Synthesis and experimental validation of a new probabilistic strategy to minimize heat transfers used in conditioning of dry air in buildings with fluctuating ambient and room occupancy

by

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[1] Chu, J.Y.G., Davey, K.R., O'Neill, B.K., 2016. A preliminary simulation of strategies for cooling of air in buildings with unplanned traffic flow during summer. In: Proc. APCChE 2015 Congress (Asia-Pacific Century – Growth & Innovation) incorporating CHEMECA 2015, Sept. 27-Oct. 1, Melbourne, Australia. Paper 3135128, pp. 396-405. ISBN: 9781922107473

Chu, J.Y.G., Davey, K.R., 2015. A probabilistic *Fr 13* simulation of strategies for cooling of air in buildings with unplanned traffic flow during summer. In: Proc. 3rd International Workshop on Simulation for Energy, Sustainable Development & Environment-SESDE 2015, Sept. 21–23, Bergeggi, Italy. Paper 45, pp. P1, 51-59. ISBN: 9788897999614

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Chu, J.Y.G., Davey, K.R., 2017 c. An extended experimental validation of daily electrical energy used in conditioning of air in a commercial building with fluctuating ambient and room occupancy over four seasons. Chemical Engineering Science – *in preparation*.

Chu, J.Y.G., Davey, K.R., 2017 d. Synthesis and demonstration of a quantitative *App* to minimize heat energy used in conditioning of bulk room air. Chemical Engineering Science – *in preparation*.

EXECUTIVE SUMMARY

Steady-state unit-operations are globally used in chemical engineering. Advantages include ease of control and a uniform product quality. Nonetheless there will be naturally occurring, random (stochastic) fluctuations about any steady-state ‘set’ value of a process parameter. Traditional chemical engineering does not explicitly take account of these. This is because, generally, fluctuation in one parameter appears to be off-set by change in another – with the process outcome remaining apparently steady.

However Davey and co-workers (e.g. Davey et al., 2015; Davey, 2015 a; Zou and Davey, 2016; Abdul-Halim and Davey, 2016; Chandrakash and Davey, 2017 a) have shown these naturally occurring fluctuations can accumulate and combine unexpectedly to leverage significant impact and thereby make apparently well-running processes vulnerable to sudden and surprise failure. They developed a probabilistic and quantitative risk framework they titled *Fr 13* [2] (*Friday 13th*) to underscore the nature of these events. Significantly, the framework can be used in ‘second-tier’ studies for re-design to reduce vulnerability to failure.

Here, this framework is applied for the first time to show how naturally occurring fluctuations in peak ambient temperature (T_o) and occupancy (room traffic flows) (L_T) can impact heat transfers for conditioning of room air. The conditioning of air in large buildings, including hotels and hospitals, is globally important (Anon., 2012 a). The overarching aim is to quantitatively ‘use’ these fluctuations to develop a strategy for minimum energy.

A justification is that methods that permit quantitative determination of reliable strategies for conditioning of air can lead to better energy use, with potential savings, together with reductions in greenhouse gases (GHG). Oddly many buildings do not appear to have a quantitative strategy to minimize conditioning heat transfers. Wide-spread default practice is to simply use an *on-off* strategy i.e. conditioning-on when the room is occupied and conditioning-off, when un-occupied. One alternative is an *on-only* strategy i.e. leave the conditioner run continuously.

A logical and stepwise combined theoretical-and-experimental, approach was used as a research strategy.

A search of the literature showed that work had generally focused on discrete, deterministic aspects and not on mathematically rigorous developments to minimise overall whole-of-building conditioning heat transfers. A preliminary steady-state convective model was therefore synthesized for conditioning air in a (hotel) room (4.5 x 5.0 x 2.5, m) in dry, S-E Australia during summer

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[2] *see* Appendix A for a definition of important terms used in this research.

($20 \leq T_o \leq 40$, ^{O}C) to an *auto-set* room bulk temperature of 22 ^{O}C for the first time. This was solved using traditional, deterministic methods to show the alternative *on-only* strategy would use less electrical energy than that of the default *on-off* for $L_T > 36$ % (Chu et al., 2016). Findings underscored the importance of the thermal capacitance of a building. The model was again solved using the probabilistic *Fr 13* framework in which distributions to mimic fluctuations in T_o and L_T were (reasonably) assumed and a new energy risk factor (p) was synthesized such that all $p > 0$ characterized a failure in applied energy strategy (Chu and Davey, 2015).

Predictions showed *on-only* would use less energy on 86.6 % of summer days. Practically, this meant that a continuous *on-only* strategy would be expected to fail in only 12 of the 90 days of summer, averaged over the long term.

It was concluded the *Fr 13* framework was an advance over the traditional, deterministic method because all conditioning scenarios that can practically exist are simulated. It was acknowledged however that: 1) a more realistic model was needed to account for radiative heat transfers, and; 2) to improve predictive accuracy, local distributions for T_o and L_T were needed.

To address these: 1) the model was extended mathematically to account for radiative transfers from ambient to the room-interior, and; 2) distributions were carefully-defined based on extensive historical data for S-E Australia from, respectively, Bureau of Meteorology (BoM) (Essendon Airport) and Clarion Suites Gateway Hotel (CSGH) (Melbourne) – a large (85 x 2-room suites) commercial hotel (latitude -37.819708, longitude 144.959936) – for T_o and L_T for 541 summer days (Dec. 2009 to Feb. 2015) (Chu and Davey, 2017 a). Predictions showed that radiative heat transfers were significant and highlighted that for $L_T \geq 70$ %, that is, all commercially viable occupancies, the *on-only* conditioning strategy would be expected to use less energy.

Because findings predicted meaningful savings with the *on-only* strategy, 'proof-of-concept' experiments were carried out for the first time in a controlled-trial *in-situ* in CSGH over 10 (2 x 5 contiguous) days of summer with $24.2 \leq T_o \leq 40.5$, ^{O}C and $13.3 \leq L_T \leq 100$, %. Independent invoices (*Origin Energy Ltd*, or *Simply Energy Ltd*, Australia) (at 30 min intervals from nationally registered 'smart' power meters) for geometrically identical *control* and *treated* suites showed a mean saving of 18.9 % (AUD $2.23 per suite per day) with the *on-only* strategy, with a concomitant 20.7 % reduction (12.2 kg CO_2-e) in GHG.

It was concluded that because findings supported model predictions, and because robust experimental SOPs had been established and agreed by CSGH, a large-scale validation test of energy strategies should be undertaken in the hotel.

Commercial-scale testing over 77 contiguous days of summer (Jan. to Mar., 2016 [3]) was carried out in two, dimensionally-identical 2-room suites, with the same fit-out and (S-E) aspect, together with identical air-conditioner (8.1 kW) and nationally registered meters to automatically transmit contiguous (24-7) electrical use (at 30 min intervals) (n = 3,696) for the first time. Each suite (10.164 x 9.675, m floor plan) was *auto-set* to a bulk air temperature of 22 ^{O}C (Chu and Davey, 2017 b). In the *treated* suite the air-conditioner was operated *on-only*, whilst in the *control* it was left to wide-spread industry practice of *on-off*. The suites had (standard) single-glazed pane windows with heat-attenuating (fabric) internal curtains. Peak ambient ranged from $17.8 \leq T_o \leq 39.1$, ^{O}C. There were 32 days with recorded rainfall. The overall occupancy L_T of both suites was almost identical at 69.7 and 71.2, % respectively for the *treated* and *control* suite. Importantly, this coincided with a typical business period for the CSGH hotel. Based on independent electrical invoices, results showed the *treated* suite used less energy on 47 days (61 %) of the experimental period, and significantly, GHG was reduced by 12 %.

An actual reduction in electrical energy costs of AUD $0.75 per day (9 %) averaged over the period was demonstrated for the *treated* suite.

It was concluded therefore that experimental findings directly confirmed the strategy hypothesis that continuous *on-only* conditioning will use less energy.

Although the hypothesis appeared generalizable, and adaptable to a range of room geometries, it was acknowledged that a drawback was that extrapolation of results could not be reliably done because actual energy used would be impacted by seasons.

The *in-situ* commercial-scale experimental study was therefore extended to encompass four consecutive seasons. The research aim was to provide sufficient experimental evidence (n = 13,008) to reliably test the generalizability of the *on-only* hypothesis (Chu and Davey, 2017 c). Ambient peak ranged from $9.8 \leq T_o \leq 40.5$, ^{O}C, with rainfall on 169 days (62 %). Overall, L_T was almost identical at 71.9 and 71.7, % respectively, for the *treated* and *control* suite. Results based on independent electrical energy invoices showed the *on-only* strategy used less energy on 147 days (54 %) than the *on-off*. An overall mean energy saving of 2.68 kWh per suite per day (9.2 %) (i.e. AUD $0.58 or 8.0 % [4]) with a concomitant reduction in indirect GHG of 3.16 kg CO_2-e was demonstrated. Extrapolated for the 85 x 2-room suites of the hotel, this amounted to a real saving of AUD $18,006 per annum - plus credit [5] certificates that could be used to increase savings.

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[3] A leap year.

[4] The result is non-linear because of the impact of tiered-tariffs.

[5] The commercial and monetary value of the GHG reduction was not quantified.

Overall, it was concluded therefore the *on-only* conditioning hypothesis is generalizable to all seasons, and that there appears no barrier to adaption to a range of room geometries. Highly significantly, the methodology could be readily applied to existing buildings without capital outlays or increases in maintenance. A total of five (5) summative research presentations of results and findings were made to the General Manager and support staff of CSGH over the period to July 2017 inclusive (*see* Appendix I) that maintained active industry-engagement for the study.

To apply these new findings, the synthesis of a computational algorithm in the form of a novel *App* (Anon., 2012 b; Davey, 2015 b) was carried out for the first time (Chu and Davey, 2017 d). The aim was to demonstrate an *App* that could be used practically to minimize energy in conditioning of dry air in buildings that must maintain an *auto-set* temperature despite the impact of fluctuations in T_o and L_T.

The *App* was synthesized from the extensive experimental commercial-scale data and was applied to compute energy for both strategies from independently forecast T_o and L_T. Practical performance of the *App* was shown to be dependent on the accuracy of locally forecast T_o and L_T. Overall results predicted a saving of 2.62 kWh per 2-room suite per day ($47,870 per annum for CSGH) where accuracy of forecast T_o is 77 % and L_T is 99 %, averaged over the long term. A concomitant benefit was a predicted reduction greenhouse emissions of 3.1 kg CO_2-e per day.

The *App* appears generalizable – and importantly it is not limited by any underlying heat-model. Its predictive accuracy can be refined with accumulation of experimental data for a range of geo-locations and building-types to make it globally applicable.

It was concluded that the *App* is a useful new tool to minimize energy transfers in conditioning of room dry air in large buildings – and could be readily developed commercially [6]. Importantly, it can be applied without capital outlays or additional maintenance cost and at both *design* and *analysis* stages.

This research is original and not incremental work.

Results of this research will be of immediate benefit to risk analysts, heat-design engineers, and owners and operators of large buildings.

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[6] Following a final presentation (18 July 2017, Appendix I), the CSGH hotel management agreed to commercially trial the new *App* in a controlled-experiment using wireless-control to the conditioner thermostat in the *treated* suite – this work is outside the present research scope however.

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I trust that the results of my research justify the expectations and confidence of all the people concerned, and the interest and encouragement of my extended family, friends and colleagues.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Steady-state unit-operations are predicated on established chemical engineering principles (Foust et al., 1980; McCabe et al., 2001; Wankat, 2007) and are used globally. Advantages of steady-state operation include ease of control and a uniform product quality.

There will, nonetheless, be naturally occurring, stochastic (random) fluctuations about the steady-state 'set' value of parameters. Traditional chemical engineering does not explicitly take account of these, largely, because fluctuation in one parameter is often off-set by change in another with the process outcome behaviour remaining apparently steady.

However Davey and co-workers (e.g. Davey et al., 2015; Davey, 2015 a; Zou and Davey, 2016; Abdul-Halim and Davey, 2016; Chandrakash and Davey, 2017 a) have shown these naturally occurring fluctuations can accumulate and combine unexpectedly to leverage significant impact and thereby make apparently well-running processes vulnerable to sudden and surprise failure; these failures therefore are not due to 'human error' or 'faulty' equipment (Cerf and Davey, 2001; Davey and Cerf, 2003; Suddath, 2009; Davey, 2010; 2011). They developed a probabilistic and quantitative risk framework they titled *Fr 13* (*Friday 13th Syndrome*) to underscore the nature of these events. Significantly, the framework can be used in 'second-tier' studies for re-design to reduce vulnerability to failure. It can be applied in the *design* and *synthesis* stages. They have progressively demonstrated their risk framework for a range of 1-step (e.g. Davey, 2015 a; Davey et al., 2015; Abdul-Halim and Davey, 2015; 2016; Davey et al., 2016), 2-step (Zou and Davey, 2016), 3-step (Chandrakash and Davey, 2017 a), and 4- and generic n-step (Chandrakash and Davey, 2017 b; Davey, 2017) processes in which they introduced the probabilistic element to mimic quantitatively, naturally occurring chance fluctuations in the process and outcome behaviour. Because findings have revealed no methodological complications to simulation of increasingly integrated processes, they postulated that it is generalizable.

The heat transfers for conditioning of air in large buildings are impacted by natural fluctuations in ambient temperature and room occupancy and traffic flows. These buildings include hospitals, hotels and civic structures, in which conditioning is globally important. Many building operators however do not appear to have a quantitative strategy to minimize conditioning heat transfers. Wide-spread 'default' practice is to simply use an *on-off* strategy i.e. conditioning-on when the room is occupied and conditioning-off, when un-occupied. One alternative is an *on-only* strategy i.e. leave the conditioner run continuously.

A research program was therefore undertaken to apply for the first time the *Fr 13* framework to heat transfer unit-operations: 1) quantitatively assess how naturally occurring fluctuations in peak ambient temperature (T_o) and occupancy (traffic flows) (L_T) can impact heat transfers and costs for conditioning of air, and; 2) develop a strategy for minimum energy use.

A logical and stepwise, combined theoretical-and-experimental approach was implemented as the research strategy.

1.2 Research aims

The principal aim of this research is to apply the *Fr 13* risk framework for the first time to heat transfers in conditioning of air in large buildings and to develop a quantitative energy strategy to minimize energy used.

Specific aims are to:

1. Model quantitatively the impact of naturally occurring random fluctuations in bulk ambient temperature and room occupancy on heat transfers for conditioning of air in a large building
2. Develop a new risk hypothesis for minimizing energy used
3. Carry out extensive experimental validation studies in a commercial setting in a large public building
4. Apply findings in a convenient new *App* that has potential for commercial exploitation.

1.3 Research justification

A justification for this new research is that results for a reliable strategy for heat transfers for conditioning of air will lead to better energy use and cost savings, together with reductions in greenhouse gas (GHG) emissions.

1.4 Thesis structure

The relevant literature is reviewed in Chapter 2. Management practices for conditioning are reviewed and the probabilistic *Fr 13* framework is appraised. Results from case studies of successful application of the framework to traditional chemical engineering unit-operations are discussed, and; it is concluded the framework could be advantageously applied to heat transfers in conditioning of air in buildings impacted by fluctuations in ambient temperature and room occupancy traffic flows.

In Chapter 3 a preliminary model synthesis for steady-state convective heat transfers is presented. The wide-spread default *on-off* and an alternative *on-only* conditioning strategy are assessed and compared using traditional deterministic single value assessment (SVA) methodology for combined impact of ambient temperature and room occupancy traffic flows. Predictions for summer show the alternative *on-only* energy strategy will use less energy to condition air in an identical room.

This model is then solved using the methodology of the *Fr 13* risk framework to take account of the impact on energy for the heat transfers of naturally occurring fluctuations in ambient (T_o) and occupancy (L_T). This work is presented in Chapter 4. Results show the *Fr 13* framework is an advance over the traditional methodology because all possible practical heat transfer scenarios that can exist are simulated.

In Chapter 5 an extended model synthesis for heat transfers is presented that includes radiative impacts and which makes use of historical distributions to mimic T_o and L_T to improve predictive accuracy. Because predictions showed radiative transfer is significant, and importantly, that an alternative *on-only* conditioning of air would use less energy than the industry default *on-off*, 'proof-of-concept' experimental validation of the *on-only* hypothesis over 10 contiguous days in summer in a commercial hotel in S-E Australia was undertaken for the first time. Results confirm the alternate conditioning hypothesis.

With confidence gained, a more developed experimental validation was continued *in situ* for 77 contiguous days of summer. These data (n = 3,696) are summarized and analysed in Chapter 6 where it is shown, based on independent energy invoices, the *on-only* hypothesis did in fact use less energy to condition room air in summer.

To test generalizability of the hypothesis an extensive experimental validation (n = 13,008) of the *on-only* strategy was carried out for 271 (nearly contiguous) days over four consecutive seasons. Results and analyses of these extensive new data are presented in Chapter 7. Based on independent invoices for energy it is shown the *on-only* strategy resulted in real savings of 2.68 kWh per suite per day over the *on-off* with concomitant 9.2 % reduction (3.16 kg CO_2-e) in GHG. Humidity and humidity control need not be accounted for in a low humidity clime away from the Equator, for example in S-E Australia, in this work. However results of the commercial-scale experimental validation reported in Chapters 6 & 7 make no such assumptions on the heat model. In high humidity climes humidity will be significant and humidity control and needs to be considered.

It is concluded overall that the alternative hypothesis is substantiated and that an *on-only* strategy should be adopted to minimize energy for conditioning of air in large buildings.

To generalize and apply these findings a new quantitative algorithm in the form of an *App* is synthesized and presented in Chapter 8. Its utility, performance and limitations as a new predictive tool for managing conditioning of air in public buildings is demonstrated and discussed.

Chapter 9 presents conclusions available from this research and discusses possible future study.

Appendix A is a list of important terms used in this research and the Standard Operating Procedures (SOPs) developed for the experimental validations are presented in Appendix B. Additional relevant detail is presented in Appendices C - J.

All symbols used in this research are carefully defined and listed separately in the Nomenclature.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Most large public buildings have room air-conditioning. Generally, the conditioner is switched-on when the room is occupied and off when un-occupied. This is termed an *on-off* conditioning energy strategy.

However there has not been a whole-of-building approach to the heat transfers required for conditioning, especially as impacted by natural fluctuations in ambient temperature and room occupancy and traffic flows. Generally, work has focussed on discrete and deterministic aspects.

In this chapter the relevant literature on heat transfers and energy management practices for conditioning are reviewed, and the probabilistic *Fr 13* framework appraised. Results from case studies of successful application of the framework to traditional chemical engineering unit-operations are discussed. It is concluded the framework could be advantageously applied to heat transfers in conditioning of air in buildings as impacted by natural fluctuations in ambient temperature and room occupancy traffic flows.

2.2 Heat transfers and energy management strategy in conditioning studies

All three modes of heat transfer impact air conditioning energy management practices. A fundamental treatment of these is available in standard texts widely consulted in chemical engineering (e.g. Perry and Green, 1997; Holman, 2010). Research on the design, construction and calibration of conditioning equipment however is relatively recent and has largely focussed on discrete conditioning components in large buildings, using traditional deterministic methodologies (Glicksman and Taub, 1997; Voeltzel et al., 2001; Martani et al., 2012; Eisenhower et al., 2012).

The early literature shows little that is devoted to energy strategy, apart from a patent in 1930s (Patent US2210458 A, filed 16 Nov. 1936, granted 6 Aug. 1940). Most work that is dedicated to discrete components of conditioning includes, for example, motor-driven fans (Patent US2488467), fan assembly (Patent US7972111) etc. and, interestingly, not on whole-of-building heat transfers. This overall finding permits speculation, that it was the rapid rise in energy cost accompanying increases in oil prices in the 1990s that drove interest in energy used in the conditioning of air in large buildings.

An early, relevant, study was that of Glicksman and Taub (1997) who studied the thermal environment of open-plan rooms (and spaces) and the behaviour of the room-occupant in controlling and managing air-conditioning using a simplified model created by a task (occupant-controlled) conditioning-system. This deterministic steady-state model accounted for temperature differences and heat transfer between adjacent work stations, common areas, and the behaviour of occupants. Random processes were used to simulate traffic flow of individual occupants and heating, ventilation and air-conditioning (HVAC) control behaviour. The model was used to identify those parameters that would have the greatest influence on energy use. The model was based on a much-simplified heat balance and transport computations familiar in chemical engineering. They concluded that energy used with occupant-controlled HVAC required 10 % more energy than that in maintaining a uniform temperature condition independent of occupant control.

Voeltzel et al. (2001) synthesized a deterministic steady-state model (*AIRGLAZE*) to study conditioning energy used in highly-glazed buildings. This involved conductive and radiative heat transfers, including heat reflection back to ambient, absorption by the glass, and; re-transmitted heat energy to adjacent rooms. They concluded that heat transfers in highly-glazed buildings were significantly greater than those in conventional buildings. Comparison of findings with data from two experiments showed good agreement between measurements and predicted results. They suggested model refinements including: 1) improved modelling and impact of the location of conditioning vents; and, 2) inclusion of a sensitivity analysis to improve confidence in output. They acknowledged however a challenge was to collect ‘good’ thermal and flow measurements in highly-glazed buildings.

