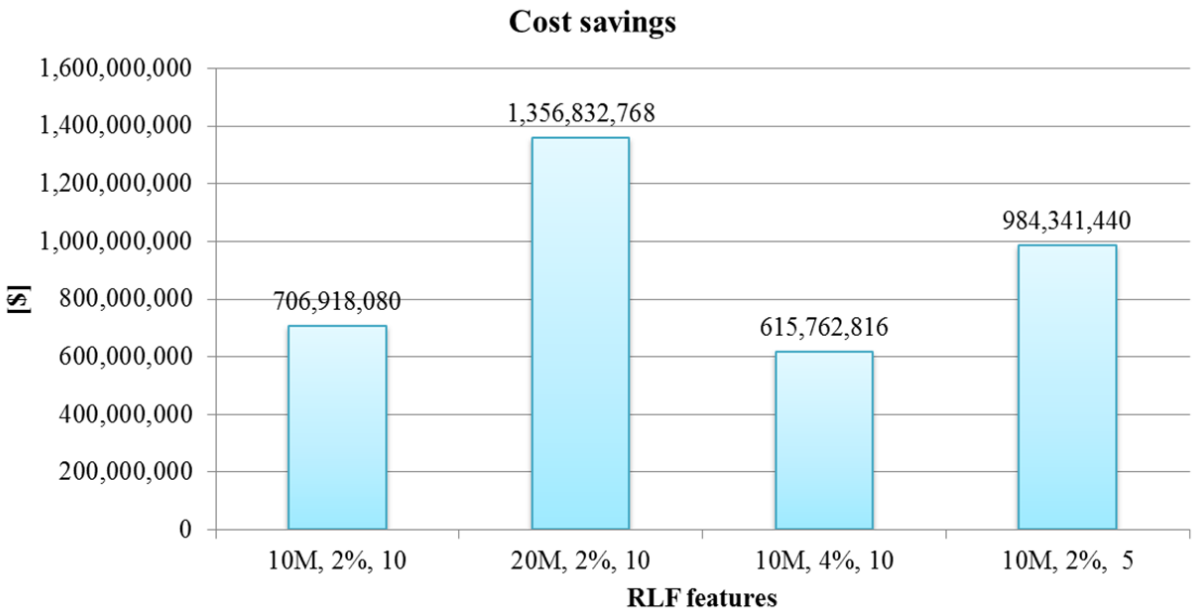

Figure 14 – Predicted cost savings from LED lights and tap aerators retrofits based on SD simulations for RLF