A different deterministic approach was that reported by Martani et al. (2012) who modelled energy use and its dependence on occupant traffic flow(s). An interesting aspect was that Wi-Fi connections were used as a proxy for actual room occupancy i.e. when the Wi-Fi was activated it was assumed the room was occupied and when not activated, the room was un-occupied. The overall aim was to determine any dynamic relationship between energy use and occupancy using deterministic methods. They experimentally compared the two buildings on the Massachusetts Institute of Technology (MIT) campus to test predictions. Findings showed that HVAC systems depended more on ambient temperature and not room occupancy, as there was a lack of correlation between occupancy and energy used. Findings were applied to occupant behaviour through the sharing of rooms and reduced thermostat-control to minimize energy use.

Eisenhower et al. (2012) simulated conditioning energy use in a mixed analytical ‘meta-model’ based on room layout and aspect. They modelled an existing building using *EnergyPlus* software, and concluded that an advantage of the approach was that once the meta-model was generated, data could be readily analysed. A major drawback however is that the work was not predicated on fundamental heat transfer operations familiar in chemical engineering.

The use of probabilistic methods to address the impact of stochastic changes has been investigated by a number of other researchers e.g. Kotek et al. (2007), Jacob et al. (2010), Hopfe and Hensen (2011); Coakley et al. (2012) and Horikiri et al. (2014).

Kotek et al. (2007), for example, used Monte Carlo (MC) simulation (*see* for e.g. Vose, 2008) to investigate the impact of stochastic changes in key inputs on energy used in conditioning air. Although a useful conclusion was that computer simulations could be used as 'strong supporting tool' in design to reduce energy use, a major problem was that because the work was not predicated on equations fundamental to heat transfers it was difficult to understand and to practically apply to building that use conditioning of air.

Jacob et al. (2010) acknowledged it was difficult to quantify the impact of stochastic changes in conditioning parameters. They used MC sampling of distributions in a simplified model of a building that was conditioned by solar-collector and gas-fired hot-water boiler. Notably, because outputs did not show signs of non-linearity, a conclusion was that there was no significant difference in predicted outcome behaviour using deterministic and probabilistic simulation for the particular building. They acknowledged however this might not be true for buildings that are highly-glazed – where probabilistic sampling would be more appropriate.

Hopfe and Hensen (2011) compared uncertainty analysis in a (un-referenced) building performance simulation (*BPS*) and a refined MC (with *Latin Hypercube* sampling) (r-MC) to investigate the impact of stochastic changes on energy used in an office building (heating and cooling). They concluded that r-MC sampling was robust.

Coakley et al. (2012) modelled conditioning energy used based on an existing naturally-ventilated library at the National University of Ireland, Galway. They synthesized a probabilistic model in a (un-referenced) Building Energy Simulation (*BES*) model to which inputs were ambient temperature, room dimensions and behaviour of HVAC. Probability functions were based on normal distributions. The model was simulated with limited (100) random samplings (generated using *R-Script*). An increased granularity of input data, from monthly to hourly, did not significantly improve accuracy of predictions. A major drawback however is that the method was not tested experimentally.

Horikiri et al. (2014) illustrated, using computational flow dynamics and numerical iterative analyses, the impact of natural and forced convection from a heat source (e.g. room heater, window glazing arrangement, wall thickness, and; material property variation) on thermal performance within a room. Results showed that the particular heat-source and extent of glazing have significant impact on the energy used to maintain a given room bulk temperature. Because this research was more about energy transport and distribution, rather than energy strategy, the unit-operations for heat transfer was very much simplified. Moreover, because their research was focused on the particular position(s) of the heat-source, window and the room wall material of construction in a domestic building, the findings may not reflect thermal behaviour and energy use in commercial buildings, and; therefore might not be generalizable. Importantly, results were not corroborated by experimental validation.

Other researchers have synthesized predictive algorithms to assist with management of energy use, and thereby cost. For example Ma et al. (2012) synthesized a model to simulate the impact of occupants, lighting, electrical equipment, ambient temperature, and humidity on the building conditioning energy load. They developed a relatively sophisticated linear-programing prediction algorithm to reduce building energy demands and energy costs. The effectiveness of a model predictive-control (*MPC*) was demonstrated in reducing energy use and cost of operating HVAC system. By knowing the tariff beforehand, *MPC* resulted in a claimed 'substantial' cost saving by shifting peak demand away from peak hours. However the algorithm did not take into account actual ambient temperature and occupancy and is therefore limited.

Similarly, Oldewurtel et al. (2012) investigated how model predictive-control (*MPC*) and utilizing forecast weather (as a prediction) can be used to decrease the energy used in conditioning without sacrificing occupant comfort. They developed a stochastic model predictive-control (*SMPC*). The results of the *SMPC* were compared with those from the deterministic model predictive-control (*DMPC*). Their aim was to extend the use of low energy-cost actuators, such as internal blinds and curtains, to control the environment without loss of occupant comfort and to avoid the use of high-cost actuators, such as chillers, boilers and conventional radiators. The results of simulation of large-scale showed that a significant energy saving with *MPC*. It was therefore considered an advance in control technique over more conventional controls. By comparison, *SMPC* was found to be better than *DMPC*. However, the actual energy used depended on the accuracy of weather prediction. Overall they concluded that *SMPC* was a promising approach to room temperature conditioning control. A drawback was that performance was not tested by any practical application.

Although Ma et al. (2012) and Oldewurtel et al. (2012) used simulation as a predictive tool to reduce energy use in conditioning of room air, from a practical view, their work was actually complicated and complex to apply, and therefore potentially costly to implement on a commercial-scale. Significantly, whist the mathematical model appeared attractive, a major drawback is that it has not been practically tested *in-situ*. Further, from an engineering view, no quantitative heat transfer equations were used in development of these models.

In summary, it can be concluded from this review of the literature on conditioning of air in large buildings that, the research is relatively recent and there has not been a whole-of-building approach to the heat transfers required for conditioning. Generally, work has focussed on discrete and deterministic aspects with little or no experimental validation of predictions. A salient feature is a general lack of mathematically quantitative approaches predicated on established unit-operations in chemical engineering.

In particular however, a major limitation is that there has been no quantitative treatment of energy needed in conditioning of room air as impacted by natural fluctuations in (uncontrolled) ambient temperature and room occupancy and traffic flows.

This represents a risk to optimal energy use to condition air.

2.3 Risk assessments and communication of findings

In steady-state operations, risk falls into three (3) categories (Chandrakash, 2017). Those that are:

1. Identifiable and characterized, but about which experts have a reasonable understanding
2. Identified, but which little about them is understood
3. Difficult to identify, even by experts.

Risk assessments [7] are used to identify the likelihood of particular outcome behaviours. There are three (3) principal ways to undertake a risk assessment:

1. **Deterministic Single-value Assessment Approach.** This is traditionally used to quantitatively evaluate the likelihood of impact from single specific-scenarios, generally a worst-case scenario, or, *via* sensitivity analyses (Sinnott, 2005)
2. **Non-numerical (Qualitative) Approach.** In this method a subjective consensus value is used. HAZOPs are one example (e.g. Swann and Preston, 1995)
3. **Probabilistic Approach.** This is used to evaluate the likelihood of different levels of outcome behaviours for a range of practically possible scenarios. Decisions are made based on a set-level of tolerance to risk and likely values. An advantage is this can be completed expeditiously by one person (e.g. Aven, 2010; Chandrakash and Davey, 2017 a; Vose, 2008).

Clarity is important to communication of risk findings. This is a particular challenge highlighted in the recent Blackett Review (Anon., 2012 c) on high-impact, low-probability risk events. A main recommendation is made that probabilistic analyses should be used wherever and whenever

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[7] 'Risk' in much of the literature actually represents 'hazard'. Strictly, RISK = probability of an event occurring, and; HAZARD = dormant (potential) threat. Therefore, RISK = HAZARD + VULNERABILITY (*pers. comm.*, K.R. Davey).

applicable. This is because these methods take into account all plausible scenarios (including plant and process failures).

2.4 Single value assessment (SVA)

The traditional solution in chemical engineering unit-operations is a deterministic one, or, single value assessment (SVA) (e.g. Sinnott, 2005; Davey and Cerf, 2003).

SVA is used to solve unit-operations models with a single value or ‘best guess’ estimate (generally the mean) of the value of each input parameter, such as ambient temperature and traffic flow (occupancy rate), to obtain a single value predictive outcome, for example, energy used.

The output parameters in an SVA model are linked as a series of equations via standard mathematical operations e.g. multiplication, addition, subtraction, exponentiation etc. Output sensitivities to input parameters can be determined by varying the values of inputs by an amount, usually ± 1 – 5 % (Sinnott, 2005).

However, naturally occurring random fluctuations on inputs and possible impact on plant outcome behaviour are not accounted for implicitly with this deterministic approach.

2.5 Non-numerical assessments

Currently, there are three (3) main risk assessment techniques used. These are:

1. Hazard Analysis Critical Control Point (HACCP)
2. HAZard and OPerability studies (HAZOP)
3. Reliability Engineering (RE).

HACCP is the most widely used (particularly in food processing industries) and recognized risk assessment (Whiting and Buchanan, 1997). It focuses mainly on identifying and controlling the key process steps that most significantly affect safety of production. HACCP is a systematic approach to produce acceptable, safe product based on identification and management of critical control points [8] (Notermans and Mead, 1996). HACCP was first developed and established by the National Aeronautics and Space Administration (NASA) in the 1960s to help prevent food poisoning in astronauts.

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[8] A critical control point is defined as any point or procedure in a specific food system where loss of control may result in an unacceptable health risk; it is a point where the loss of control might result in failure to meet (non-critical) quality specifications.

A main drawback with HACCP however is that the person carrying out the study can make his or her findings fit existing controls, rather than changing them. This was highlighted by Whiting and Buchanan (1997) that, as HACCP becomes more widely adopted, there are areas within this approach that need to be strengthened if researchers are able to quantitatively link product attributes with public health concerns.

HAZard and OPerability (HAZOP) studies are a ‘systematic, structured approach to questioning the sequential stages of a proposed operation in order to optimize the efficiency and the management of risk’ (Swann and Preston, 1995). However, Swann and Preston (1995) underscored the problem with HAZOP actions is that they are created at a stage when detailed design is underway or ‘frozen’, and to make a number of changes at this stage is inevitably expensive and causes potential delay. They also stated that HAZOP is often impracticable.

Reliability Engineering (RE) is a widely used capability to predict something to ‘fail-well’ i.e. to fail expectedly, but without catastrophic consequences (O’Connor et al., 2002).

2.6 Probabilistic assessments

In contrast to the traditional SVA, and the three non-numerical assessments, a probabilistic assessment takes a quantitative account of all ‘possible’ values that the input parameters can take (Vose, 2008; Chandrakash and Davey, 2017 a). Input parameters for probabilistic assessments are distributions of possible values, together with the probability of each occurring. These are linked via identical mathematical functions as with the SVA.

Importantly, this means the output from a probabilistic assessment is also a distribution of values. The mean value will be nearly equal to that of the SVA.

The risk that naturally occurring, stochastic fluctuations in parameter values can have on apparent steady-state output behaviour can be accounted for implicitly within probability assessments (Haimes, 2009 a; b; Haimes, 1991; 2004; 2006; Nilsen and Aven, 2003; Flage and Aven, 2009; Aven, 2010; Milazzo and Aven, 2012).

For example, Milazzo and Aven (2012) used a quantitative risk approach for surprise failures of the rupture of pipes in the chemical industry. These authors suggested that while a probabilistic approach is useful, uncertainties still remain as to whether data used is applicable to a specific scenario.

Two techniques to overcome this drawback were proposed. The first was to use chance (variability) distributions (e.g. Beta-distribution; Triangular distribution or Uniform distribution) for plant parameters together with an event-tree model to propagate the uncertainties for risks. However, their preference was to use a quantitative risk approach, together with a qualitative risk technique, e.g. ‘score system’ of Low (L), Medium (M) and High (H) to further investigation of process uncertainties.

A drawback was that this approach remains largely qualitative or subjective relying on a ‘scored’ system and is therefore not rigorously quantitative. As acknowledged by Milazzo and Aven (2012) this approach restricts attention to the most credible scenarios.

A different probabilistic approach is to use the emerging *Fr 13* framework of Davey and co-workers (e.g. Davey et al., 2015; Davey, 2015 a; Zou and Davey, 2016; Abdul-Halim and Davey, 2016; Chandrakash and Davey, 2017 a) to address the impact on outcome behaviour of naturally occurring random fluctuations in parameters.

2.7 Probabilistic *Fr 13* framework

Davey and co-workers have successfully demonstrated that failures in processes can occur due to the impact of random, naturally occurring fluctuations in key input parameters.

Their research hypothesis is that ‘random, (often surprisingly small) changes in process parameters can add together in one direction in amounts sufficient to leverage significant change and thereby making processes vulnerable to sudden and unexpected failure’. This implies therefore that no matter how well a process is designed or operated, these naturally occurring fluctuations can result in failure.

Traditional chemical engineering does not explicitly take account of these fluctuations, because, generally, fluctuation in one parameter appears to be off-set by change in another with the process outcome behaviour apparently steady.

They titled their approach *Fr 13* (*Friday 13th*) to underscore the unexpected and surprise nature of these failure events in otherwise well-operated steady-state plant and processes. Interestingly, unexpected (surprise) failure of apparent steady plant and process (‘shit happens’) has long been acknowledged in the industrial West (*see* for e.g. Suddath, 2009; Anon., 2012 c). The Blackett Review (Anon., 2012 c) highlighted that these high-impact low-probability events are a growing risk to government and industry, especially because of increasing global inter-dependence of product and (downstream) processes.

This new risk framework has been successfully applied in a number of published steady-state 1-step case studies (e.g. Davey et al., 2016; Abdul-Halim and Davey, 2016; 2015; Davey, 2015 a; Davey et al., 2015), and, recently to 2- and 3-step studies (Zou and Davey, 2016; Chandrakash and

Davey, 2017 a). A 4-step (Chandrakash and Davey, 2017 b) and generic n-step (Davey, 2017) case study are in preparation.

Because a *Fr 13* risk model provides a picture of all practically possible outcome scenarios, including failures, it is claimed it is an advance over that of Aven and co-workers for example.

2.7.1 Stepwise approach of the **Fr 13** *assessment framework*

The five (5) identifiable components of a *Fr 13* risk assessment are (e.g. Davey, 2011):

1. Synthesis of an underlying unit-operations model

   An underlying unit-operations model (e.g. Foust et al., 1980; Wankat, 2007) is established from predicated on chemical engineering principles
2. Selection of probability distribution for parameters

   A probability distribution is used for all practically possible values that parameters may take, together with the likelihood that a parameter will take a particular value. (There are some 40 theoretical probability distributions that could be used including Normal, Betageneral, Log-normal, e.g. Vose, (2008)).

   Historical data is a good guide to establishing a most likely distribution. However, this could not be relied on to precisely predict future outcomes because historical data might be incomplete. In the absence of a fitted distribution, a possibility is that these distributions could also be based on expert experience or even opinion (Davey, 2010; 2011; Zou and Davey, 2016; Law, 2011)
3. Establishment of a clear definition of unit-operation process failure

   A practical and clear mathematical definition of failure of operation must be established. In chemical engineering processes this is usually an outcome such as an unwanted reduction in efficiency (e.g. Davey, 2015 a; Davey et al., 2016). In the food or pharmaceutical industries failure could be loss of productivity (Zou and Davey, 2016), or the unwanted survival of contaminant pathogens (Davey and Cerf, 2003), or spoilage microbes (Abdul-Halim and Davey, 2016; Chandrakash and Davey, 2017 a)
4. Sampling using refined Monte Carlo (r-MC) (*Latin Hypercube*)

   The *Fr 13* probabilistic simulation framework predicated on Monte Carlo (MC) routine; is a statistical technique used to investigate the impact of risk by using randomly selected ‘what if’ scenarios for simulation. It involves the random sampling of each probability distribution within a parameter to produce up to 100,000 of iterations.

The number of iterations required is evident when the simulations had plateaued in a plot of number of failures versus number of samples.

Each probability distribution is sampled in a manner that reproduces the shape of the distribution. Importantly, the MC simulation accounts for stochasticism (i.e. both uncertainty and variability are components) (Vose, 2008).

Because 'pure' MC can over- and under- sample from the distribution a refined MC (r-MC) with *Latin Hypercube* sampling is used in *Fr 13* (*see* Zou and Davey, 2016; Chandrakash and Davey, 2017 a). This refinement ensures samples cover the entire distribution. A sufficiently large number of samples will ensure that the output mean of a product of a large number of independent positive parameters with different distribution functions will be approximately normally distributed (Vose, 2008).

Overall, because a large number of r-MC samples are used in the *Fr 13* simulation, it can reasonably be assumed that all process scenarios that can actually occur in practical operation, including failures, are included

5. Interpretation of unit-operations simulation outcomes with potential second-tier studies to reduce vulnerability to failure

   A sufficiently large number of iterations (usually 1000 to 100,000) is required to ensure that the outcome from a *Fr 13* sampling is normal and covers all possible process scenarios, including failures (e.g. Davey, 2015 a; Abdul-Halim and Davey, 2016).

   Because *Fr 13* risk assessment is quantitative, an advantage claimed is that repeat simulations or 'second-tier' studies can be used to investigate changes to plant design or operations (*see* e.g. Chandrakash and Davey, 2017 a; Zou and Davey, 2015; Abdul-Halim and Davey, 2015 a, 2016; Davey, 2015 a) to reduce risks.

   These second-tier studies can be applied at both the concept (*synthesis*) and detailed (*analysis*) design stages.

2.8 *Fr 13* case studies

Table 2-1 presents a chronological listing and comparative summary of 14 *Fr 13* case studies. Each contribution is reviewed in chronological order.

It is seen from the table that the initial *Fr 13* study was of a 1-step steady-state, ultra-high temperature (UHT) sterilization of milk (Cerf and Davey, 2001; Davey and Cerf, 2003) in which persistent and surprise survival of contaminant spores was explained by the impact of naturally occurring chance fluctuations in the thermal behavior of *Bacillus stearothermophilus* and *Bacillus* *thermodurans*. Results showed that the traditional SVA implied greater safety than was actually the case. Importantly, failure rates of sterilization of the 1-L packs predicted by *Fr 13* was equal to the that which was known to be found in well-operated UHT plants worldwide. The cause of the non-sterility of these packs, traditionally attributed to leakage of pack material, or seal, and contamination either in processing, or storage and distribution was actually the failure of the SVA to take into account the distribution of values of UHT parameters.

Patil et al. (2005) and Patil (2006) applied a *Fr 13* risk assessment, for the first time, to a model of batch-continuous Monod fermenter for growth of *Escherichia coli*, with the aim to investigate the impact of naturally occurring, random fluctuation (5 to 15, %) in micro-organism growth on fermenter outcome behavior. Simulations showed that variability (15 %) about a mean value significantly impacted, unwanted 'washout' (*see* Bailey and Ollis, 1986) and consequent failure of the fermentation. This practical insight into an otherwise well-operated continuous fermenter contrasted sharply with the SVA analysis in which the natural variability in microbiological parameters was simply not accounted for.

A *Fr 13* risk assessment of steady-state 2- and 3-stage Clean-In-Place (CIP) models was carried out for the first time by, respectively, Chandrakash (2012) and Davey et al. (2013; 2015). The aim was to gain insight into random errors that could unexpectedly lead to sudden failure of an otherwise well-operated CIP plant. CIP failure was defined as failure to remove whey protein deposits on wet- or metal-surfaces in an *auto-set* processing time. Results revealed that for the 2-stage CIP process (*Bird model*) with an alkali cleaning fluid at $T = 50\ ^{O}C$ plus a 5 % tolerance, CIP will fail in 4.2 % of all operations, and; for the 3-stage CIP process (*Xin model*) with a cleaning fluid of $T = 75\ ^{O}C$ some 2 % of all alkali CIP operations will fail despite a 2 % tolerance, over the long term. Second-tier studies were carried out to investigate intervention strategies to improve process reliability and safety. The controlling parameter was found to be fluctuation in cleaning alkali temperature (T). Precision temperature control was recommended to reduce the underlying vulnerability to failure.

Table 2-1: Summary of 1- to generic n-step *Fr 13* risk assessments for steady-state unit-operations

No. of steps	**Unit-operation**		***Fr 13* model**	**Reference(s)**
1	1.1	Ultra-high temperature (UHT) milk sterilization	Failure of UHT sterilization in this assessment was defined as non-sterility of a 1 L pack of UHT milk. UHT parameters (D_r, z, T, t, C_0) were defined by probability distributions. Simulations showed 16 of 100,000 scenarios as failed operations. The possible risk was shown to be 16 times greater than industrially accepted criteria (= 10^{-5}).	Cerf and Davey, (2001); Davey and Cerf (2003)
	1.2	Monod Fermentation	Here failure was defined as unexpected 'washout' of *E. coli*. They investigated impact of variation (5 to 15 %) of micro-organism growth characteristics i.e. μ_{max}, $Y_{x/s}$, K_s, on the output dilution rate, D_{max}. Results underscored that small random changes in microbiological parameters significantly affect the productivity of fermentation.	Patil et al. (2005); Patil (2006)
	1.3	Clean-In-Place(CIP) processing	A 2- and 3-stage CIP model was developed to illustrate *Fr 13* failure. In this research failure was defined as failure to remove whey protein on metal surfaces within an auto-set cleaning time i.e. $t'_T < t_T$. Results predicted 4.2 % of 2-stage (T = 50 ^{O}C) and 2 % of 3-stage (T = 75 ^{O}C) CIP operations will fail despite a tolerance as a margin of safety. CIP was shown to be a combination of successful and failed operations. Second-tier studies showed that vulnerability to failures is reduced by better control of parameters such as temperature (T).	Chandrakash (2012); Davey et al. (2013; 2015)
	1.4	UV irradiation for potable water	UV irradiation of *E. coli* in potable water (turbulent flow) was assessed using *Fr 13* assessment. Failure was defined in terms of design and actual reduction of *E. coli*. Simulation of parameters (I_0, k, Q) showed 16 % of UV operations failed to reduce *E. coli* to a Regulatory level ($10^{-4.35}$), with a 10 % tolerance. Increased control of physical system e.g. Q and I_0 shown to reduce vulnerability to failures. The model was refined with second-tier studies. Chance failure due to naturally fluctuations in suspended solids concentration was demonstrated. Failure was defined by a factor p in terms of the ratio of actual and design $\log_{10}$ reduction in viable *E. coli* such that the irradiation process failed for all values of $p > 0$. Random fluctuations of feed water flow (Q), lamp intensity (I_o), and concentration of UV shielding and absorbing suspended solids ([*conc*]) were simulated using the same *Fr 13* framework. Results showed that the probability of failure UV irradiation due to suspended solids increased to 4 failures per calendar month compared to 2 failures for water without suspended solids.	Davey et al. (2012); Abdul-Halim and Davey (2015; 2016)

Table 2-1 cont'd …

1.5	Coal-fired boiler (CFB)	*Fr 13* used to investigate fuel-to-steam efficiency of CFB. 20 parameters included coal feed and quality were simulated. 73 (per 10000) failures (as $\eta' < \eta = 77.82$ %) was found, equivalent to 3 failures per year. Pre-mixing of coal is practical strategy to reduce vulnerability to CFB efficiency failures.	Davey (2015 a)
1.6	Cooling of fish at sea	The *Fr 13* probabilistic risk analysis was used to quantitatively demonstrate the impact of natural occurring random fluctuations in parameters on cooling of fish demonstrated with Southern Bluefin Tuna (*Thunnus maccoyii*) (SBT). A dimensionless cooling risk factor, p was conveniently defined such that for all values of $p > 0$ the cooling had failed to reach the regulatory 5 ^{O}C in $\leq$ 12 h. Results of a transient cooling model simulated using a refined Monte Carlo (*Latin Hypercube*) sampling of fish mass (m_f), initial temperature of fish (T_i) and cooling time (t) showed that 6.93 % of freshly harvested SBT failed to cool to 5 ^{O}C in $\leq$ 12 h averaged over the long term. The research concluded that cooling failure could be mitigated (second-tier iteration) by keeping the ice slurry medium to 0 ^{O}C (theoretical minimum).	Davey (2015 b)
1.7	Pasteurization of raw milk	The risk to unexpected failure using the *Fr 13* probabilistic methodology was demonstrated using an interconnected in series (global) milk pasteurization process consisting of heating, holding and cooling unit-operations. Initially a 1-step process was synthesized. The model was later refined to a 3-step unit-operations. In this research failure for each operation was separately defined and is characterized by a failure risk factor p. Results showed that failure in the heating or holding operation did not automatically lead to a failure of subsequent operation(s) or the entire pasteurization process. Importantly the converse was also not necessarily true. This clearly underscored the accumulating effects of random changes. Results overall showed that the global model was at risk of failure to pasteurize milk 12.5 % of all cases over the long term.	Chandrakash et at. (2015); Chandrakash and Davey (2017 a)
1.8	Pitting of metals at sea	*Fr 13* applied to predict risk of metals (AISI 316L) pitting at sea, demonstrated for Bass Strait. Pitting potential (E_{PIT}) with key parameters i.e. T and $[Cl^{-}]$ simulated. 463 (9.26 %) failures as pitting initiation ($E_{PIT} < E_{OCP}$ + tolerance, %) found in 5000 iterations. They named the contours of equal risk probability '*isorisques*' and established a new atlas of world pitting risk.	Davey et al. (2016)

Table 2-1 cont'd ...

	1.9	Chemical taste-taint in fish	A quantitative failure risk assessment was illustrated by the impact of naturally occurring fluctuations of taste-taint chemicals geosmin (GSM) and/or 2-methylisoborneol (MIB) in Recirculated Aquaculture System (RAS) growth water on their accumulation in fish flesh demonstrated in farmed barramundi (*Lates calcarifer*). The risk of rejection by consumers was defined by a risk factor p such that for all values of $p > 0$ including a practical tolerance the taste-taint chemical in fish-flesh above a threshold concentration 0.74 and 0.7 µg kg^{-1} for GSM and MIB respectively is considered a failure (rejected). Results using refined Monte Carlo (*Latin Hypercube*) sampling of chemicals in growth water (C_w), water temperature (T) and growth time (t) showed that 10.10 and 10.56 % of all harvested fish over the long term exceeded the concentration threshold of GSM and MIB respectively. The research concluded that by keeping the fish growth time to less than 240 days (second-tier simulation) the taste-taint chemical in the fish-flesh would not exceed the rejection threshold concentration.	Hathurusingha and Davey (2016)
2	2.1	Membrane processing of fruit juices	A *Fr 13* risk assessment was demonstrated for membrane fouling of a 2-step serial integrated cross-flow ultrafiltration-osmotic distillation (UF-OD) respectively for clarifying and concentrating pomegranate (*Punica granatum*) juice. Refined Monte Carlo (*Latin Hypercube*) sampling was used to simulate membrane behaviour of transmembrane pressure for UF (ultrafiltration) and filtration time for OD (osmotic distillation). The overall failure of the 2-step UF-OD was governed by the OD process and defined mathematically by a reduction of transmembrane flux fouling risk factor, p such that the ratio of actual flux and the required flux plus a tolerance, $p > 0$. Simulation results showed that there was a 10.5% probability of failure of all the integrated UF-OD operation in the long term. The research found that fouling of the UF-OD could be reduced by second-tier simulations; for example by either improving process control to reduce naturally occurring fluctuations or/and using a regulatory accepted additional step to limit the impact of suspended solids on the membrane surface.	Zou and Davey (2016); Zou (2016)

Table 2-1 cont'd ...

	2.2	Combined SF-UV treatment for potable water	The 1-step UV irradiation for potable water model (Abdul-Halim and Davey, 2015, 2016) was further refined to a 2-step unit-operations with addition of a pre-treatment of suspended solids with rapid sand-filters (SF) in series to UV irradiation. Results showed the overall vulnerability to failure of SF-UV operations is 40.4 %. A mean reduction of suspended solids in SF of $\log_{10} = -1.11$ (90 %), with a subsequent reduction of viable *E. coli* in the UV reactor of $\log_{10} = -2.93$ (99.9 %) is a highly significant increase in UV efficacy compared with that ($\log_{10} = -0.92$) without pre-treatment of the raw feed-water. SF-UV is shown to be a mix of successful and failed operations, and; significantly that not all failed SF automatically result in failure in overall UV process efficacy.	Abdul-Halim and Davey (2017)
3	3.1	Pasteurization of raw milk	In a new research the model synthesized by Chandrakash et al. (2015); was refined to a 3-step unit-operations. Failure for each step was separately defined and was characterized by a failure risk factor *p*. The results showed that failure in the heating or holding operation did not automatically lead to a failure of subsequent operation(s) or the entire pasteurization process. Importantly the converse was also not necessarily true. This clearly underscored the accumulating effects of random changes. Results overall showed that the global model was at risk of failure to pasteurize milk 12.5 % of all cases over the long term.	Chandrakash and Davey (2017 a); Chandrakash (2017)
4	4.1		To further test applicability of the risk framework to multi-step processing, an integrated 4-step, the storage of the pasteurized milk, is added for the first time. A justification is that this simulated commercial practice more closely. Results of simulation of this 4-step model showed that with a design tolerance of 2 % for a Regulatory design reduction of $\log_{10} = 5.5$ in viable *Mycobacterium avium* subspecies *paratuberculosis* (*MAP*) on heat-up to 72 ^{O}C with 15 s holding in commercial plate equipment, there would be no further failures i.e. the rate of vulnerability to failure in a 4-step microbiological model for pasteurizing and storing milk remained 5.75 %, averaged over the long term. To improve design and safety results from 4-step investigative second-tier studies *Fr 13* model, revealed vulnerability to microbiological failure can be readily mitigated by installing precise safety-integrity-level (SIL) mass flow control on the raw milk in existing plant to ensure a holding time of ≥ 15 s.	Chandrakash and Davey (2017 b)
n	n.1		An overall conclusion is that the *Fr 13* framework appears generalizable to any general integrated step steady-state process without methodological problems and an advance over current existing risk/hazard methodologies. If properly developed, it is believed that this novel framework could be adopted as a new design tool for steady-state processing at both design and synthesis stages.	Davey (2017)

Abdul-Halim and Davey (2015) synthesized for the first time a *Fr 13* failure assessment of steady-state UV irradiation of *Escherichia coli* for potable water production. UV failure was defined in terms of design and actual reduction of *E. coli*, together with an assumed tolerance. Simulation of the impact of natural fluctuations in key parameters (I_0, k, Q) revealed that 16 % of all UV operations can fail to achieve the (Regulatory) design reduction in viable *E. coli* of $10^{-4.35}$. The model was shown to be an advance on alternate risk assessments because it produced all possible practical UV outcomes. Apparently well-operated and continuous UV irradiation for potable water production was shown to actually be a mix of successful and failed states, and neither ‘human error’ nor ‘faulty fittings’ (Davey, 2011) needed to be invoked as an explanation. Through second-tier studies it was demonstrated that reducing the variance in key parameters, through for example improved process control, whilst potentially costly, would minimize likelihood of UV failures.

The impact of fluctuations in the concentration of suspended solids on failure of UV was demonstrated by Abdul-Halim and Davey (2016) who found that the number of failures with unwanted survival of *E. coli*, averaged over the long term, would increase from 2 to 4, per month. They concluded from second-tier studies that this underlying vulnerability to failure could be reduced with better flow control to reduce variance in feed-flow, rather than by increasing UV dose.

Davey (2015, a) applied a *Fr 13* assessment, for the first time, to the fuel-to-steam efficiency of a large coal-fired-boiler (CFB) that was recently commissioned in Java, Indonesia. The aim was to determine the risk of reduced CFB efficiency in the face of naturally occurring fluctuations in key parameters, particularly in the thermal value of the coal. Based on second-tier simulations, it was concluded that coal should be pre-mixed and pre-sized to a consistent blend, rather than burn it batch-to-batch as shipped to the CFB. This gave a standardized feed and significantly reduced unwanted fluctuation and failure in the design thermal efficiency (77.82 %) of the large CFB.

A *Fr 13* framework was used by Davey (2015 b) to quantitatively demonstrate the impact of naturally occurring random fluctuations in parameters on cooling of fish – and was illustrated with Southern Bluefin Tuna (*Thunnus maccoyii*) (SBT), a major export from South Australia, for the first time. A dimensionless cooling risk factor, p was conveniently defined such that for all values of $p > 0$ the cooling had failed to reach a regulatory 5 ^{O}C in ≤ 12 h.

Results of a transient cooling model, simulated using a refined Monte Carlo (*Latin Hypercube*) sampling of fish mass (m_f), initial temperature of fish (T_i) and cooling time (t), showed that 6.93 % of freshly harvested SBT failed to cool to 5 ^{O}C in ≤ 12 h, averaged over the long term. The research concluded that the mass of fish to be cooled is the controlling parameter. However, cooling failures could be mitigated as were demonstrated in second-tier simulations, for example, by keeping the ice slurry to 0 ^{O}C (theoretical minimum without using freezing point depressants e.g. salt).

Chandrakash et al. (2015) and Chandrakash and Davey (2017 a) demonstrated the vulnerability to unexpected failure of pasteurization using a (global) milk pasteurization process consisting of: 1) heating, 2) holding, and; 3) cooling, unit operations.

In this work the risk of failure for each unit-operation was separately defined by a failure risk factor, p. For heating, the risk factor, p_1 was defined in terms of the outlet temperature of milk from the plate heat exchanger (72 ^{O}C), and for the holding operation, the risk factor, p_2 was defined as the time required to hold the temperature of the heated milk at that temperature for 15 s, and; for the cooling operation, the risk factor, p_3 was defined in terms of the outlet temperature of milk from cooling plate heat exchanger (4 ^{O}C).

Results showed that failure in heating and holding unit-operations did not automatically led to a failure in overall pasteurization of the milk. This clearly underscored the accumulating impact of naturally occurring fluctuations. Overall results showed that the global model was at risk of failure to pasteurize milk in 12.5 % of all cases averaged over the long term.

The probabilistic *Fr 13* framework was successfully applied for the first time by Davey et al. (2016) to risk of metals (AISI 316L) pitting at sea in the cold waters of the Bass Strait, Australia. Pitting can lead to metal damage, without noticeable loss of mass. Stress corrosion cracking and potential failure of marine structures can follow. A quantitative understanding of the risk of potential metals failure as pitting initiation due to natural fluctuations in sea conditions is therefore important, especially with large offshore equipment that can be required to process oil and gas 24 h a day.

Sea surface (≤ 20 m) temperature (T) and salinity ($[Cl^-]$) were defined as Normal and Truncated probability distributions. Simulations showed 463 (9.26 %) failures as pitting initiation ($E_{PIT} < E_{OCP}$ + tolerance, %) in 5000 iterations. A significant outcome was that the authors coined the term '*isorisques* = contours of equal probability of risk of pitting of metal', as impacted by naturally occurring, chance fluctuations in sea surface temperature and sea salinity – an unanticipated, but highly constructive, outcome. There were parallels with *isotherm* and *isobar*. It is intended these isorisques be used to determine the change in pitting risk after a sudden shift in sea-surface temperature or salinity following a major storm or ice (salt-free) melt, or to – the impact of (slow) climate change.

Hathurusingha and Davey (2016) quantitatively demonstrated for the first time the risk of the impact of naturally occurring fluctuations in taste-taint chemicals, geosmin (GSM) and 2-methylisoborneol (MIB) in Recirculated Aquaculture System (RAS) growth-water, accumulating in the flesh-fish using both theoretical and experimental studies with RAS farmed barramundi (*Lates calcarifer*). The accumulation of these unwanted taint molecules results in significant downgrading of the sales-value of the fish protein (by a factor of 10).

The risk of rejection by consumers was defined by a risk factor, p, such that for all $p > 0$ the taste-taint chemical in fish-flesh was above a threshold-concentration 0.74 and 0.7 $\mu g\ kg^{-1}$ for GSM and MIB, respectively, and would therefore be considered a failure (and rejected).

Results using refined Monte Carlo (with *Latin Hypercube*) sampling of chemicals in growth water (C_w), water temperature (T) and growth time (t) showed that 10.10 and 10.56, % of all harvested fish over the long term exceeded the concentration threshold of GSM and MIB respectively in typical RAS farming.

The research concluded from second-tier simulations that by keeping fish growth-time to less than 240 days the taste-taint chemical in fish-flesh would not exceed the rejection threshold. Importantly, this finding could readily be practically implemented by the RAS farmers.

Zou and Davey, 2016 and Zou, 2016 demonstrated for the first time a 2-step *Fr 13* risk assessment of membrane fouling in a serially integrated cross-flow ultrafiltration (UF) and osmotic distillation (OD) for clarifying and concentrating pomegranate (*Punica granatum*) juice.

In this work, a refined Monte Carlo (*Latin Hypercube*) sampling was used to simulate membrane behaviour of transmembrane pressure for UF, and filtration time for OD. Failure of each step was defined mathematically by a fouling risk factor, p in terms of the ratio of actual flux, and required or designed flux, plus an assumed 3 % tolerance.

The overall failure of the 2-step UF-OD was found to be controlled by the failure in OD. It was argued that even though a theoretical failure, i.e. actual permeate flux less than required of the UF membrane had occurred, concentration of juice could still practically operate with the actual steady-state flux and concentration of juice could still continue.

The research concluded that fouling of the integrated 2-step UF-OD apparent steady-state unit-operation could be reduced following second-tier simulations by two (2) practical options.

The first was reducing naturally occurring fluctuations, respectively, in transmembrane pressure of UF and filtration time of the OD, through increased process control. Results showed that by reducing stdev to 1 % of pressure, predicted membrane failure was zero. Simulation results showed that there was a 10.5 % probability of failure of all the integrated UF-OD operations (stdev = 5 %) over the long term.

The second option was reducing the flux required for either, or both, UF and OD steps, for example, by using a Regulatory acceptable additional step, such as an enzyme treatment, to limit the impact of suspended solids on the membrane surface. Results showed an apparent exponential decrease in the number of overall UF-OD failures as the OD required flux was reduced such that for a stdev = 10 % at 99, 98 and 97, % of original design the failure decreased from 20.1 to 8.9, 2.1 and

0.06, %, respectively. For a reduced stdev, for example stdev = 5 %, the predicted failure rate reduced from 10.5 to 0, % when the required flux was reduced from 100 to 99, %.

These second-tier simulation options showed, clearly, that there was a practical trade-off between capital outlay and reduction to vulnerability to failure of the combined membrane unit-operation.

Abdul-Halim and Davey (2017) refined the 1-step UV irradiation for potable water production model of Abdul-Halim and Davey (2015; 2016) to an integrated 2-step unit-operation with the addition of a pre-treatment of suspended solids with rapid sand-filters (SF) in series to UV irradiation. Results predicted the overall vulnerability to failure of combined SF-UV was 40.4 % averaged over the long term. This is a mean reduction of suspended solids in S-F of $\log_{10} = -1.11$ (90 %), with a subsequent reduction of viable *E. coli* in the UV reactor of $\log_{10} = -2.93$ (99.9 %). This was a highly significant increase in UV efficacy, compared with that ($\log_{10} = -0.92$) without pre-treatment of the raw feed-water. SF-UV was shown to be a mix of successful and failed operations, and; significantly that not all failed SF automatically result in failure in overall UV process efficacy.

The application of a *Fr 13* risk assessment was refined further in a 3-step process. In this study Chandrakash and Davey (2017 a) modified their equipment model of a 3-step milk pasteurizer to take into account the thermal inactivation of contaminant, viable *Mycobacterium avium* subsp. *paratuberculosis* (*MAP*), a common bacterial contaminant and pathogen in raw milk. This was the first demonstrated application of the *Fr 13* framework to a microbiological multi-step process.

They defined pasteurization failure in terms of unwanted levels of survival of the viable pathogen *MAP*. Their results highlighted that a failure in the heating-step did not necessarily lead to failure of pasteurization of the milk. Significantly, using second-tier studies they also showed the vulnerability to failure of the pasteurizer could be reduced by installing more precise flow control on raw milk flow.

To further test applicability of the *Fr 13* risk framework to multi-step processing, Chandrakash and Davey (2017 b) synthesized an integrated 4-step pasteurizer – this consisted of heating, holding, cooling and storage of the treated milk. A justification for the work was that this simulated commercial practice more closely.

Results showed that with a design tolerance (margin of safety) of 2 % for a Regulatory design reduction of $\log_{10} = 5.5$ in viable *MAP* on heat-up to 72 ^{O}C with 15 s holding in commercial plate equipment, there would be no increased rate in failures i.e. the rate of vulnerability to failure in a 4-step microbiological model for pasteurizing and storing milk remained 5.75 %, averaged over the long term. To improve design and safety, results from second-tier studies of this 4-step pasteurizer showed vulnerability to microbiological failure can be mitigated by installing precise safety-integrity-level (SIL) mass flow control on the raw milk in both *design* and *synthesis* stages of plant to ensure a holding time of ≥ 15 s.

To further test the generalizability of the *F13* probabilistic framework hypothesis Davey (2017) is applying it to a generic-stage (n-step) steady-state processes involving feed streams, reactor, and product and recycle streams, and purge.

Overall, it can be concluded that the *Fr 13* framework appears generalizable to integrated n-step steady-state processes – without methodological problems – and is an advance over existing risk/hazard methodologies. If properly developed, it is believed that this framework could be adapted as a new design tool for steady-state processing at both *design* and *synthesis* stages. Clearly, the literature (Table 2-1) demonstrates a wide range of successful application of the *Fr 13* framework. (However, anecdotally at least (*pers. comm.* K.R. Davey), it is worth noting that some, more traditional chemical and food engineers do not like the inclusion of the impact of (pure) chance on the output behavior of otherwise apparent steady-state processing).

Additionally, to date, there has been a scarcity of independent refereed data to test *Fr 13* predictions. One reason is limited resources, moreover however, is the reluctance of commercial operations to make available 'failure' data for independent analyses. This is particularly true with foods applications, including milk (Chandrakash and Davey, 2017 a), fruit juices (Zou and Davey, 2016) and potable water (Abdul-Halim and Davey, 2016).

It is concluded that because the *Fr 13* framework appears generalizable, and because it has been demonstrated to quantitatively take into account the impact of naturally occurring fluctuations in process parameters, it could be usefully applied to heat transfers in conditioning of air in large buildings as impacted by fluctuations in ambient temperature and traffic flow (as occupancy).

This has not been done before.