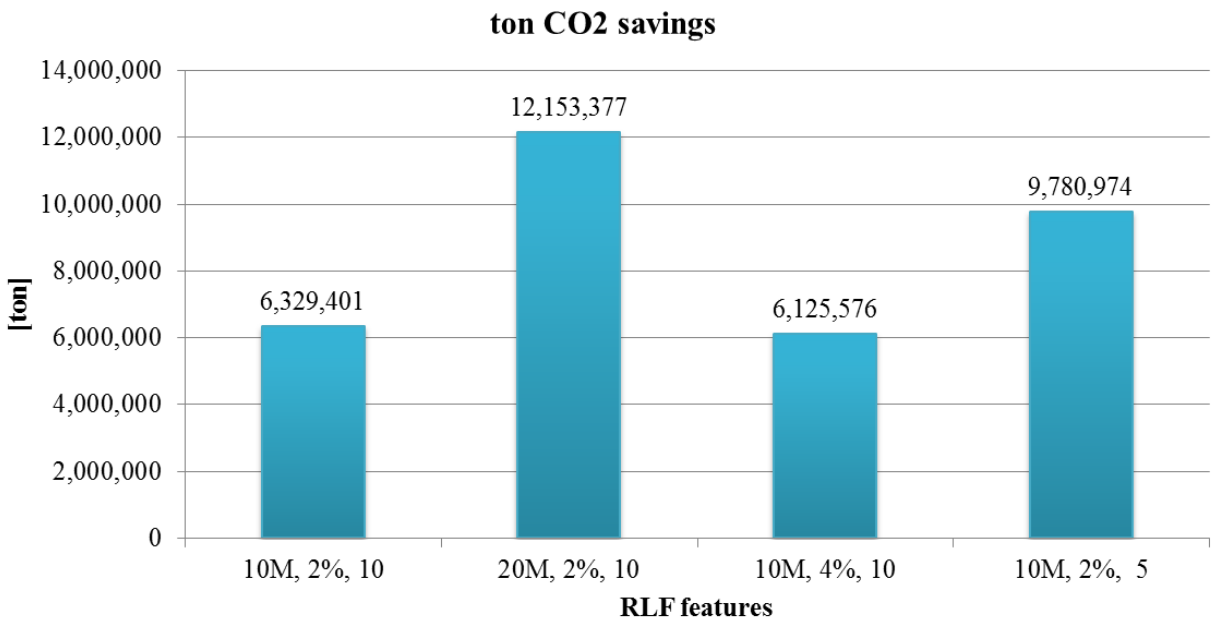

Figure 15 – Predicted carbon savings from LED lights and tap aerators retrofits based on SD simulations for RLF

7. System Dynamics model refinement

Following the PSG meeting in Brisbane on the 5th of August 2016 and further expert consultation, the system dynamics model has been edited and refined. The structure of the model regarding the funding capacity, loans approved and repayments has been merged and simplified. An "available/deployed workforce" part of the model has been added. Given a number of people needed for a certain retrofit project, this part of the model wants to show how much employment creation, if any, will be generated from an increased number of retrofitting projects. The estimation of workforce necessary for a certain retrofit project will be refined following industry experts consultation.

In addition, the variable "hospital size" has been created. The model can now be run considering 4 different hospital size categories, namely:

1. Small (< 5,000 m^2): 464 hospitals;
2. Small-to-medium (between 5,000 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

Such division allows the model to account for different average project costs (proportional to the size) and therefore to assess the potential of arranging different funding amounts/mechanisms for different hospitals size. On the other hand, given the currently available data, there is no link between hospital size and location; thus, it is not possible to know how many e.g. small hospitals are in regional Queensland, or how many large ones are located in Tasmania. This means that, at this stage, case-studies incorporating the location can be run with the BN model only, which assesses the willingness to retrofit based on, among others, factors such as accessibility and implementation attractiveness (i.e. linked to the location). The SD model instead would be deployed for national level assessments of best funding mechanism features / expected savings. Future work will focus on collecting better data for a full exploitation of such models' capabilities.