2.9 Applying the *Fr 13* framework to heat transfers in conditioning of dry air

The 5-step algorithm for *Fr 13* (e.g. Davey, 2011; Chandrakash and Davey, 2017 a) could be applied to heat transfers in conditioning of room air in large buildings as follows:

1. Synthesize a simplified heat transfer unit-operations model – and solve this using a traditional SVA for default, *on-off* conditioning, and an alternative *on-only* conditioning
2. Identify controlling parameters – these will include daily peak ambient temperature, T_o (^{O}C) and room occupancy, L_T (%)

3. Derive plausible probability distributions for these parameters – a guide will be historical data
4. Establish mathematically a definition of energy strategy risk factor, $P = q_{on\text{-}only} - q_{on\text{-}off}$ (W) and simulate energy strategies and likely failure(s) scenarios with r-MC sampling
5. Distill insights into intervention strategies via second-tier studies to optimize energy strategy.

2.10 Chapter summary and conclusions

From a critical review of the literature, the following important factors are relevant to this research:

1. In conditioning of air in large buildings research has, generally, been relatively recent. It has focused on design, calibration, and measurement using discrete and deterministic assessments, and not on rigorous development of a quantitative energy strategy that takes into account the whole-of-building heat transfer, especially as impacted by naturally occurring fluctuations in ambient temperature and room occupancy traffic flows

2. The probabilistic *Fr 13* framework developed by Davey and co-workers takes account of naturally occurring fluctuations in processes and, based on published case studies, appears to be applicable to a new quantitative risk analysis of energy use for conditioning of air in large buildings. An advantage claimed is that all possible scenarios that could exist, including failures, are evaluated and quantified.

In the following, the *Fr 13* risk framework is applied for the first time (Chapter 4) to solution of a newly synthesized model (Chapter 3) for convective whole-of-building heat transfers in conditioning of air. The model is predicated on established unit-operations in chemical engineering. A comparison is made with the traditional deterministic methodology.

CHAPTER 3

A SIMPLIFIED MODEL OF CONDITIONING OF ROOM AIR

Parts of this chapter have been published as:

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3.1 Introduction

The review of literature Chapter 2 disclosed that current methods for energy use in conditioning of room air has generally focused on discrete components of the system using deterministic methods and not on whole-of-building heat transfers.

In this chapter a new, simplified, but realistic, convective heat transfer model for whole-of-building process is synthesized for the first time. The model is used to compare the widely used default *on-off* with an alternative *on-only* conditioning heat transfer strategy as impacted by combined ambient temperature and room occupancy traffic flows using traditional deterministic (SVA) solutions.

Predictions for summer show the alternative *on-only* energy strategy will use less energy to condition air in an identical room.

3.2 Materials and methods

3.2.1 A simplified unit-operations conditioning model

Consider a single room of width *W*, vertical length (height) *L* and interior depth *D*, Fig. 3-1. A single glass pane 0.01 m thick comprises each of two opposite external walls exposed to ambient. The room ceiling and floor are assumed to be thermally insulated. The opposing internal walls are assumed to be made from commercially manufactured, residential clay bricks, laid in a standard double-brick on-flat with an air-gap (cavity brick). The wall of brick 0.110 m thick provides a thermal barrier to ambient (or adjoining room in a multiple-room building). It can be seen in Fig. 3-1 that the arrows show flow of heat transfer.

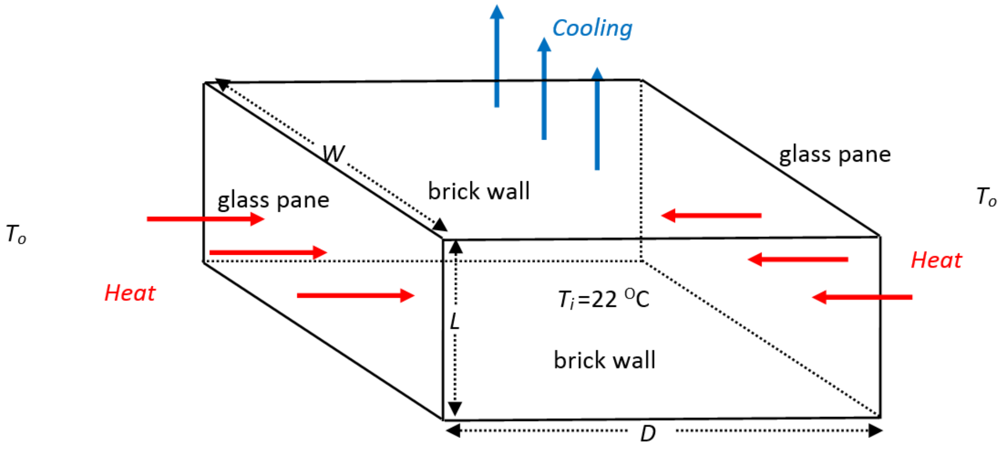

Fig. 3-1: Schematic of natural convection heat transfer unit-operations

Fig. 3-1 conveniently shows glass panes on opposite sides of the cuboid to illustrate calculation of the area exposed to ambient. These glass panes do not have to be opposite each other - and depending on room location in the building and its geometry might be on the same side or on any of the other one or two sides.

The heat energy transfer in the room, *q*, is given by (Holman, 2010; Perry and Green, 1997; Anon., 2013)

$$q = U_o A \Delta T \tag{3.1}$$

such that for the glass

$$q_{glass} = U_{o,glass} A_{glass} \Delta T \tag{3.2}$$

and for the brick

$$q_{brick} = U_{o,brick} A_{brick} \Delta T \tag{3.3}$$

All symbols used are carefully defined in the Nomenclature at the end of this thesis.

The overall heat transfer coefficient (U_o) is given by (Holman, 2010; Perry and Green, 1997; Anon., 2013)

$$U_o = \frac{1}{\frac{1}{h_o} + \frac{d}{k} + \frac{1}{h_i}} \tag{3.4}$$

such that for the glass

$$U_{o,glass} = \frac{1}{\frac{1}{h_{o,glass}} + \frac{d_{glass}}{k_{glass}} + \frac{1}{h_{i,glass}}} \tag{3.5}$$

and for brick

$$U_{o,brick} = \frac{1}{\frac{d_{brick}}{k_{brick}} + \frac{1}{h_{i,brick}}} \tag{3.6}$$

In Eq. (3.6) it is seen that it is assumed the double-brick wall has an air gap (cavity brick) and is thereby thermally insulated.

The area for heat transfer of the two panes is

$$A_{glass} = 2 \times L \times W \tag{3.7}$$

and for the brick is

$$A_{brick} = 2 \times L \times D \tag{3.8}$$

For room cooling, T_o must be greater than T_i, giving a temperature difference

$$\varDelta T = T_o - T_i \tag{3.9}$$

The temperature of the air film on the glass and of the glass is assumed to be

$$T_{air,glass} = \frac{1}{2}(T_o + T_i) \tag{3.10}$$

The temperature of the air film on the brick wall is, similarly, given by

$$T_{air,brick} = \frac{1}{2}(T_{brick} + T_i) \tag{3.11}$$

in which it is assumed that $T_{brick} = T_o$.

The convective heat transfer coefficient (Holman, 2010; Anon., 2013) for natural convection of air along a vertical glass pane (on either the outside or inside) and the brick wall (inside only) can be obtained from the Nusselt number, namely

$$\mathrm{Nu} = \frac{hL}{k} = \left[0.825 + \frac{0.387\mathrm{Ra}^{\frac{1}{6}}}{\left[1 + \left(\frac{0.492}{\mathrm{Pr}} \right)^{\frac{9}{16}} \right]^{\frac{8}{27}}} \right]^2 \quad \text{for } 10^{-1} < \mathrm{Ra} < 10^{12} \tag{3.12}$$

in which the Rayleigh (Ra) number is (Holman, 2010)

$$\mathrm{Ra} = \mathrm{GrPr} \tag{3.13}$$

with

$$\mathrm{Gr} = \frac{L^3 \rho^2 g \beta \delta T}{\mu^2} \tag{3.14}$$

and

$$\mathrm{Pr}=\frac{c\mu}{k} \tag{3.15}$$

where Eqs. (3.11) through (3.15) apply to the air film adjacent to the outside and inside of the glass window; and the inside brick wall.

For glass

$$\delta T_{o,glass}=T_o-T_{air,glass} \tag{3.16}$$

$$\delta T_{i,glass}=T_{air,glass}-T_i \tag{3.17}$$

For brick

$$\delta T_{i,brick}=T_{brick}-T_i \tag{3.18}$$

For wind speeds up to a high of 10 m s^{-1} it can be shown (Annex 3-A) that a laminar sub-layer will be maintained against the glass panes and brick walls i.e. $\mathrm{Re} \leq 5 \times 10^5$ (Holman, 2010) out to a distance of 0.7 m. Because of this the value of heat transfer coefficient, h, is unchanged from that for natural convection – and forced convective impacts can therefore be safely ignored.

Eqs. (3.1) through (3.18) define the simplified unit-operations model due to natural convective heat transfer for conditioning of the room interior air to an *auto-set* temperature in summer.

A widely adopted strategy is the conditioning is switched-on only when the room is occupied; it is switched-off when the room is unoccupied. (In hotels for example, this will actually be mid-morning when the housekeeping staff finish cleaning and leave the room). This strategy is titled *on-off*.

An alternative is to leave the room with continuous conditioning, whether it is occupied or not; this is titled *on-only*.

Both strategies of the simplified model are computed using the traditional single value (deterministic) assessment and their results compared to determine which strategy uses less electrical energy for the same set of input parameters, ambient temperature T_o and occupancy (traffic flow) η.

A simplifying assumption in the simplified model was that the temperature of the brick wall will reach equilibrium with ambient in a short period after the room air conditioning is switched-off, that is $T_{brick} = T_o$.

This assumption is sound for the uninterrupted, continuous *on-only* energy strategy as the brick will remain at T_i = 22^{O}C.

For the *on-off* strategy the period for the approach to equilibrium of the brick walls with ambient can be estimated (Annex 3-B) to be ~ 48 h.

However, this will be interrupted by *check-out check-in* times when the new occupant (or housekeeping) turns the conditioner on. The temperature rise of the walls in that time can be reliably estimated at about 4 ^{O}C (Annex 3-B) when occupancy is high (η > 90 %). However, a more meaningful comparison between the two energy strategies should made for an occupancy much less. In the worst case $T_{brick} = T_o$. The actual impact of this assumption, averaged over four consecutive seasons, is later resolved experimentally in planned large-scale commercial studies carried out in an existing hotel, and reported in Chapters 6 and 7.

3.3 Traditional deterministic single value assessment (SVA)

A traditional, deterministic and single value assessment (SVA) (Sinnott, 2005) of the unit-operations model for conditioning of the air is carried out as follows: for the (commercial silica type) glass pane, typically L = 2.5 m, W = 4.5 m and d = 0.01 m, k_{glass} = 0.78 W m^{-1} K^{-1}. Typically, k_{brick} = 0.69 W m^{-1} K^{-1}. The mean thermal properties of air ($20 \leq T \leq 40$, ^{O}C) are ρ = 1.1774 kg m^{-3}, g = 9.81 m s^{-2}, μ = 1.8642 x 10^{-5} kg m^{-1} s^{-1}, c = 1005.7 J kg^{-1} K^{-1}, k = 0.02624 W m^{-1} K^{-1} with β = 3.3333 x 10^{-3} K^{-1} (at 300 K) (Holman, 2010).

From Eq. (3.7) the area for heat transfer through the glass is A_{glass} = 22.5 m^{2}. For an assumed ambient day summer temperature (December through February, S-E Australia) of T_o = 35 ^{O}C, the value ΔT = (35 – 22) = 13 K, is obtained from Eq. (3.9). $T_{air,glass}$ = ½(35 + 22) = 28.5 ^{o}C (301.65 K) is computed from Eq. (3.10). From Eqs. (3.16) and (3.17), δT = 6.5 K = $\delta T_{o,glass} = \delta T_{i,glass}$.

Substituting values for each of L, ρ, g, μ, k, c, β and δT into Eqs. (3.14) and (3.15), the Grashof and Prandtl numbers for air adjacent to the glass pane are, respectively, Gr = Gr$_{glass}$ = 1.33 x 10^{10} and Pr = 0. 71. From Eq. (3.13) the Rayleigh number, Ra = Ra$_{glass}$ = 9.5 x 10^{9}. Because, 10^{-1} < Ra < 10^{12}, Eq. (3.12) applies for the air outside and inside, yielding the convective heat transfer coefficient, $h_{o,glass}$ = 2.61 W m^{-2} K^{-1} and $h_{i,glass}$ = 2.61 W m^{-2} K^{-1} respectively.

Substituting $h_{o,glass}$, $h_{i,glass}$, d_{glass} and k_{glass} into Eq. (3.5), yields the overall heat transfer coefficient for the glass, $U_{o,glass}$ = 1.28 W m^{-2} K^{-1}. Substituting $U_{o,glass}$ into Eq. (3.2), the rate of heat energy transferred from ambient to the interior of the room, q_{glass} = 375 W.

3.3.1 On-off strategy

Because in the *on-off* strategy, where the conditioning is switch on when the room is occupied and off when unoccupied, the brick walls remain near to T_i will reach equilibrium with ambient soon after switching off. Therefore heat energy will need to be removed from the glass and brick each time the room is again occupied i.e.

$$q_{on-off} = q_{glass} + q_{brick} \tag{3.19}$$

The energy q_{brick} is calculated as follows: from Eq. (3.18) $\delta T_{i,brick} = 13$ K. Substituting $\delta T_{i,brick}$ together with values for each of L, ρ, g, μ, k, c, β into Eqs. (3.14) and (3.15), the Grashof and Prandtl numbers for the air adjacent to the brick wall are, respectively, $\mathrm{Gr} = \mathrm{Gr}_{brick} = 2.66 \times 10^{10}$ and $\mathrm{Pr} = 0.71$. From Eq. (3.13) the Rayleigh number, $\mathrm{Ra} = \mathrm{Ra}_{brick} = 1.90 \times 10^{10}$. Because, $10^{-1} < \mathrm{Ra} < 10^{12}$ Eq. (3.12) applies for the air adjacent to the brick walls, yielding the convective heat transfer coefficient $h_{i,brick} = 3.24$ W m^{-2} K^{-1}. Substituting $h_{i,brick}$, d_{brick} and k_{brick} into Eq. (3.6), yields the overall heat transfer coefficient for the brick wall, $U_{o,brick} = 2.14$ W m^{-2} K^{-1}. For $D = 5$ m from Eq. (3.8) the area for heat transfer from the brick walls is $A_{brick} = 25.0$ m^2. Substituting $U_{o,brick}$, A_{brick} and ΔT into Eq. (3.3), the rate of heat energy transferred from the brick wall to the interior of the room, $q_{brick} = 695$ W.

That is, for a uniform ambient summer temperature of 35 ^{O}C, the energy transfer from Eq. (3.19) is $q_{on-off} = 375 + 695 = 1070$ W.

However, the room is unlikely to be occupied each contiguous day. Anecdotally the most likely occupancy, based on industry-wide four-year historical data (Clarion Suites, Gateway Hotel (CSGH), Melbourne, *unpublished data*), is $\eta = 75$ % (Anon., 2015).

This means that for the *on-off* strategy, energy use is a linear function of η, %, and Eq. (3.19) can be written as

$$q_{on-off} = \frac{\eta}{100}\left(q_{glass} + q_{brick}\right) \tag{3.20}$$

That is for an occupancy $\eta = 75$ % the energy use for the *on-off* strategy in Eq. (3.20) $q_{on-off} = 0.75 \times 1070 = 802$ W.

3.3.2 On-only strategy

In the *on-only* strategy, because the room air is continuously conditioned, the interior walls of the room can be assumed to be at the room interior *auto-set* temperature T_i (= 22 ^{O}C). Therefore in *on-only* conditioning, only the energy transferred from ambient through the glass panes will need to be removed. The overall energy is

$$q_{on-only} = q_{glass} \tag{3.21}$$

That is, following an initial start-up with conditioning, given a uniform ambient summer temperature of 35 ^{O}C, 375 W will need to be removed to keep the room interior air at a bulk temperature of 22 ^{O}C.

3.4 Results

Eqs. (3.20) and (3.21) are important because their solution will permit a practical comparison and estimation of the difference of the energy used in the two strategies for conditioning the room bulk air. The peak ambient temperature will be sufficient for this purpose.

Table 3-1 presents a comparative summary simulation of the two strategies for conditioning the room consisting of two glass panes, and two brick walls, with a summer ambient temperature, T_o = 35 ^{O}C being conditioned to an *auto-set* room interior temperature, T_i = 22 ^{O}C for a range of values of occupancy (traffic flow) $0 \leq \eta \leq 100$, %.

It is seen in column 4 of the table that for $0 \leq \eta \leq 40$, % the *on-off* strategy results in overall less energy (and therefore cost) in maintaining the conditioned room. However, at a value between $30 \leq \eta \leq 40$, % the *on-only* strategy emerges as superior. To highlight this, these data are presented visually in Fig. 3-2. It can be seen in the figure that at $\eta \sim 36$ % both strategies have identical energy use.

A resulting family of curves represented by these data is readily apparent in schematic form, Fig. 3-3. It is seen from Fig. 3-3 that at any value of occupancy rate η, as T_o approaches T_i the amount of energy to be transferred to maintain the *auto-set* temperature of the room, expectedly decreases; at $T_o = T_i$, $(q_{on\text{-}only} - q_{on\text{-}off}) = q_{difference} = 0$ W.

Table 3-2 presents a summary of the impact of change in ambient together with η, % on energy use for conditioning of the air in the room with an *auto-set* temperature T_i = 22 ^{O}C. The shaded section of the table, columns 4 through 8, with $40 \leq \eta \leq 100$, %, show that the *on-only* strategy is superior for a wide range of ambient $24 \leq T_o \leq 44$, ^{O}C i.e. all $q_{difference} \leq 0$ W underscore the *on-only* strategy to be superior in energy use to condition the air in the room.

Table 3-1: Comparative summary of the two strategies for conditioning the room with ambient temperature, $T_o = 35$ ^{O}C and *auto-set* interior temperature, $T_i = 22$ ^{O}C for a range of values of occupancy (traffic flow) $0 \leq \eta \leq 100$, %

η (%)	$q_{on\text{-}off}$ (W)	$q_{on\text{-}only}$ (W)	$q_{difference}$ (W)
0	0	375	375
10	107	375	268
20	214	375	161
30	321	375	544
40	428	375	-53
50	535	375	-160
60	642	375	-267
70	749	375	-374
75	802	375	-428
80	856	375	-481
90	963	375	-588
100	1070	375	-695

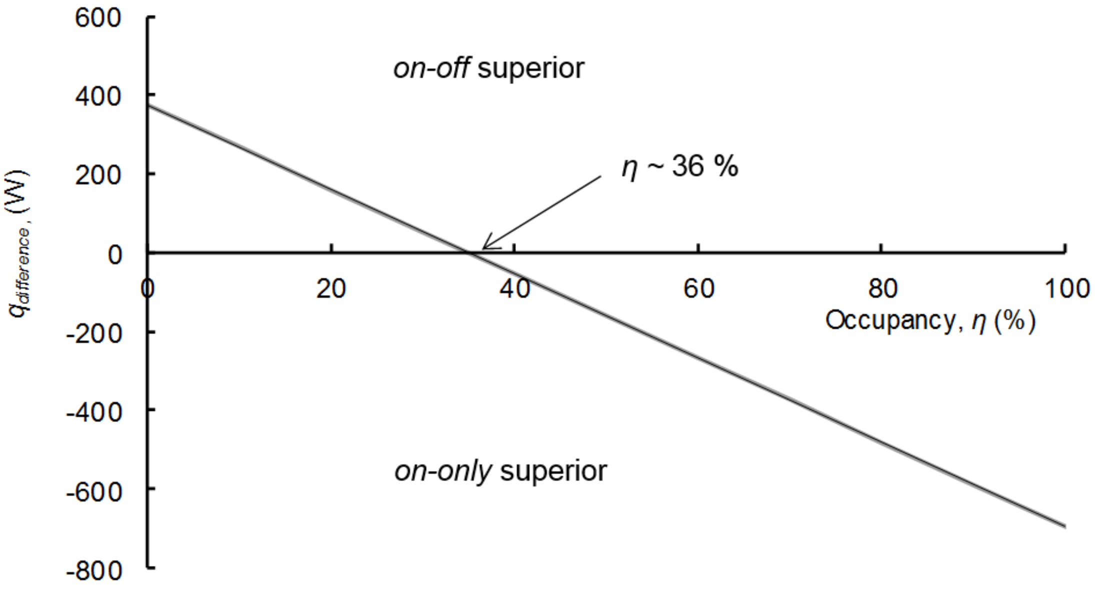

Fig. 3-2: Impact of occupancy on energy difference in the two strategies for the data of Table 3-1

Table 3-2: Impact of ambient temperature (T_o, ^{O}C) together with occupancy (η, %) on the difference in energy use ($q_{on\text{-}only}$ - $q_{on\text{-}off}$) = $q_{difference}$ (W) for conditioning of the air in the room with *auto-set* temperature T_i = 22 ^{O}C

T_o (^{O}C)	**($q_{on\text{-}only}$ - $q_{on\text{-}off}$) (W)**						
	η (%)						
	0	20	40	60	75	80	100
24	32	12	-9	-29	-44	-49	-70
26	80	31	-18	-67	-104	-116	-165
28	136	55	-27	-108	-169	-190	-271
30	198	82	-35	-152	-239	-269	-385
32	266	111	-43	-197	-313	-351	-506
34	337	144	-50	-244	-389	-437	-631
35	375	161	-53	-267	-428	-481	-695
36	413	178	-56	-291	-467	-526	-760
38	492	215	-62	-339	-547	-616	-893
40	574	253	-67	-388	-628	-708	-1,029
42	659	294	-72	-437	-711	-803	-1,168
44	747	336	-76	-487	-795	-898	-1,309

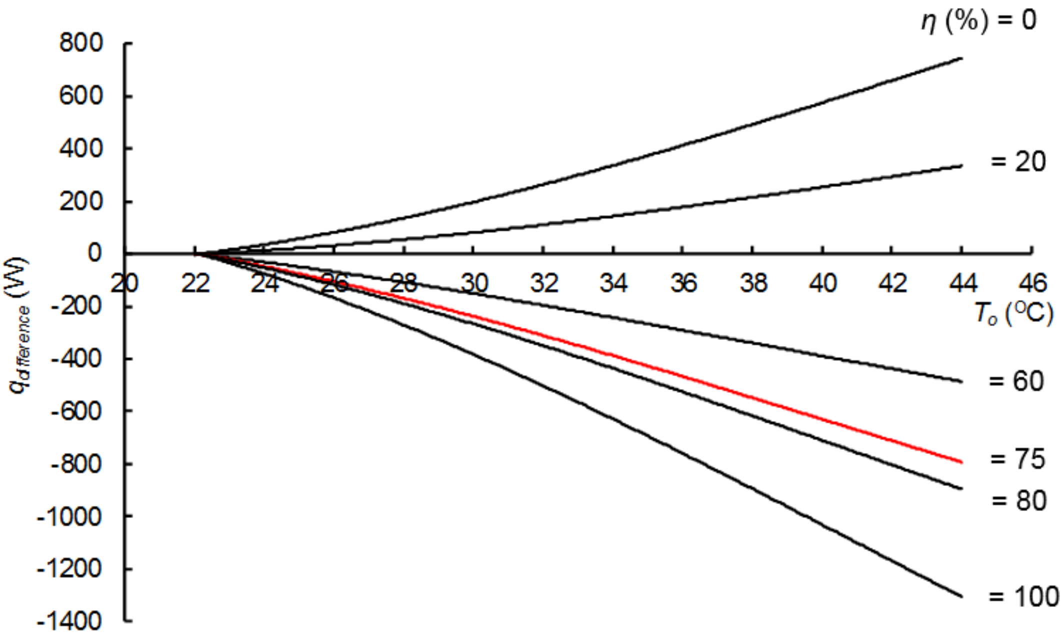

Fig. 3-3: Impact of ambient temperature (T_o, ^{O}C) and occupancy (η, %) on $q_{difference}$ (W) for data of Table 3-2

3.5 Discussion

Despite (judicious) simplifying assumptions, the *on-only* conditioning strategy is the economically elegant alternative for all traffic flows defined by occupancy greater than a threshold value of about 36 %.

Because the thermal properties of the air and room structure can be modelled as a function of bulk temperature, this threshold value of occupancy may change with iterative simulations.

A present drawback with this work however is, clearly, the ambient temperature will not remain at (or possibly near) 35 ^{O}C the entire day, nor will occupancy be a fixed value in time, although the long term historical average is accepted at about 75 %. Both these key parameters will be subject to naturally occurring random fluctuations in value about a long-term mean. The possible impact of these fluctuations on the conditioning strategy is yet to be quantitatively determined.

To quantitatively determine these affects this work is being extended in a long-term study to incorporate the emerging probabilistic methodology of Davey and co-workers (Davey et al., 2015; Davey, 2015 a) in which both ambient temperature and the traffic flow will be simulated using a suitable distribution to emulate the naturally occurring fluctuations in value of occupancy and temperature.

It is expected that small changes in both ambient temperature and occupancy will have a significant impact on the heat to be transferred and of conditioning strategy.

3.6 Chapter summary and conclusions

1. Results from a traditional deterministic SVA solution to a newly synthesized, whole-of-building convective heat model for the conditioning of room air with a range of traffic flow in summer in S-E Australia show an *on-only* i.e. continuous conditioning strategy requires less energy than the widely adopted *on-off* strategy to maintain a room at an *auto-set* temperature 22 ^{O}C with typical occupancy of 75 %

2. Because the model is based on established unit-operations principles (Foust et al., 1980; Wankat, 2007; McCabe et al., 2001) it is concluded quantitative simulations could be readily generalized

3. A present drawback however with model predictions is that they do not take into account the impact of naturally occurring fluctuations about the mean value for ambient temperature and traffic flow (occupancy).

To account for the possible impact of naturally occurring fluctuations in ambient temperature and traffic flow on energy used for conditioning of air, the probabilistic *Fr 13* framework of Davey and co-workers is used in model simulations. This work is presented in the Chapter 4.

Annex 3-A: Forced convective air flow and heat transferred externally to glass panes

3-A 1.1 Introduction

Here, the forced air convection and heat transferred from external ambient to the glass panes is considered.

It is shown that a laminar sub-layer exists against the external building surfaces out to 0.7 m. Because this is rate determining, the value of heat transfer coefficient for a temperature range $258.15 \leq T_o$ (K) ≤ 318.15 is not meaningfully different to that for natural convection, and it is concluded that forced convection, with increases in wind velocity to 10 m s^{-1} and 0.7 m out from the glass pane, does not impact the heat transferred – and can therefore be ignored.

3-A 2.1 Materials and Methods

The Reynolds number (Re) for forced convection against the external surface to a distance of 0.7 m away from the glass pane was computed for a temperature range $258.15 \leq T_o$ (K) ≤ 318.15 and $0 \leq$ wind velocity ≤ 10, m s^{-1} (Table 3-A1).

Using the same mean density and viscosity of air as in Chapter 3 (Holman, 2010) for the temperature range $250 \leq T$ (K) ≤ 350 are ρ = 1.1774 kg m^{-3}, μ = 1.8642 x 10^{-5} kg m^{-1} s^{-1} such that flow of air over a flat surface is laminar if

$$\mathrm{Re} = \frac{\rho \upsilon x}{\mu} \leq 5 \times 10^5 \qquad (3A.1)$$

where all symbols are defined in the Nomenclature.

3-A 3.1 Results

Table 3-A1 is a summary of computations for the convective (Re ≤ 5 x 10^5) laminar sub-layer to 0.7 m from glass panes with airspeed (wind velocity) up to 10 m s^{-1} and with $258.15 \leq T_o$ (K) ≤ 318.15. (A larger value of 0.7 m was selected to illustrate definitively that the film is laminar against the large-scale building - a range of lower values could have been used).

The shaded area of the table highlights the region of convective laminar sub-layer i.e. Re ≤ 5 x 10^5.

Because Re is directly proportional to x in Eq. (3A.1) it can be interpreted from Table 3-A1 that the value of Re is larger and; therefore a lower airspeed or wind velocity is required for forced convection to have an impact the further away from the glass pane and vice-versa.

Table 3-A1: Summary computations for the convective ($\mathrm{Re} \leq 5 \times 10^5$) laminar sub-layer to 0.7 m from glass panes with airspeed (wind velocity) up to 10 m s^{-1} and with $258.15 \leq T_o$ (K) ≤ 318.15

Ambient T_o (K)	**Density of air, ρ (kg m^{-3})**	**Viscosity of air, μ (kg m^{-1} s^{-1} x 10^5)**	**Distance from glass pane 0.7 m**					
			Airspeed (wind velocity) over glass pane (m s^{-1} x 10^4)					
			0	**2**	**4**	**6**	**10**	**12**
			Re (dimensionless)					
258.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3
263.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3
268.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3
273.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3
278.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3
283.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3
288.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3
293.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3
298.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3
303.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3
308.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3
313.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3
318.15	1.18	1.86	0	8.88	17.8	26.6	44.4	53.3

The shaded area highlights the region of convective laminar sub-layer i.e. $\mathrm{Re} \leq 5 \times 10^5$.

3-A 4.1 Conclusions

1. Because a laminar sub-layer on the glass panes is rate determining the value of the heat transfer coefficient h for $258.15 \leq T_o$ (K) ≤ 318.15 is not meaningfully different to that for natural convection

2. At a distance of 0.7 m away from the glass pane increases in wind velocity to 10 m s^{-1} therefore do not impact the heat transferred

3. The forced convective impact on the heat transferred to the glass panes is negligible and can be ignored.

Annex 3-B: Transient period for the surface of the interior wall to approximate ambient temperature after conditioning is switched off in the *on-off* energy strategy

3-B 1.1 Introduction

In this Annex, the transient period for the surface of the room interior brick walls to approximate equilibrium with ambient temperature after the air conditioning is switched off in the *on-off* energy strategy is quantitatively computed.

It is shown that an uninterrupted time for the surface of interior brick walls to approximate equilibrium with an ambient T_o = 35 ^{O}C and room interior *auto-set* temperature T_i = 22 ^{O}C considering combined conduction, convection and radiative impacts, would be about 48 h.

However, because the room occupancy for any commercial, and therefore practical, operation is high, and based on historical summer occupancy data between Dec. 2009 and Feb. 2015 (n = 541) is actually η = 90 % (Chapter 5 p. 58), it is concluded that this period will be 4 h. This is because the conditioning will be switched on by the room occupants or hotel staff, within the standard *check-out* and *check-in* times (respectively, 10.00 and 14.00, h).

The actual temperature of the room brick walls following this 4 h transient period in the *on-off* strategy is computed to be 25.78 ^{O}C, or a rise of only 3.78 ^{O}C above the *auto-set* conditioning room temperature.

Importantly, this transient computation does not apply to the thesis hypothesis of *on-only* conditioning energy strategy. This is because with that strategy the walls are maintained continuously at the *auto-set* temperature T_i = 22 ^{O}C.

3-B 2.1 Materials and Methods

The computational approach, assuming a one dimensional heat transfer, is to:

1. Carefully label a schematic of the heat transfers (Fig. 3-B1)
2. Reject a lumped-capacity analysis (Bi < 0.1) (Holman, 2010) from a reliably determined Biot number = 0.52
3. Use detailed thermal diffusivity computations (α') to estimate the transient period for the surface of the brick walls to approximate equilibrium with ambient (Tables 3-B1 and 3-B2).

All the symbols used in the following computations are defined in the Nomenclature.

1. Fig. 3-B1 is a schematic of the heat transfers. It is seen from the figure that the ceiling and floor are assumed to be thermally insulated, and that heat transfer to the surface of the brick walls of the room interior is via the window panes.

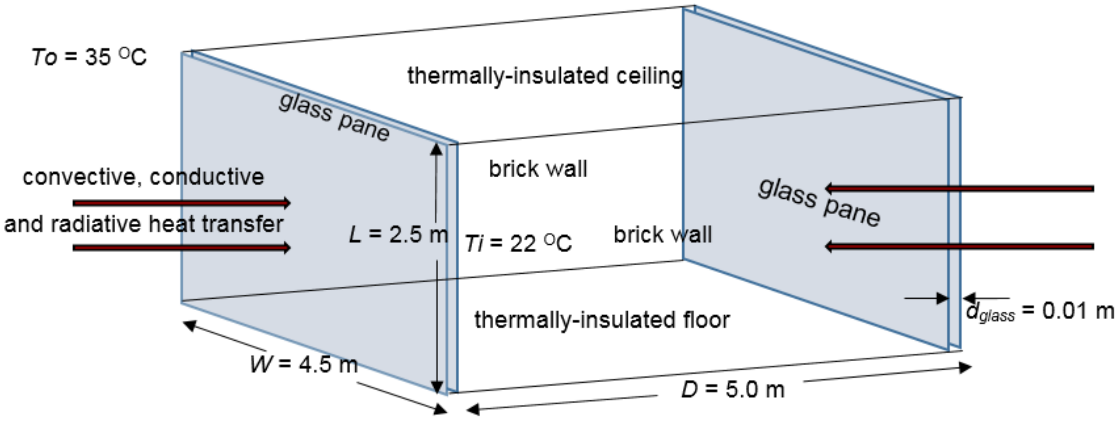

Fig. 3-B1: Schematic of convective, conductive and radiative heat transfers to walls

2. The Biot number (Bi_{brick}) for the interior walls is obtained (Holman, 2010) [9] from

$$\mathrm{Bi}_{brick} = \frac{h_{brick} d_{brick}}{k_{brick}} \tag{3B.1}$$

3. The thermal diffusivity (α_{brick}', m^2 s^{-1}) of brick is given by

$$\alpha_{brick}' = \frac{k_{brick}}{\rho_{brick} c_{brick}} \tag{3B.2}$$

The computation of the total resistance to heat transfer due to convection and conduction is

$$R_{convection\ and\ conduction} = R_{i,brick} + R_{i,air} + R_{i,glass} + R_{o,glass} + R_{glass} \tag{3B.3}$$

where the convective resistance of the surface of the brick that is adjacent to the room interior is given by

$$R_{i,brick} = \frac{1}{h_{i,brick} A_{brick}} \tag{3B.4}$$

---

[9] Holman (2010) pp. 4, 28, 36, 37, 101, 142, 146, 227, 653 ff.

and the conductive resistance of the room air is

$$R_{i,air} = \frac{D}{k_{air} A_{air}} \tag{3B.5}$$

The convective resistance of inside of glass pane adjacent the room interior air is

$$R_{i,glass} = \frac{1}{h_{i,glass} A_{glass}} \tag{3B.6}$$

and the convective resistance of outside of glass pane adjacent the ambient air is given by

$$R_{o,glass} = \frac{1}{h_{o,glass} A_{glass}} \tag{3B.7}$$

The conductive resistance of glass pane is

$$R_{glass} = \frac{d_{glass}}{k_{glass} A_{glass}} \tag{3B.8}$$

The overall heat transfer coefficient due to convection and conduction is

$$U_{convection\ and\ conduction} = \frac{1}{R_{convection\ and\ conduction} A_{glass}} \tag{3B.9}$$

and the heat flux for convection and conduction is

$$\frac{q_{convection\ and\ conduction}}{A_{glass}} = U_{convection\ and\ conduction} \Delta T \tag{3B.10}$$

The surface temperature ($T_{convection\ and\ conduction}$ ($d_{brick} = 0$), K) of the room interior brick walls due to $q_{conection\ and\ conduction}/A_{glass}$ at a given time (τ, s) is given as

$$T_{convection\ and\ conduction}\left(d_{brick} = 0\right) = T_i + 273.15 + \frac{\left(2\frac{q_{convection\ and\ conduction}}{A_{glass}}\right)\left\{\frac{\alpha_{brick}{}' \tau}{\pi}\right\}^{0.5}}{\kappa_{brick}} \tag{3B.11}$$

However this analysis does not account for radiative heat transfer.

The heat flux for radiative heat transfer is

$$\frac{q_{radiation}}{A_{glass}} = IAC\varepsilon\sigma\left(T_o^4 - T_{air,glass}^4\right) \tag{3B.12}$$

The total heat flux due to convection, conduction and radiation from Eqs. (3B.10) and (3B.12) is therefore

$$\frac{q_{total}}{A_{glass}} = \frac{q_{convection\ and\ conduction}}{A_{glass}} + \frac{q_{radiation}}{A_{glass}} \tag{3B.13}$$

Eq. (3B.13) gives the surface temperature (T_{total} ($d_{brick} = 0$), K) of the room interior brick walls due to q_{total}/A_{glass} at a given time (τ, s) as

$$T_{total}\left(d_{brick} = 0\right) = T_i + 273.15 + \frac{\left(2\frac{q_{total}}{A_{glass}}\right)\left\{\frac{\alpha_{brick}'\tau}{\pi}\right\}^{0.5}}{\kappa_{brick}} \tag{3B.14}$$

3-B 3.1 Results

The Biot number for the brick walls is obtained from Eq. (3B.1) and can be shown to be $\mathrm{Bi}_{brick} = 0.52$. Because this is > 0.1, it cannot be relied on to apply a lumped-capacity approach.

To compute the transient period for the brick to approximate equilibrium with ambient detailed thermal diffusivity (α') computations of Eq. (3B.2) are therefore needed, and are carried out as follows:

The convective heat transfer resistance to the surface of the brick walls is computed from substituting $h_{i,brick} = 3.24$ W m^{-2} K^{-1}and $A_{brick} = 25.0$ m^2 into Eq. (3B.4) to give $R_{i,brick} = 1.23 \times 10^{-2}$ K W^{-1}. The conductive heat transfer resistance through the room interior air is computed by substituting $D = 5$ m, $k_{air} = 2.62 \times 10^{-2}$ W m^{-1} K^{-1} and $A_{room\ interior\ air} = 12.5$ m^2 into Eq. (3B.5) to obtain $R_{i,air} = 13.74$ K W^{-1}.

The convective heat transfer resistance through the glass pane adjacent inside air is computed as follows - substituting $h_{i,glass} = 2.61$ W m^{-2} K^{-1} and $A_{glass} = 22.5$ m^2 into Eq. (3B.6) gives $R_{i,glass} = 1.70 \times 10^{-2}$ K W^{-1}. The convective resistance through the glass pane and outside ambient air is determined by substituting $h_{o,glass}$ = 2.61 W m^{-2} K^{-1} and A_{glass} = 22.5 m^{2} into Eq. (3B.7) such that $R_{o,glass}$ = 1.70 x 10^{-2} K W^{-1}. The conductive resistance through glass pane is obtained by substituting d_{glass} = 0.01 m, k_{glass} = 0.78 W m^{-1} K^{-1} and A_{glass} = 22.5 m^{2} into Eq. (3B.8) such that R_{glass} = 5.70 x 10^{-4} W K^{-1}.

The total convective and conductive resistance heat transfer through from ambient through the glass pane and the room interior air to the surface of the brick walls is the aggregate of all resistances as shown in Eq. (3B.3) and can be solved to yield $R_{covection\ and\ conduction}$ = 13.79 K W^{-1} giving an overall convective and conductive heat transfer coefficient $U_{convection\ and\ conduction}$ = 3.22 x 10^{-3} W m^{-2} K^{-1} (Eq. (3B.9)).

The heat flux from convection and conduction $q_{convection\ and\ conduction}/A_{glass}$ is computed from Eq. (3B.10) as 4.19 x10^{-2} W m^{-2}.

The heat flux from radiation $q_{radiation}/A_{glass}$ is computed from Eq. (3B.12) as 26.82 W m^{-2}.

The total heat flux from combined convection, conduction and radiation q_{total}/A_{glass} is computed from Eq. (3B.13) as 26.86 W m^{-2}.

Substituting the heat flux $q_{convection\ and\ conduction}/A_{glass}$ and q_{total}/A_{glass}, into Eqs. (B3.11) and (3B.14) respectively together with α_{brick}' and k_{brick} yield the time (τ, s) for the surface of the brick walls to approximate equilibrium with the ambient temperature T_o = 35 ^{O}C.

Summary sample computational results are presented in Tables 3-B1 and 3-B2.

Table 3-B1: Transient period for surface of interior wall to approximate ambient temperature (35 ^{O}C) after conditioning is switched off in the *on-off* energy strategy considering combined convection and conduction

τ (s)	$T_{convection\ and\ conduction}$ (d_{brick} = 0) (K)
0	295.15
8640000	295.29
31548960	295.43
157744800	295.78
315489600	296.02

Table 3-B2: Transient period for surface of interior wall to approximate ambient temperature (35 ^{O}C) after conditioning is switched off in the *on-off* energy strategy considering combined convection, conduction and radiative impacts

τ (s)	T_{total} (d_{brick} = 0) (K)
0	295.15
3600	297.04
43200	301.69
86400	304.40
172800	308.23

3-B 4.1 Discussion

4.1.1 Transient period in on-off *energy strategy*

It can be seen from Table 3-B1 (row 7) that the uninterrupted transient period computed without considering radiation would be greater than 31,548,9600 s (~ 10 year) in summer in the dry climate of S-E Australia. Notably however, if radiative heat transfer is considered, it can be seen from Table 3-B2 (row 7) this is much less at 172,800 s = 48 h.

The radiative impact is therefore highly significant in impacting the transient period for the surface of the interior wall to approximate ambient temperature after conditioning is switched off in the *on-off* energy strategy.

This is therefore investigated in an extended heat transfer model and is presented in Chapter 5.

Overall therefore, the maximum period that the room will remain unoccupied with the conditioning switched off is 4 h – the time between *check-out* and *check-in*.

The actual temperature of the wall after 4 h can be estimated.

4.1.2 Actual temperature of wall during transient period between **check-out** *and* **check-in** *in* **on-off** *energy strategy*

The temperature of the surface of the brick after 4 h is estimated from interpolation of the data of Table 3-B2. The result is presented in Table 3-B3.

It can be seen from the table that the surface brick walls of the room interior for the 4 h ($\tau = 14400$ s) transient period will be a temperature of 25.78 ^{O}C, or a rise of only 3.78 ^{O}C above the *auto-set* conditioning room temperature.

Table 3-B3: Summary computations for the surface temperature of the brick walls of the room interior for the 4 h ($\tau = 14400$ s) transient period between room *check-out* and *check-in* times

τ (s)	$T_{total}(d_{brick} = 0)$ (K)
14400	298.93

3-B 5.1 Conclusions

1. The uninterrupted transient period for the brick wall to approximate equilibrium with an ambient $T_o = 35$ ^{O}C and a room interior *auto-set* temperature $T_i = 22$ ^{O}C would be 48 h with the *on-off* energy strategy applied in the dry climes of S-E Australia

2. However, because in practice the room conditioner will be switched off for a period of only 4 h, that is, between *check-out* and the *check-in* times, the temperature of the surface brick will reach 25.78 ^{O}C, or a rise of only 3.78 ^{O}C above the *auto-set* conditioning room temperature.