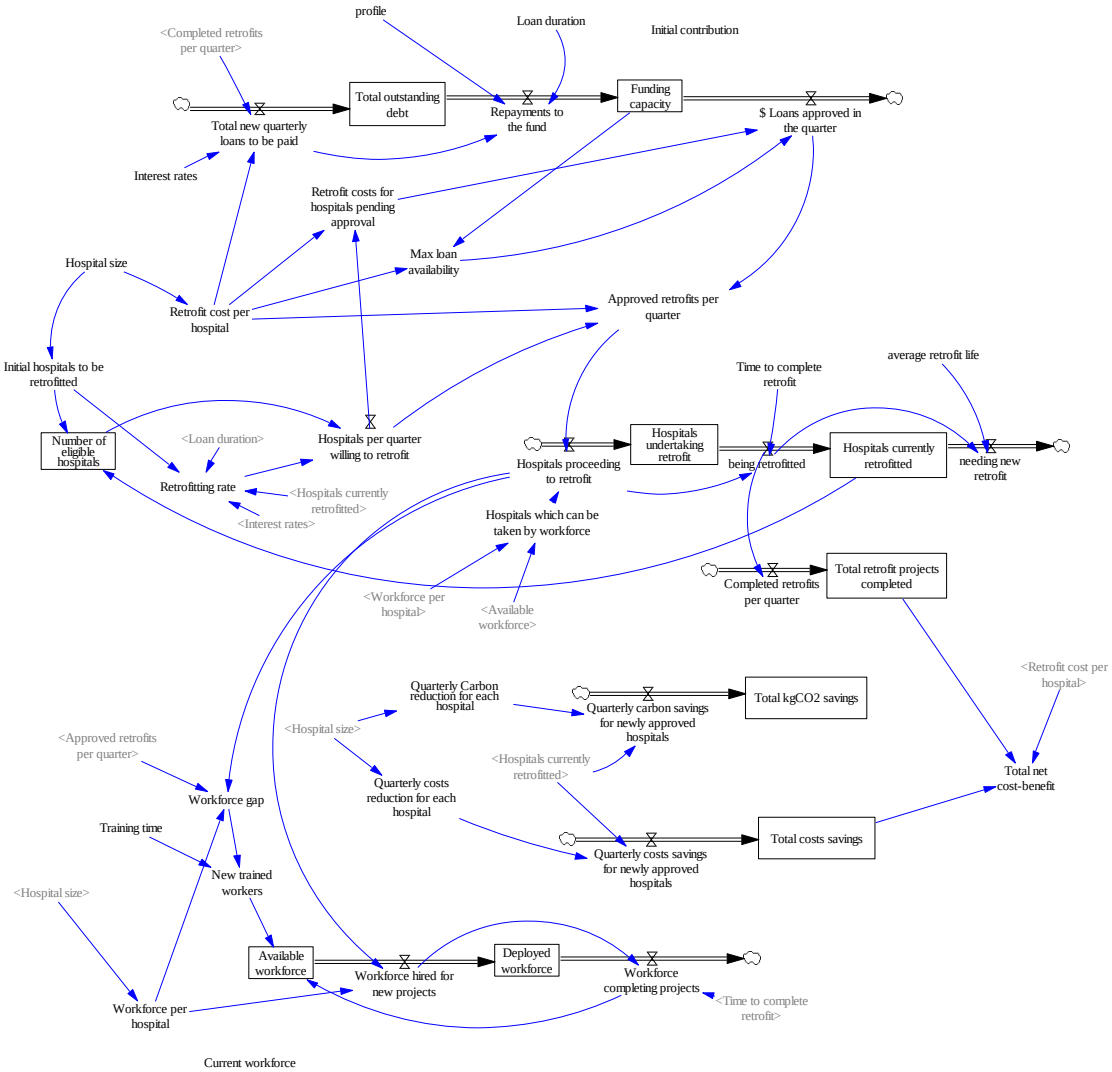

Figure 16 – Refined SD model

8. Case studies

The willingness to retrofit of a number of different hospitals was modelled through the BN. As, at this stage of the research, no data for a specific hospital was available, the model was run considering different characteristics of a hypothetical hospital (e.g. size, energy/water consumption, location).

Case study 1: Small, inefficient hospital in regional WA

In this case study, we have analised a hospital assuming such data:

- Size: 4500 m^2
- Water consumption: 2.2 kL/m^2

- Energy consumption: 2200 MJ/m^2
- Location: regional Western Australia

The BN model estimated that the willingness to retrofit such hospital with solar panels, without any particular financing mechanism in place, would be only 0.54%; this is because, despite the great potential for WA for solar, regional areas would be quite inaccessible and generating little interest also given the (small) size of the project, when considering procurement costs. However, setting up a revolving loan fund, accessible by energy performance contractors, would increase such willingness to 16.2%. By comparison, the installation of LED lights instead would lead to a willingness to retrofit of 21.6%. Adding the installation of tap aerators would further increase such willingness to 27%.

From Table 1 it can be noticed how such outputs are different when a larger hospital (30,000 m^2), with same water and energy efficiency, is considered. It can be seen how, without any funding mechanism in place, the willingness is even lower (0.38%) than for the smaller hospital. This is mainly driven by the higher upfront cost, which cannot be avoided due to the lack of financial incentives to spread it over time. However, once this problem is overcome (i.e., having a revolving loan fund in place), then the willingness to retrofit is generally higher than for the small hospital, generally due to the potential for greater energy/water consumption reductions and thus greater savings.

Table 1. Willingness to retrofit – comparison between two hospital's sizes; Case study 1

Scenario	Hospital size: 4500 m^2	Hospital size: 30000 m^2
Solar, no financial scheme	0.54%	0.38%
Solar, RLF	16.2%	19.5%
LED, RLF	21.6%	29.7%
LED+aerators, RLF	27%	30.7%

Case study 2: Large, average efficiency hospital in Sydney

In this second case study, the model was run considering a hospital with the following characteristics:

- Size: 25000 m^2
- Water consumption: 1.5 kL/m^2
- Energy consumption: 1500 MJ/m^2

- Location: Sydney (i.e. metropolitan NSW)

Similarly to Case study #1, a hospital of a different size (smaller in this case), but with identical features in terms of energy and water efficiency, was considered.