CHAPTER 4

A PROBABILISTIC *FR 13* SIMULATION OF CONDITIONING OF ROOM AIR WITH UNPLANNED HEAT TRANSFERS AND TRAFFIC FLOWS DURING SUMMER

Parts of this chapter have been published as:

Chu, J.Y.G., Davey, K.R., 2015. A probabilistic *Fr 13* simulation of strategies for cooling of air in buildings with unplanned traffic flow during summer. In: Proc. 3rd Int. Workshop on Simulation for Energy, Sustainable Development & Environment-SESDE 2015, Sept. 21-23, Bergeggi, Italy, Paper 45, pp. P1, 51-59. ISBN: 9788897999614

4.1 Introduction

Findings from Chapter 3 highlighted that a traditional, deterministic SVA solution to the simplified heat-model for conditioning of air predicted the alternative *on-only* conditioning would use less energy than the *on-off* default used widely in industry, and; that this solution did not take into account possible impact from naturally occurring fluctuations in ambient temperature and room occupancy.

In this chapter the model is solved using the methodology of the *Fr 13* framework that takes into account impact from naturally occurring, stochastic fluctuations in ambient temperature and room occupancy. An advantage over the traditional solution is that all practical scenarios that could exist operationally can be quantified and evaluated.

An energy strategy risk factor (p) is quantitatively defined such that for all $p > 0$ adoption of the alternative *on-only* energy strategy will have failed.

A comparison is made with the traditional deterministic SVA solution.

4.2 Material and methods

Consider again Fig. 3-1 and Eqs. (3.1) through (3.21).

4.2.1 An energy strategy risk factor

The difference in energy used between the two energy strategies is, from Eqs. (3.20) and (3.21)

$$P = q_{on-only}{}' - q_{on-off}{}' = q_{glass}{}' - \left[\frac{\eta}{100}\left(q_{glass} + q_{brick}\right)\right]' \tag{4.1a}$$

$$= \left[q_{qlass}\left(1 - \frac{\eta}{100}\right)\right]' - \left[q_{brick}\left(\frac{\eta}{100}\right)\right]'$$

Simplifying Eq. (4.1a) gives

$$\frac{P}{\left[q_{brick}\left(\frac{\eta}{100}\right)\right]'} = \frac{\left[q_{glass}\left(1 - \frac{\eta}{100}\right)\right]'}{\left[q_{brick}\left(\frac{\eta}{100}\right)\right]'} - 1 \tag{4.1b}$$

in which $\left[q_{glass}\left(1-\frac{\eta}{100}\right)\right]'$ and $\left[q_{brick}\left(\frac{\eta}{100}\right)\right]'$ are particular (instantaneous) values (or more strictly, mathematically, one probabilistic simulation).

A computationally more convenient form of the risk factor is

$$p=\frac{\left[q_{glass}\left(1-\frac{\eta}{100}\right)\right]'}{\left[q_{brick}\left(\frac{\eta}{100}\right)\right]'}-1 \tag{4.1}$$

where $p=\frac{P}{\left[q_{brick}\left(\frac{\eta}{100}\right)\right]'}$

Eq. (4.1) is convenient because for all $p > 0$ the alternative *on-only* strategy will use more energy than the *on-off* and its application can be said to be a ‘fail’.

Importantly, it must be noted that a failed *on-only* air-conditioning strategy ($p > 0$) does not mean a loss, but rather that no real gain is made in savings of electrical energy to condition the room bulk air to the *auto-set* temperature over the default *on-off* energy strategy.

Eqs. (3.1) through (3.21) together with Eq. (4.1) define the *Fr 13* model for failure of the *on-only* energy strategy.

4.2.2 **Fr 13** ***simulations***

To mimic the naturally fluctuations in ambient temperature and hotel room occupancy a distribution is used. Therefore the output from the *Fr 13* simulation is also a distribution – of output behaviours. There are some 40 distribution types (Vose, 2008).

Simulations proceed through a refined MC (r-MC) random sampling of the distributions and solution of the heat model. A random number generator is used (Vose, 2008).

A r-MC is used because ‘pure’ MC can both over- and under- sample from various parts of the distribution and it cannot be relied on to replicate the distribution (Abdul-Halim and Davey, 2016; Vose, 2008; Chandrakash and Davey, 2017 a). The refinement is *Latin Hypercube* sampling. This is used to ensure values are sampled that cover the entire practical range of the distributions.

Davey and co-workers (e.g. Zou and Davey 2016; Chandrakash and Davey, 2017 a) have reported that some 1,000 to 50,000 samples are needed for a typical unit-operation. This number can be readily established when a plot of number of failures, all $p > 0$, versus number of r-MC samples has plateaued to a constant value and the output mean is normally distributed (Davey, 2015 a).

Importantly, with a sufficiently large number of r-MC samples, all possible combinations of resulting output process scenarios that could occur in conditioning the room air will have been simulated, including failures in the energy strategy adopted.

The r-MC sampling of the distributions can be readily carried out using Microsoft Excel^{TM} with a commercially available add-on *@Risk*™ (version 5.5, Palisade Corporation).

An advantage of this particular spread sheeting tool is that the distributions can be entered, copied, pasted and viewed as Excel™ formulae (Zou and Davey 2016; Chandrakash and Davey, 2017 a).

4.3 Results

Table 4-1 presents a comparative summary of results of *Fr 13* with this from the traditional deterministic SVA solution.

Computations were carried out using Microsoft Excel™ with commercially available add-on *@Risk*™ (version 5.5, Palisade Corporation). The use of spread sheeting is advantageous as it has nearly universal use and the distributions defining naturally occurring fluctuations in parameters can be entered, viewed, copied, pasted and manipulated as Excel™ formulae.

The table permits the simulations to be read systematically down each of the columns. The parameters that define the unit-operation for conditioning of the room interior air are given in column 1 of Table 4-1. The SVA computations are given in column 2. For example, inspection of column 2 shows the input data and resulting values for the intermediate calculations, and finally, for each of the two strategies, respectively, the value $q_{on\text{-}only}$ and $q_{on\text{-}off}$, (W).

The distributions used for the *Fr 13* simulations for each of ambient temperature (T_o, ^{O}C) and traffic flow (as occupancy) (η, %) are defined in column 4 of Table 4-1. For example, occupancy, (row 2 of Table 4-1) is defined by the distribution **RiskTriang** (5, 75, 100). This produces a triangle distribution with a minimum, most likely and maximum occupancy of 5, 75 and 100, % respectively. This triangle distribution is shown graphically as Fig. 4-1.

However, to emulate fluctuations in the ambient temperature the distribution used is **RiskNormal** (35, 5, **RiskTruncate** (25, 45)). This produces a normal distribution with a mean of 35, standard deviation (stdev) of 5, and which is truncated to a minimum of 25, and a maximum of

45, ^{O}C. These truncations are used to restrict r-MC sampling to realistic temperatures that could actually occur.

5,000 simulations were found sufficient. Each can be regarded as a possible next-day scenario.

A total of 670 (13.4 %) scenarios were identified with $p > 0$ in the 5,000 simulations, Fig. 4-2. In this figure the x-axis is the value of the energy strategy risk factor, p, from Eq. (4.1) and because the *@Risk* output is a discrete histogram, the y-axis is the probability of p actually occurring (Vose, 2008). The failures are seen to the right of the figure ($p > 0$) and are therefore readily identified.

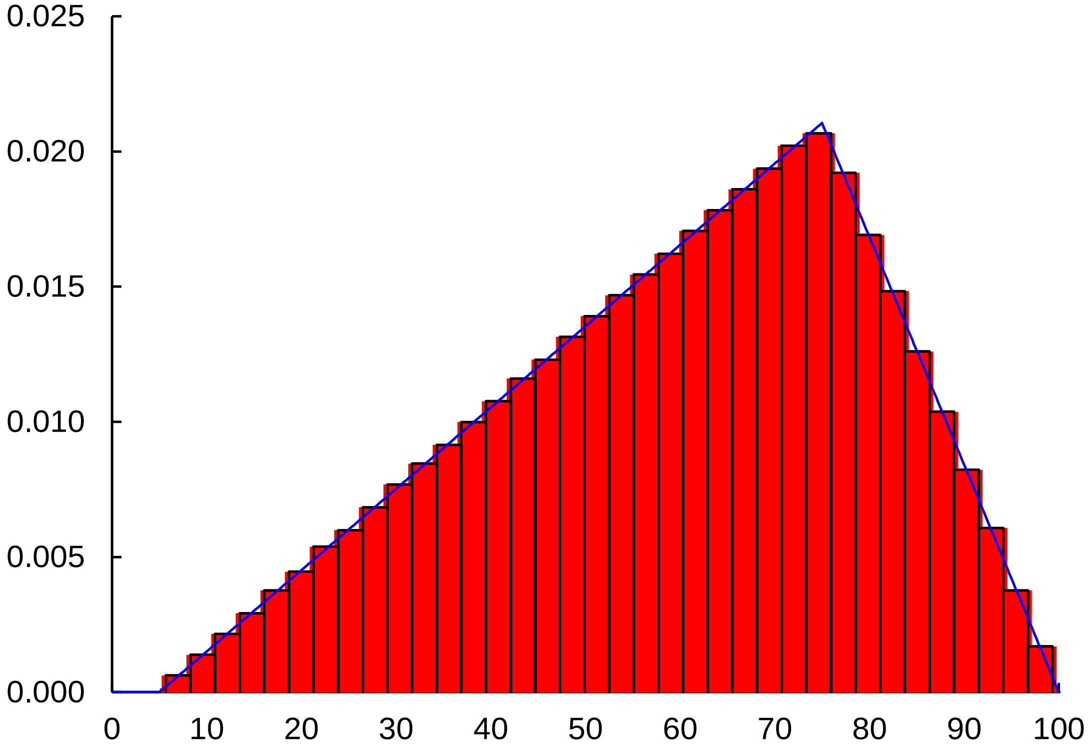

Fig. 4-1: Distribution **RiskTriang** (5, 75, 100) for room traffic flow showing a minimum, most likely and maximum 5, 75, 100, % occupancy, η

Ten (10) of these 670 failures which could occur as a result of adopting the *on-only* energy strategy are presented in Table 4-2.

It can be seen that in all cases the value $p > 0$, indicating a failure of the *on-only* energy strategy. The bold text in Table 4-2 (row 6, for failure scenario 4) is the particular scenario reported in Table 4-1.

Table 4-1: Summary comparison of the traditional SVA with the new *Fr 13* simulation of applying the *on-only* conditioning strategy

Row	Conditioning parameter	SVA[*]	***Fr 13* simulation**[†]	
1	T_o (^{O}C)	35	**33.46**[††]	**RiskNormal**(35,5,**RiskTruncate**(25,45))
2	η (%)	75	**21.66**[††]	**RiskTriang**(5,75,100)
3	T_i (^{O}C)	22	22	Constant
4				
5	L (m)	2.5	2.5	Constant
6	W (m)	4.5	4.5	Constant
7	d_{glass} (m)	0.01	0.01	Constant
8	k_{glass} (W m^{-1} K^{-1})	0.78	0.78	Constant
9	ρ (kg m^{-3})	1.18	1.18	Constant
10	g (m s^{-2})	9.81	9.81	Constant
11	μ (kg m^{-1} s^{-1})	1.86×10^{-5}	1.86×10^{-5}	Constant
12	c (J kg^{-1} K^{-1})	1005.70	1005.70	Constant
13	k (W m^{-1} K^{-1})	2.62×10^{-2}	2.62×10^{-2}	Constant
14	β (K^{-1})	3.33×10^{-3}	3.33×10^{-3}	Constant
15				
16	L (m)	2.5	2.5	Constant
17	D (m)	5	5	Constant
18	d_{brick} *(m)*	0.11	0.11	Constant
19	k_{brick} (W m^{-1} K^{-1})	0.69	0.69	Constant
20				
21	A_{glass} (m^2)	22.5	22.5	Eq. (3.7)
22	ΔT (K)	13	11.46	Eq. (3.9)
23	$T_{air,glass}$ (K)	28.5	27.73	Eq. (3.10)
24	$\delta T_{o,glass}$ (K)	6.5	5.73	Eq. (3.16)
25	$\delta T_{i,glass}$ (K)	6.5	5.73	Eq. (3.17)
26	Gr$_{glass}$ (dimensionless)	1.33×10^{10}	1.17×10^{10}	Eq. (3.14)
27	Pr$_{glass}$ (dimensionless)	0.71	0.71	Eq. (3.15)
28	Ra$_{glass}$ (dimensionless)	9.48×10^{9}	8.35×10^{9}	Eq. (3.13)
29	$h_{o,glass}$ (W m^{-2} K^{-1})	2.61	2.50	Eq. (3.12)
30	$h_{i,glass}$ (W m^{-2} K^{-1})	2.61	2.50	Eq. (3.12)
31	$U_{o,glass}$ (W m^{-2} K^{-1})	1.28	1.23	Eq. (3.5)
32	q_{glass} (W)	374.75	317.67	Eq. (3.2)
33				
34	A_{brick} (m^2)	25	25	Eq. (3.8)
35	ΔT (K)	13	11.5	Eq. (3.9)
36	$T_{air,brick}$ (K)	28.5	27.73	Eq. (3.11)
37	$\delta T_{i,brick}$ (K)	13	11.5	Eq. (3.18)
38	Gr$_{brick}$ (dimensionless)	2.66×10^{10}	2.34×10^{10}	Eq. (3.14)
39	Pr$_{brick}$ (dimensionless)	0.71	0.71	Eq. (3.15)
40	Ra$_{brick}$ (dimensionless)	1.90×10^{10}	1.67×10^{10}	Eq. (3.13)
41	$h_{i,brick}$ (W m^{-2} K^{-1})	3.24	3.12	Eq. (3.12)
42	$U_{o,brick}$ (W m^{-2} K^{-1})	2.14	2.08	Eq. (3.6)
43	q_{brick} (W)	695.05	596.65	Eq. (3.3)
44				
45	$q_{on\text{-}off}$ (W)	802.35	198.04	Eq. (3.20)
46	$q_{on\text{-}only}$ (W)	374.75	317.67	Eq. (3.21)
47	p (dimensionless)		**92.55**	Eq. (4.1)

[*] Traditional, Single Value Assessment.

[†] One only of 5,000 scenarios

[††] Values as reproduced from the r-MC sampling – it is not implied these need to be measured to this accuracy.

4.4 Discussion

4.4.1 Model confirmation

An extensive test of model simulations showed them to be stable. It was concluded the simulations were free of programming and computational errors and that the *Fr 13* model was therefore suitable for the present purpose.

4.4.2 Failures of on-only *strategy*

The *Fr 13* findings, practically interpreted so that each simulation is thought of as a possible next operational day in any summer (assumed to be 90 days), show that adopting the *on-only* energy strategy could result in (670/5,000 x 90 =) 12 failures (13.4 % failure rate) each summer. However, these will occur randomly and therefore will not be spaced evenly in time.

It should not be implied by the reader that the numerical values given in Tables 4-1 and 4-2 would need to be measured to these exactly; these values are reproduced simply as the exact value sampled randomly in the r-MC simulations.

This result however is based on the simplified model for conditioning, but more particularly the distributions chosen to emulate the ambient temperature and traffic flow. The impact of varying these is therefore investigated.

Table 4-2: Ten (10) selected failures of the *on-only* strategy from 670 in 5,000 scenarios

Scenario	**η (%)**	**T_o (^{O}C)**	**p (dimensionless)**
1	5.67	30.16	757.77
2	15.02	40.08	215.84
3	18.8	34.38	131.67
4[&]	**21.66**	**33.46**	**92.55**
5	24.94	39.7	67.56
6	26.45	34.01	48.76
7	29.35	40.49	34.69
8	31.24	38.46	21.63
9	33	38.86	12.47
10	32.95	27.22	0.94

[&] Particular scenario of Table 4-1.

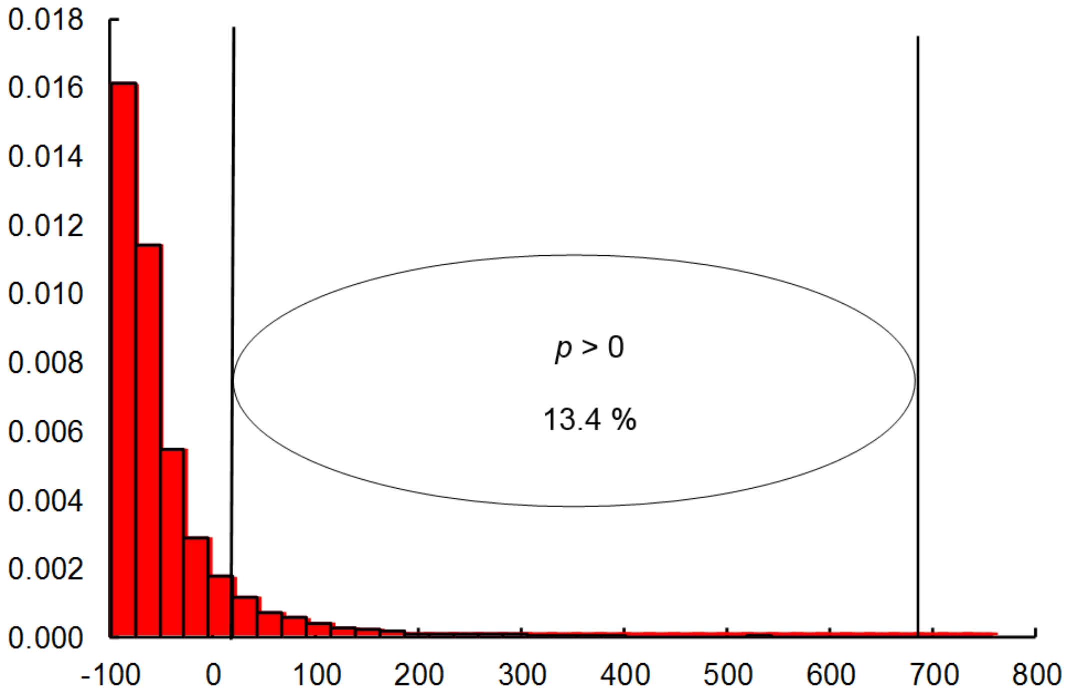

Fig. 4-2: *Fr 13* simulation of *on-only* energy conditioning strategy with 5,000 scenarios. The 670 failure scenarios (13.4 %) are shown to the right of the figure ($p > 0$)

4.4.3 Establishing appropriate probability distributions

It appears reasonable that the ambient temperature would be normally distributed as has been assumed. The distribution is seen (Table 4-1) to be defined with a 2 x stdev about the mean to establish the minimum and maximum temperatures probable (25 and 45, ^{O}C). This ensures that 95.45 % of all r-MC samples will fall in this interval (Sullivan, 2004; Vose, 2008). Therefore the distribution of values sampled to emulate the naturally occurring fluctuations in ambient temperature will cover a realistic range.

However, a potential problem is to accurately reflect the traffic flow (as occupancy).

Historical records are a very good guide to a long term mean and seasonal trend, but could not be relied upon to accurately predict a next-day event. This is because there will be irregular events such as transport strikes (rail, air or road), road and freeway closures due to accidents, or loss of electrical and other utilities to the building.

Unlike temperature, there could therefore be extremes with traffic flow; a very low value of η, % (possibly not zero), but also a large and finite value of η = 100 % (ideal for hoteliers and public building use). Given these two values and the industry wide knowledge that the most likely mean value is η = 75 % a triangle distribution was selected (Anon., 2015).

In the absence of unconditional data, a reasonable alternative however is pert (Vose, 2008). This distribution is also defined by a minimum, most likely and maximum. Repeat simulations of the *Fr 13* model with traffic flow as occupancy η, % defined by **RiskPert** (5, 75, 100) showed the failure rate could reduce to about 6 %. However, in the absence of more extensive trials, this is not seen at present as a meaningful change in the failure rate of the *on-only* energy strategy for conditioning during summer.

The Spearman rank correlation coefficient (Snedecor and Cochran, 1989) readily available in *@Risk*, can be used to highlight the highly significant dependency of the conditioning model on the distribution chosen for traffic flow, Table 4-3. The data of the table underscore a strong inverse correlation (coefficient = -1.00) between occupancy and the energy strategy risk factor, p. The impact of ambient temperature can be seen to be low (coefficient = 0.05).

Applied, this means that it is the change in traffic flow that will control the energy use and therefore should be used to adopt a particular energy strategy for conditioning in this model.

Table 4-3: Spearman rank correlation coefficient (Snedecor and Cochran, 1989) for the two input parameters to the *Fr 13* conditioning model for traffic flow (as occupancy, η, %) and ambient temperature (T_o, ^{O}C) on the energy strategy risk factor, p

Input parameter	**Coefficient**
η (%)	-1.0
T_o (^{O}C)	0.05

4.4.4 Results overview

A key insight is that the alternative *on-only* energy strategy advocated is predicted to fail in only about 13.4 % of all cases, averaged over the long term. This information is not currently available from alternative risk and hazard analyses.

A crucial reason is that these alternative methods do not take into account the possible impact of naturally occurring, random, and unpredictable fluctuations in the value of occupancy.

A major benefit with *Fr 13* model is that both the facts about the process and the effects of random change in parameters are separated (Abdul-Halim and Davey, 2015). This is highly advantageous because it permits the effect of each parameter in this research the ambient temperature and the occupancy to be studied (second-tier simulations) separately.

4.5 Chapter summary and conclusions

1. A probabilistic *Fr 13* simulation of a proposed *on-only* conditioning strategy for heat transfers in a convective heat model for room air highlights that adoption will fail in 13.4 % of cases i.e. translated practically, there would be 12 failures each summer, averaged over a prolonged period of the strategy

2. Simulations underscore that this conditioning strategy is highly dependent on traffic flow (as room occupancy)

3. A drawback however is that radiative transfers have not been taken into account

4. Because all scenarios that could practically are simulated it is concluded that the probabilistic *Fr 13* assessment is an advance over more traditional assessments.

In the next chapter, Chapter 5, the heat model is extended to include radiative impacts - and temperature effects on thermal properties of the air.

Additionally, to improve predictive accuracy, the distributions for T_o and L_T are derived from historical data for summer ambient temperature and hotel occupancy over a 5-year time-frame.

CHAPTER 5

AN IMPROVED HEAT TRANSFER MODEL FOR CONDITIONING OF AIR IN SUMMER WITH FLUCTUATING AMBIENT AND ROOM OCCUPANCY RATE

Parts of this chapter have been published as:

Chu, J.Y.G., Davey, K.R., 2017 a. Synthesis of a quantitative strategy to minimize energy used in conditioning of air in buildings in summer with fluctuating ambient and room occupancy rate. Chemical Engineering Science – *submitted* (*May*).

5.1 Introduction

A simplified convective model for whole-of-building was presented in Chapter 4. To more realistically simulate heat transfers this model is extended in this chapter, Chapter 5, to include significant radiative impacts as highlighted in Annex 3-B and historical distributions are used to realistically mimic T_o and L_T. Correlations are produced to predict thermal properties of the air.

The extended model is solved to quantify a more realistic failure probability of the alternative *on-only* strategy. Results are compared with the traditional solution method.

5.2 Materials and Methods

5.2.1 An extended model

Fig. 5-1 schematically illustrates the typical (hotel) room, together with natural convective and incident radiative heat transfers.

If internal heat energy generation, due to metabolism of occupants or room lighting and refrigeration, is (reasonably) considered negligible in comparison with the energy required to condition the air, the heat energy in the room will be due to convective and incident radiative transfer through the glass pane and from the supporting brick wall to the room interior.

The volumetric expansion coefficient (β) of air is

$$\beta = \frac{1}{T} \qquad (5.1)$$

Additionally the respective values of thermal properties of air such as, density (ρ), dynamic viscosity (μ), specific heat (c) and thermal conductivity (k) of the air film on the glass (outside and inside) and thermal conductivity of the air on the brick (inside only) are computed from correlations fitted to the tabulated data of Holman (2010) using regression analyses (Snedecor and Cochran, 1989) to give

$$\rho = 370.77T^{-1.009} \qquad (R^2 = 0.99,\ n = 4) \qquad (5.2)$$

$$\mu = 4\text{x}10^{-6}T^2 + 0.0069T + 0.0921 \qquad (R^2 = 1,\ n = 4) \qquad (5.3)$$

$$c = 0.0005T^2 - 0.2402T + 1036.5 \qquad (R^2 = 0.99,\ n = 4) \qquad (5.4)$$

$$k = -4\times10^{-8}T^2 + 1\times10^{-4}T - 0.0006 \qquad (R^2 = 1,\ n = 4) \qquad (5.5)$$

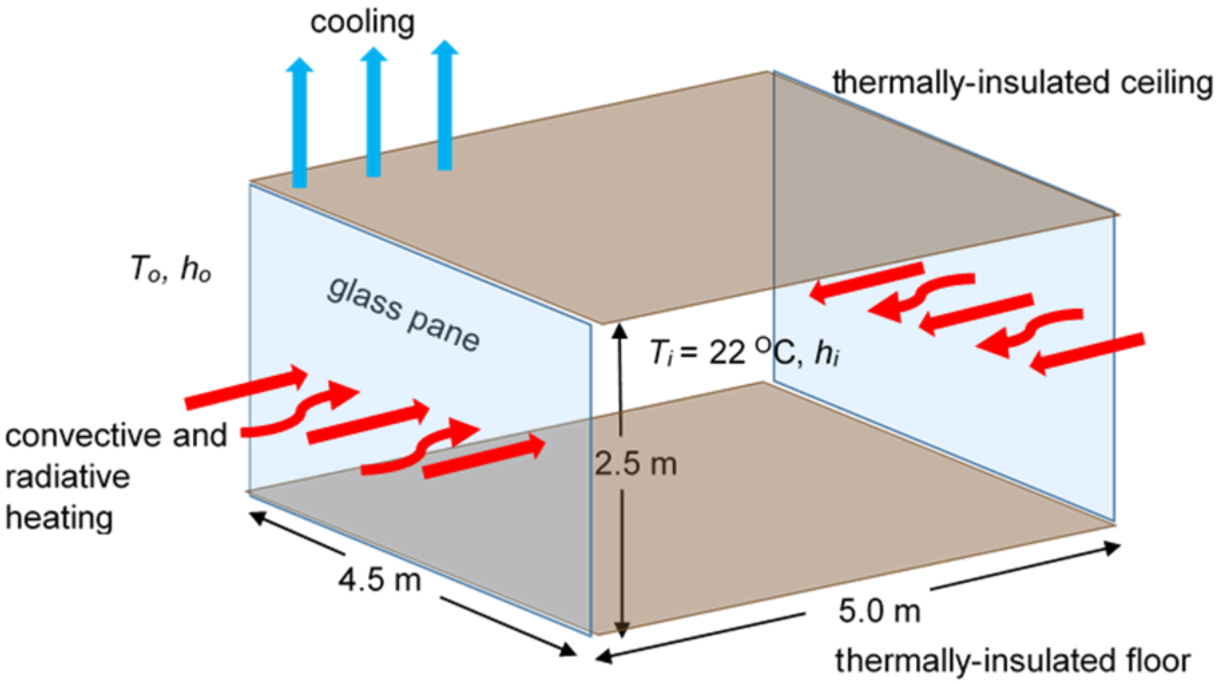

Fig. 5-1: Schematic of convective plus radiative heat transfer to the room

To include incident radiative energy from ambient through the glass to the room air, $q^*_{radiation}$, in the underlying model the ambient and room temperatures are needed. The generalized radiative energy equation is given (Anon., 2013; Holman, 2010; Perry and Green, 1997) by

$$q^*_{radiation} = \varepsilon \sigma A_{glass} (T_o^4 - T_{air,glass}^4) \tag{5.6}$$

where ε = 0.8 for the emissivity of the ordinary commercial silica window glass (Holman, 2010) and for the Stefan-Boltzmann constant σ = 5.667 x 10-8 W m^{-2} K^{-4} (Anon., 2013; Holman, 2010).

However it is especially common for hotel rooms with glass walls to have fabric curtains i.e. drapery on the interior. These are habitually drawn around mid-morning by housekeeping during room-service. Their aim is to attenuate radiative heat from outside. This radiative attenuation is defined as the indoor solar attenuation coefficient (*IAC*) (Anon., 2013) which represents the fraction of the heat flow that enters the room – some heat energy having been excluded by the window and the shading of the fabric curtain. The degree of attenuation will, among other influencing parameters, depends on the type of glass e.g. low emissivity (low-e glass™), the number of panes, whether it has reflective coating and the curtain fabric material (dark to light), weave or openness (closed or open), and; fabric reflectance (Anon., 2013).

It is assumed that $IAC = 0.8$ (Anon., 2013). That is, with the heat-attenuating (fabric) curtain drawn, 80 % of the transmitted radiative heat from ambient will potentially reach the room interior, adding to the heat transferred by natural convection.

Therefore Eq. (5.6) can be written as

$$q_{radiation} = IAC\varepsilon\sigma A_{glass}(T_O^4 - T_{air,glass}^4) \tag{5.7}$$

Eqs. (3.1) through (3.18) together with Eqs. (5.1) through (5.7) define the extended heat-transfer unit-operations model for conditioning of the room interior air that includes an incident radiative component, together with heat-attenuating room curtains and temperature dependent properties of the air.

5.2.2 Conditioning strategies

In the widely used default *on-off* strategy, once the hotel room is let, air-conditioning is turned on manually with occupant traffic inflows i.e. whilst the room is occupied, and turned off when unoccupied. Because it has been assumed the brick walls will reach thermal equilibrium with ambient temperature soon after the air-conditioning is switched-off, the heat energy that will need to be removed from the room interior including the brick walls each time the room is again occupied to maintain the *auto-set* temperature is given by

$$q_{on-off}^{*} = (q_{glass} + q_{radiation} + q_{brick}) \tag{5.8}$$

If L_T = room occupancy rate i.e. the number of days the room is let per 100 days, or the number of hours per day a room is let, (%), and n = room traffic flow, or, the number of times the conditioner is manually switched-on per day (this will be equal to the number of times the building brick materials must be conditioned to the *auto-set* bulk room air temperature), then for the *on-off* strategy [10]

$$q_{on-off} = \frac{L_T n}{100}(q_{glass} + q_{radiation} + q_{brick}) \tag{5.9}$$

---

[10] Here traffic flow (n) is defined as the number of times the conditioner is manually switched-on in a room. This is more mathematically correct than the term ‘occupancy’ used in Chapters 3 and 4 which can be confused with an occupant simply being in the room.

Commercially viable room occupancy rates will require that $L_T \geq 70$ to 75, % (Anon., 2015). Clearly, room traffic flow will be an integer number with a minimum possible $n = 1$, to account for the mid-morning housekeeping and cleaning staff that leave the air-conditioning manually switched-off.

In contrast, with the alternative *on-only* strategy, because the room air is continuously conditioned irrespective of occupant room traffic flows, the interior walls of the room can be assumed to remain at equilibrium with the room interior *auto-set* temperature T_i (= 22, ^{O}C). This is true of course except for the one-off initial conditioning of the room interior air and walls. In practice, these rooms will be those first-let in a commercially viable multi-room hotel. If the hotel is in business these rooms will therefore will in fact be practically conditioned continuously.

Only the energy transferred from ambient through the glass walls into the room interior will, therefore, need to be conditioned with the *on-only* strategy. This is given by

$$q_{on-only} = (q_{glass} + q_{radiation}) \tag{5.10}$$

The difference in energy required between the two conditioning strategies will therefore be

$$(q_{on\text{-}only} - q_{on\text{-}off}) = (q_{glass} + q_{radiation}) - \frac{L_T n}{100}(q_{glass} + q_{radiation} + q_{brick}) \tag{5.10a}$$

Solution for Eqs. (5.9) and (5.10) will enable a practical comparison and estimation of the difference of the energy used in the two strategies for conditioning the room bulk air. The peak ambient temperature will be sufficient for this purpose.

5.3 Traditional deterministic solution

A traditional deterministic Single Value Assessment (SVA) (Sinnott, 2005) solution of the extended steady-state conditioning model is demonstrated in Chapter 3 for a typical summer day peak ambient temperature of 35 ^{O}C together with an *auto-set* bulk room temperature of 22 ^{O}C and typical commercial occupancy rate of 70 to 75, % i.e. averaged over the long term, the room must be let ≥ 70 to 75, % of the time, or alternatively, the room is let for ~ 16.8 to 18, h per 24 h day (Anon., 2015).

In summary, these computations show for *on-off* as the air-conditioning strategy with $L_T = 75$ % and $n = 1$, from Eq. (5.9) $q_{on\text{-}off} \sim 1208$ W, and; for the alternative continuous *on-only* from Eq. (5.10) $q_{on\text{-}only} \sim 949$ W. That is, the continuous *on-only* strategy is predicted use some 21.4 % less energy for room air-conditioning with the minimum possible occupant traffic flow.

With increased occupant traffic flow, that is, an increase in the number of times the air-conditioner is manually switched-on in the room ($n > 1$), the energy (and cost) benefit of the *on-only* strategy will increase linearly over that of the *on-off*.

5.4 Probabilistic *Fr 13* simulation

An inherent drawback with the traditional SVA however is that it does not take into account the naturally occurring fluctuations in the daily ambient peak temperature and hotel occupancy rates. In *Fr 13* simulation however (*see* e.g. Zou and Davey (2016) for a discussion) ambient temperature and hotel occupancy rate will be defined by distributions. The output is therefore a distribution of values of the probability of particular outcomes, including unwanted outcomes i.e. a failure of an air-conditioning strategy.

A requirement however is an unambiguous definition of energy strategy failure.

The difference in the amount of energy used in each of the two air-conditioning strategies can be used to define an energy strategy risk factor (P, W) such that

$$P = q_{on-only} - q_{on-off} \tag{5.11a}$$

For all $P > 0$ the alternative *on-only* strategy will be seen from Eq. (5.11a) to have 'failed' because it uses more energy than the *on-off*. However a computationally more convenient form of the energy strategy risk factor (p) can be defined by dividing both sides of Eq. (5.11a) by $q_{on-only}$ and multiplying by 100 such that

$$p = \left(\frac{P}{q_{on-only}} \right) 100 = \left(1 - \frac{q_{on-off}}{q_{on-only}} \right) 100 \tag{5.11}$$

Eq. (5.11) is computationally convenient because it is dimensionless (expressed as %). Further, because all $p > 0$ underscores a 'failed' *on-only* air-conditioning strategy, a direct comparison can be made for a range of different energy units. It can be readily computed in standard spread sheeting.

It must be noted that a failed *on-only* air-conditioning strategy ($p > 0$) does not however mean a loss, but rather that no real gain is made in savings of electrical energy to condition the room bulk air to the *auto-set* temperature over the *on-off* strategy.

Eqs. (3.1) through (3.18) and (5.1) through (5.11) define the extended unit-operations model for a more realistic assessment of the risk of failure in the *on-only* conditioning strategy used for the room air and the outputs compared. The model is identical in form to the SVA. However in *Fr 13* simulations, distributions are used to mimic fluctuations in ambient temperature and hotel room occupancy rate. Because 'pure' MC can both over- and under- sample from various parts of the distribution (*see* Chapter 4 for a discussion) r-MC random sampling of the distribution is used. These can be readily carried out in Microsoft Excel^{TM} with the commercially available add-on *@Risk*™ (version 5.5, Palisade Corporation).

5.5 Results

Table 5-1 presents a summary of the traditional deterministic SVA computations for conditioning of the room air with an *auto-set* room interior temperature T_i = 22 ^{O}C, typical summer ambient peak temperature T_o = 35 ^{O}C and commercially viable hotel room occupancy rate L_T = 75 % with minimum possible room traffic flow (n = 1).

From the table, respectively rows 45, 46 and 47, show the incident thermal radiative heat to the room (601 W), the energy required for the *on-off* air-conditioning strategy (1208 W), and the energy required for the proposed alternative *on-only* air-conditioning strategy (949 W).

The incident radiant heat to the room from ambient is therefore seen to be significant.

Table 5-2 presents a summary of predictions of the impact of both ambient temperature (T_o, ^{O}C) and occupancy rate (L_T, %) (with n = 1) on the difference in air-conditioning energy ($q_{on\text{-}only}$ - $q_{on\text{-}off}$) used for the two strategies. It can be readily seen from the shaded area of this table that for all $T_o > 30$ ^{O}C, together with $L_T > 60$ %, the *on-only* air-conditioning strategy is predicted to use less energy. For example, at L_T = 80 % and T_o = 35 ^{O}C (row 10, column 12), the difference in energy between the two conditioning strategies is -339 W. Similarly for all $T_o < 20$ ^{O}C, together with $L_T > 70$ %, the *on-only* air-conditioning (heating) strategy is predicted to use less energy.

Repeat computations were also made to show the impact of increasing room traffic flow, and therefore the manual switching-on of the conditioner, on the difference in energy used between the two strategies for conditioning of the room air, Table 5-3.

It was assumed that there would not be more than 10 occupant traffic flows per room in any period the room is let. It is seen in the table that as n increases the alternative *on-only* strategy uses less conditioning energy. Importantly, this can be seen in the data to be true for all n including for the minimum possible, n = 1.

Table 5-1: Summary of traditional SVA computations for conditioning of room interior air to an *auto-set* T_i = 22 ^{O}C with summer peak ambient temperature T_o = 35 ^{O}C and room occupancy rate L_T = 75 % with minimum room traffic flows (n = 1)

(Row)	**Parameter**	**SVA**[*]	
1	**Inputs**		
2	T_o (^{O}C)	35	Constant
3	L_T (%)	75	Constant
4	T_i (^{O}C)	22	Constant
5	*n (dimensionless)*	1	Constant
6	L (m)	2.5	Constant
7	W (m)	4.5	Constant
8	D (m)	5.0	Constant
9	d_{glass} (m)	0.01	Constant
10	k_{glass} (W m^{-1} K^{-1})	0.78	Constant
11	d_{brick} (m)	0.11	Constant
12	k_{brick} (W m^{-1} K^{-1})	0.69	Constant
13	g (m s^{-2})	9.81	Constant
14	σ (W m^{-2} K^{-4})	5.67 x 10^{-8}	Constant
15	ε (dimensionless)	0.8	Constant
16	IAC (dimensionless)	0.8	Constant
17			
18	**Computations**		
19	ΔT (^{O}C)	13.0	Eq. (3.9)
20	β (K^{-1})	3.32 x 10^{-3}	Eq. (5.1)
21	ρ (kg m^{-3})	1.17	Eq. (5.2)
22	μ (N s m^{-2})	2.64 x 10^{-5}	Eq. (5.3)
23	c (J kg^{-1} K^{-1})	1009.54	Eq. (5.4)
24	k (W m^{-1} K^{-1})	2.59 x 10^{-2}	Eq. (5.5)
25	A_{glass} (m^{2})	22.5	Eq. (3.7)
26	$T_{air,glass}$ (^{O}C)	28.5	Eq. (3.10)
27	$\delta T_{o,glass}$ (^{O}C)	6.5	Eq. (3.16)
28	$\delta T_{i,glass}$ (^{O}C)	6.5	Eq. (3.17)
29	Gr_{glass} (dimensionless)	6.47 x 10^{9}	Eq. (3.14)
30	Pr_{glass} (dimensionless)	1.03	Eq. (3.15)
31	Ra_{glass} (dimensionless)	6.65 x 10^{9}	Eq. (3.13)
32	$h_{o,glass}$ (W m^{-2} K^{-1})	2.42	Eq. (3.12)
33	$h_{i,glass}$ (W m^{-2} K^{-1})	2.42	Eq. (3.12)
34	$U_{o,glass}$ (W m^{-2} K^{-1})	1.19	Eq. (3.5)
35	q_{glass} (W)	348	Eq. (3.2)
36	A_{brick} (m^{2})	25.0	Eq. (3.8)
37	$T_{air,brick}$ (^{O}C)	28.5	Eq. (3.11)
38	$\delta T_{i,brick}$ (^{O}C)	13.0	Eq. (3.18)
39	Gr_{brick} (dimensionless)	1.29 x 10^{10}	Eq. (3.14)
40	Pr_{brick} (dimensionless)	1.03	Eq. (3.15)
41	Ra_{brick} (dimensionless)	1.33 x 10^{10}	Eq. (3.13)
42	$h_{i,brick}$ (W m^{-2} K^{-1})	3.01	Eq. (3.12)
43	$U_{o,brick}$ (W m^{-2} K^{-1})	2.03	Eq. (3.6)
44	q_{brick} (W)	661	Eq. (3.3)
45	$q_{radiation}$ (W)	601	Eq. (5.7)
46	$q_{on\text{-}off}$ (W)	1208	Eq. (5.9)
47	$q_{on\text{-}only}$ (W)	949	Eq. (5.10)

[*] Traditional, deterministic Single Value Assessment.

Table 5-2: Impact of ambient temperature (T_o, ^{O}C) and hotel occupancy rate (L_T, %) on difference in energy between the two conditioning strategies ($q_{on\text{-}only}$ - $q_{on\text{-}off}$) (W) with an *auto-set* bulk room temperature T_i = 22 ^{O}C with minimum possible room traffic flow (n = 1) in traditional SVA computations. Shaded area highlights *on-only* strategy uses less energy

	T_o (^{O}C)	**$q_{on\text{-}only}$ - $q_{on\text{-}off}$ (W)**											
		L_T (%)											
(Row)		**0**	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**75[*]**	**80**	**90**	**100**
1	18	238	199	159	119	80	40	1	-39	-59	-78	-118	-158
2	20	113	95	77	59	41	23	5	-13	-22	-22	-49	-67
3	22	0	0	0	0	0	0	0	0	0	0	0	0
4	24	116	97	79	61	43	25	6	-12	-21	-30	-48	-66
5	26	248	207	167	127	86	46	5	-35	-56	-76	-116	-157
6	28	391	326	261	196	131	66	1	-63	-96	-128	-193	-258
7	30	542	451	360	269	178	87	-3	-94	-140	-185	-276	-367
8	32	700	528	464	346	227	109	-9	-127	-186	-245	-363	-481
9	34	865	718	572	425	279	132	-14	-161	-234	-307	-453	-600
10	35	949	788	627	466	305	144	-17	-178	-259[&]	-339	-500	-661
11	36	1036	866	684	508	322	157	-19	-195	-238	-371	-547	-722
12	38	1212	1006	800	594	388	182	-24	-230	-333	-436	-642	-848
13	40	1395	1157	920	636	446	209	-28	-265	-384	-503	-740	-977

[*] The long-term occupancy rate for commercial viability.