It can be noticed, compared to the regional WA case, how in absence of any financial scheme, the willingness to retrofit is higher, on an average. Being in Sydney, there is more availability of experts/companies willing to do the work, and lower procurement costs. However, also in this case, a revolving loan fund would enhance such probability of retrofitting, with the larger hospital having usually higher percentages than the smaller one, although such numbers are not proportional among the different scenarios; thus indicating the complexity and nonlinearity of such system, which is captured by the BN.

Table 2. Willingness to retrofit – comparison between two hospital's sizes; Case study 2

Scenario	Hospital size: 25000 m^2	Hospital size: 6000 m^2
Solar, no financial scheme	0.60%	0.82%
Solar, RLF	20.2%	18.4%
LED, RLF	30.8%	19.7%
LED+aerators, RLF	31.9%	27.8%

9. Long-term generalised case-study

Although being very preliminary considerations at this stage, we also used the SD model to optimise the funding capacity given different hospitals sizes.

Smaller hospitals (Category 1) would have lower project costs and thus a small funding capacity could be enough 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 10$ was enough to get 161 small hospitals retrofitted after 24 quarters, however the same amount would lead to only 13 Category #4 hospitals retrofitted after 20 quarters. The following table summarises our preliminary model outputs. In this case, we consider as a retrofitting option, a combination of LED lights and taps aerators. The common inputs are: a low (2%) interest rate, and a loan duration of 10 years.

Table 3 – Predicted retrofitting projects given different funding pools

Hospital size category	1	2	3	4	Total
Funding amount proposed	$10M	$5M	$10M	$50M	$75M

Number of retrofitted hospitals after 5 years	151	71	34	128	384
Number as a % of the category's total	32%	28%	26%	27%	29%
Cost savings after 10 years	$140.5M	$140.3M	$98.35M	$431.5M	$810.65M
MtonCO2 emission savings after 10 years	930.3	606.2	425.8	1.427	3389.3

As a confirmation of a number of findings previously reported, it is clear how there is a huge return of investment by incentivising buildings retrofits. With a total investment of $75 million, spread differently across the four size categories, monetary savings in energy and water use of more than ten times such investment can be achieved in ten years, and more than 3,000 Mton of emitted CO2 could be avoided. This is also limited by the workforce availability constraint (which will be further explored and refined); the increased demand for retrofitting projects would lead to more specialised companies providing such services and thus those numbers could potentially further increase.

10. Conclusions

A modelling framework has been developed in order to numerically quantify the attractiveness and potential benefits of a number of financing options previously identified in the literature review. Data were collected from available sources and, at this stage, the research team has focused on hospitals as they are responsible for the highest consumption of energy among different public buildings' categories.

Firstly, a BN model was developed to evaluate and rank different financing mechanisms and contextual factors based on how they would affect the willingness to retrofit of a given hospital. Energy upgrade agreements and RLF resulted to be the most attractive options, which is in line with the findings of the review. Secondly, a SD model was developed to quantify the monetary and carbon emission savings resulting from a RLF being in place to finance (1) solar panels retrofits and (2) LED lights and taps aerators retrofits.

A number of case studies were run; given the current limited available data, the models were run assuming a number of hypothetical hospital size, location, and efficiency. It was noticed how large hospitals in regional areas have a lower attractiveness in absence of financing mechanisms given the higher upfront project and procurement costs. However, given a revolving loan fund is in place, the attractiveness sharply increases for both regional and metropolitan hospitals, with larger ones also being more attractive than smaller ones.

The SD model was also used to propose different funding budgets for different hospitals sizes. Hospitals were divided into 4 size categories and funding amounts optimised to achieve a reasonable amount of retrofitting project funded and implemented. Preliminary results show, once more, how with a relatively small investment (i.e. $75 million), large savings (over $800 million in ten years) are achievable.

It must be emphasised that this is a preliminary model and future work over the next months will seek to improve it by:

- Refining the BN with further input from other industry collaborators; for instance, to consider the option of incentives for less attractive regional retrofits. Such options will be partially explored during the next project meeting in Perth at the end of September.

- Improving the SD by considering alternative funding opportunities especially for small (e.g. < $250,000) projects, and the involvement of private banks.

- Considering retrofit alternatives (e.g. building tuning) and estimating the "cost of waiting"; considering the integration of different retrofit alternatives in the same financial model

- Adapting the models to other public buildings categories.

Nevertheless, the main goal will be to collect more accurate and comprehensive data, as this represents the foundation for a more accurate and reliable model.

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