[&] Particular scenario of Table 5-1.

Table 5-3: Impact of room traffic flow (1 ≤ n ≤ 10) on the difference in energy between the two conditioning strategies ($q_{on\text{-}only}$ - $q_{on\text{-}off}$) (W) with an *auto-set* bulk room temperature T_i = 22 ^{O}C and ambient temperature 25 ≤ T_o ≤ 35, ^{O}C with a commercially viable hotel occupancy rate L_T = 75 %

n (integer)	**($q_{on\text{-}only}$ - $q_{on\text{-}off}$) (W)**		
	T_o (^{O}C)		
	25	30	35
1	-37	-140	-259
2	-225	-821	-1466
3	-473	-1502	-2673
4	-690	-2184	-3881
5	-908	-2865	-5089
10	-1996	-6271	-11127

For the probabilistic *Fr 13* simulations the distribution that best fitted the independent historical, ambient peak temperatures for 541 summer days (between Dec. 2009 and Feb. 2015) in S-E Australia (-37.819708, 144.959936) and supplied by Bureau of Meteorology, Australia) (Anon., 2016 a), was found to be a **RiskNormal** distribution with a mean and standard deviation (stdev), respectively [11], 26.5322 and 5.9497, ^{O}C. This is shown as Fig. 5-2.

However, to limit the temperature predicted from this function in Fig. 5-2 to realistic day values it was judiciously truncated to give **RiskNormal** (26.5322, 5.9497, **RiskTruncate** (15, 45)). This is a Normal distribution with a mean 26.5322 ^{O}C and a minimum and maximum, respectively, 15 and 45, ^{O}C.

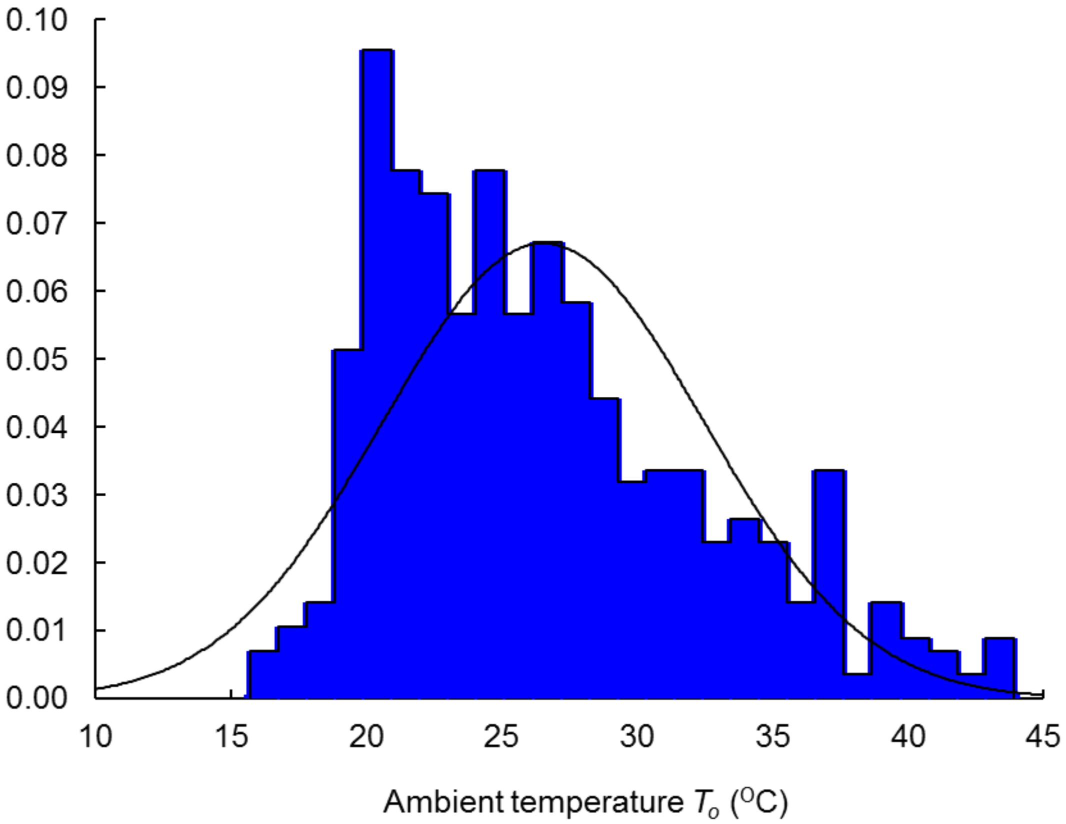

Fig. 5-2: Historical ambient temperature for 541 summer days (between Dec. 2009 and Feb. 2015 (Anon., 2016 a) for the hotel in S-E Australia, -37.819708, 144.959936), T_o, fitted to a **RiskNormal** (26.5322, 5.9497) distribution

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[11] It is not implied that these mean values are exact for this and the other risk functions; the significant figures shown nevertheless are important because they are used to generate a wide range of possible impacts on output behaviour from fluctuations arising from combined temperature-hotel occupancy room rates.

The distribution that best fitted the independent historical, commercial-data for summer occupancy rate of a hotel room for the same 541 summer days (Dec. 2009 to Feb. 2015) in S-E Australia (latitude -37.819708, longitude 144.959936) and supplied by Clarion Suites Gateway Hotel, Australia) (Anon., 2015), was found to be described by **RiskBetageneral** (1.8812, 0.30645, 0.28784, 1). This is a Betageneral distribution with a minimum of 28.784, and a maximum of 100, % occupancy rate (and shape factors α_1 = 1.8812 and α_2 = 0.30645 (Vose, 2008)), Fig. 5-3.

The fitting of these distributions to data was carried out using *@Risk*™.

Table 5-4 presents a summary comparison of the results from the traditional deterministic SVA with those of the probabilistic *Fr 13* framework in which the impact of naturally occurring random fluctuations in both ambient summer temperature (T_o, ^{O}C) and room occupancy rate (L_T, %) and minimum possible traffic flow (n = 1) are accounted for.

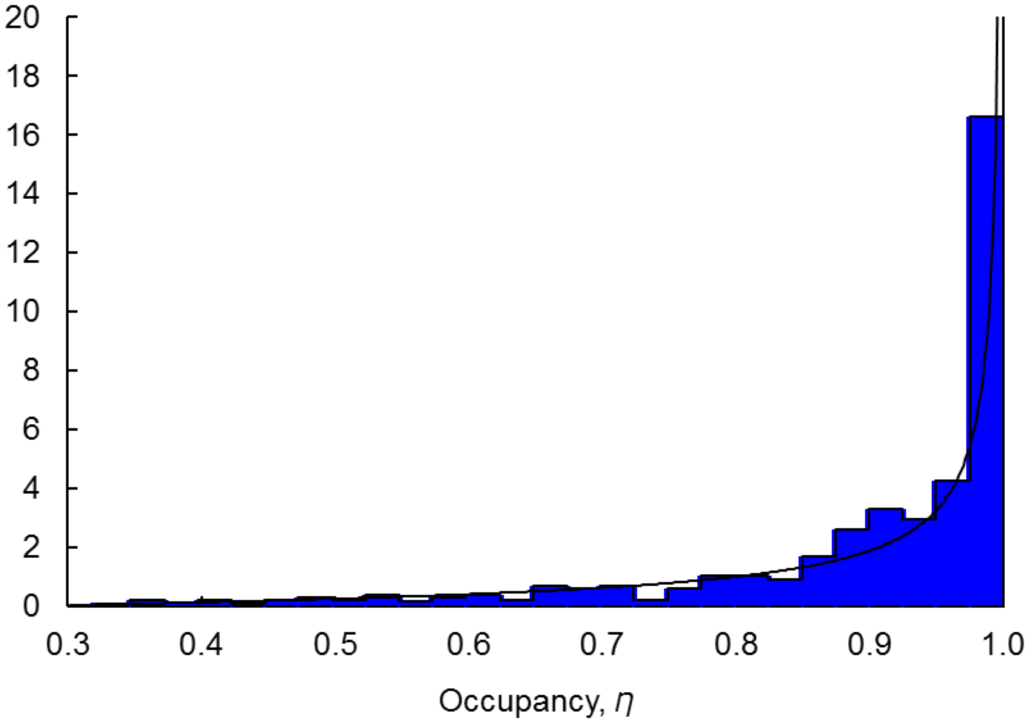

Fig. 5-3: Historical occupancy rate for 541 summer days (between Dec. 2009 and Feb. 2015 for the hotel in S-E Australia, -37.819708, 144.959936) (Anon., 2015), L_T, fitted with a **RiskBetageneral** (1.8812, 0.30645, 0.28784, 1) distribution

Table 5-4: Summary comparison of the traditional deterministic SVA with the probabilistic *Fr 13* simulation of *on-only* air-conditioning strategy

Row	Parameters	SVA[*]	*Fr 13*[†]	
1	**Inputs**			
2	T_o (^{O}C)	35	**22.49**[††]	RiskNormal(26.5322,5.9497,RiskTruncate(15,45))
3	L_T (%)	75	**56.99**[††]	RiskBetaGeneral(1.8812,0.30645,0.28784,1)
4	T_i (^{O}C)	22	22.0	Constant
5	n (dimensionless)	1	1	Constant
6	L (m)	2.5	2.5	Constant
7	W (m)	4.5	4.5	Constant
8	D (m)	5.0	5.0	Constant
9	d_{glass} (m)	0.01	0.01	Constant
10	k_{glass} (W m^{-1} K^{-1})	0.78	0.78	Constant
11	d_{brick} (m)	0.11	0.11	Constant
12	k_{brick} (W m^{-1} K^{-1})	0.69	0.69	Constant
13	g (m s^{-2})	9.81	9.81	Constant
14	σ (W m^{-2} K^{-4})	5.67 x 10^{-8}	5.67 x 10^{-8}	Constant
15	ε (dimensionless)	0.80	0.80	Constant
16	IAC (dimensionless)	0.80	0.80	Constant
17				
18	**Computations**			
19	ΔT (K)	13.0	0.5	Eq. (3.9)
20	β (K^{-1})	3.32 x 10^{-3}	3.39x 10^{-3}	Eq. (5.1)
21	ρ (kg m^{-3})	1.17	1.19	Eq. (5.2)
22	μ (N s m^{-2})	2.64 x 10^{-5}	2.61 x 10^{-5}	Eq. (5.3)
23	c (J kg^{-1} K^{-1})	1009.54	1009.18	Eq. (5.4)
24	k (W m^{-1} K^{-1})	2.59 x 10^{-2}	2.54 x 10^{-2}	Eq. (5.5)
25	A_{glass} (m^{2})	22.5	22.5	Eq. (3.7)
26	$T_{air,glass}$ (K)	28.5	22.2	Eq. (3.10)
27	$\delta T_{o,glass}$ (K)	6.5	0.2	Eq. (3.16)
28	$\delta T_{i,glass}$ (K)	6.5	0.2	Eq. (3.17)
29	Gr_{glass} (dimensionless)	6.47 x 10^{9}	2.66 x 10^{8}	Eq. (3.14)
30	Pr_{glass} (dimensionless)	1.03	1.04	Eq. (3.15)
31	Ra_{glass} (dimensionless)	6.65 x 10^{9}	2.76 x 10^{8}	Eq. (3.13)
32	$h_{o,glass}$ (W m^{-2} K^{-1})	2.42	0.88	Eq. (3.12)
33	$h_{i,glass}$ (W m^{-2} K^{-1})	2.42	0.88	Eq. (3.12)
34	$U_{o,glass}$ (W m^{-2} K^{-1})	1.19	0.44	Eq. (3.5)
35	q_{glass} (W)	347.93	4.87	Eq. (3.2)
36	A_{brick} (m^{2})	25.0	25.0	Eq. (3.8)
37	$T_{air,brick}$ (K)	28.5	22.2	Eq. (3.11)
38	$\delta T_{i,brick}$ (K)	13.0	0.5	Eq. (3.18)
39	Gr_{brick} (dimensionless)	1.29 x 10^{10}	5.33 x 10^{8}	Eq. (3.14)
40	Pr_{brick} (dimensionless)	1.03	1.04	Eq. (3.15)
41	Ra_{brick} (dimensionless)	1.33 x 10^{10}	5.51 x 10^{8}	Eq. (3.13)
42	$h_{i,brick}$ (W m^{-2} K^{-1})	3.01	1.09	Eq. (3.12)
43	$U_{o,brick}$ (W m^{-2} K^{-1})	2.03	0.93	Eq. (3.6)
44	q_{brick} (W)	661	11.45	Eq. (3.3)
45	$q_{radiation}$ (W)	601	20.71	Eq. (5.7)
46	$q_{on\text{-}off}$ (W)	1208	21.10	Eq. (5.9)
47	$q_{on\text{-}only}$ (W)	949	25.58	Eq. (5.10)
48				
49	p (%)		17.51[††]	Eq. (5.11)

[*] Traditional, Single Value Assessment.

[†] One only of 5,000 scenarios.

[††] Values as reproduced from the r-MC sampling – it is not implied these need to be measured to this accuracy.

The parameters that define the unit-operations for conditioning of the room interior air are given in column 2 of the table. The SVA computations are given in column 3. For example, inspection of column 3 of Table 5-4 shows the input data, and resulting values, for the intermediate calculations, and finally, for each of the two strategies, respectively, the value $q_{on\text{-}only}$ and $q_{on\text{-}off}$, (W). The distributions derived for the *Fr 13* simulations for each of ambient temperature (T_o, ^{O}C) and hotel occupancy rate (L_T, %) are defined in column 4.

5,000 r-MC simulations were found sufficient. Each can be regarded as a possible next-day scenario. This is reasonable, as occupants generally *check-in* in the early afternoon (14.00 h) and *check-out* by mid-morning (10.00 h) the following day.

A total of 319 (6.4 %) scenarios were identified with $p > 0$ in the 5,000 simulations, (Fig. 5-4). In the figure the x-axis is the value of the energy strategy risk factor, p, from Eq. (5.11) and because the software output is a discrete histogram, the y-axis is the probability of p actually occurring (Vose, 2008). The area under the curve can be seen to be (~ 115 x 0.009 ~) = 1. The failures are seen to the right of the figure ($p > 0$) and are therefore readily identified.

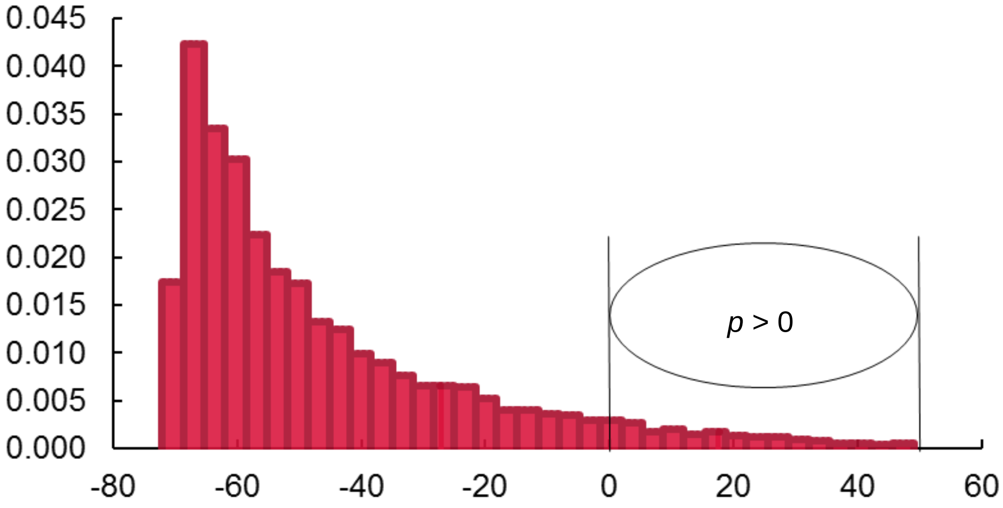

Fig. 5-4: *Fr 13* simulation of *on-only* energy conditioning strategy with 5,000 scenarios. The 319 failure scenarios (6.4 %) are shown R of the figure ($p > 0$). The area under the curve is (~ 115 x 0.009 ~) = 1

Ten (10) of these 319 failures which could occur as a result of adopting the *on-only* energy strategy are presented in Table 5-5.

Table 5-5: Ten (10) selected failures of *on-only* air-conditioning strategy ($n = 1$) from 319 in 5,000 scenarios

Scenario	**Ambient peak** T_o (°C)[†]	**Occupancy rate** L_T (%)[†]	**Energy risk factor** p (%)[†]
1	23.23	33.29	54.02
2	27.70	39.02	35.33
3	24.84	44.53	28.53
4	22.04	61.92	22.54
5[&]	**22.49**	**56.99**	**17.51**
6	27.22	52.11	13.94
7	35.85	53.28	9.56
8	30.23	56.08	5.86
9	22.91	64.69	2.72
10	29.54	59.73	0.01

[&] Particular scenario of Table 5-4.

[†] Values as reproduced from the r-MC sampling – it is not implied these need to be measured to this accuracy.

In the table all cases of $p > 0$, indicating a failure of the alternative *on-only* energy strategy, can readily be seen. The bolded text in Table 5-5 (row 8, for failure scenario 5) is the particular scenario reported in Table 5-4.

5.6 Discussion

5.6.1 Extended model and computations

The extended model predictions rely on a single (peak) daily ambient temperature to compute the energy required for conditioning of the bulk room air. In practice the ambient temperature will, of course, vary throughout the day (diurnal cycle) around the peak. The predicted energy computed to condition the room air will therefore be conservatively 'high'. It is evident however that because the same temperature is applied in computations for both strategies, the model is consistent and fit for the purpose of assessment and comparison of energy strategy and estimation of the difference in the values of the two energy strategies.

Daily peak ambient summer temperatures were used in the model simulations because these values were reliably available. The independent historical ambient temperature data used for the room (located at -37.819708, 144.959936) were supplied (at 30 min intervals) by the Bureau of

Meteorology (Anon., 2016 a) (automatic weather station Essendon Airport Australia, ID 086038), located sufficiently nearby (at -37.73, 144.91).

It should be noted that the predicted difference in conditioning energy used between the two strategies will not be identical with equal differences in ambient temperature values either side of the room *auto-set* of 22 ^{O}C. This is because the equations used for computing the air thermal properties (Eqs. (5.2) through (5.5)) are a function of absolute temperature. For example from Table 5-2 with L_T = 75 % and a 4 ^{O}C difference in ambient temperature value either side of the *auto-set* to give T_o = 18 ^{O}C, the difference in energy used between the strategies is -59 W, whereas at 26 ^{O}C this is -56 W.

With a more refined granularity of, say, 0.2 ^{O}C in ambient peak temperature for the range $21.6 \leq T_o \leq 22.4$, ^{O}C and $L_T \sim \geq 75$ % model computations would show the *on-off* as a marginally better strategy with values of $(q_{on\text{-}only} - q_{on\text{-}off}) \leq 1.50$ W (*see* Appendix E) This however is interpreted as not practically meaningful as both strategies are clearly more or less equal bounded by these ranges.

Importantly, the underlying model simulations proved to be stable in Excel. Because mean simulation outputs agreed with SVA values it was concluded that results were free of computational and programmable errors. Importantly, it is not to be inferred that the numerical values shown (as significant figures) in Table 5-4 are actually achieved; these values are those sampled randomly in the r-MC simulations.

It is concluded therefore that as shown overall in Table 5-2 the *on-only* conditioning strategy will use less energy than the presently used industry default *on-off* for all commercially viable occupancy rates of $L_T \geq 60$ % and all possible values of traffic flow of $n \geq 1$ with a range of typical summer ambient peak temperatures.

5.6.2 Incident radiant energy and interior curtains

From the results of Table 5-1 it can be concluded that incident radiant energy is a significant contributor to the heat load for conditioning of air required during summer for the hotel room. For example, for an ambient peak summer day temperature T_o = 35 ^{O}C (row 2) and a room interior *auto-set* temperature T_i = 22 ^{O}C (row 4), the radiant heat $q_{radiation}$ = 601 W (row 45) equals 49.8 % of $q_{on\text{-}off}$ (row 46).

The amount of incident radiant heat transmitted to the room will depend on the value of *IAC* – as this increases so too does $q_{radiation}$. For example when *IAC* = 1, that is if the window solar heat gain is high and its fabric curtain is not drawn, or is ineffective, the additional heat load due to radiant heat required can be computed as 150 W, as compared with the natural convection heat load of 348 W in Chapters 3 and 4.

It is not surprising therefore that means to reduce the impact of incident radiative heat on buildings with glass walls are widely used. One alternative to using interior curtains as is modelled here is to employ fenestration systems; these are reflective and non-heat absorbing coatings on the glass that permit natural light, desirable for good daylighting, but are designed (Anon., 2013) to minimize thermal transmittance through the glass walls.

5.6.3 Occupancy rate and room traffic flow

As highlighted in Table 5-2 at $L_T \geq 70$ %, that is, the mean, long-term threshold value for hotel occupancy rate required for commercial viability, the alternative *on-only* strategy uses less energy than the *on-off* for all $T_o > 22$ ^{O}C with minimum possible occupant room traffic inflow ($n = 1$). Actually, this statement is true for almost all $18 \leq T_o \leq 40$, ^{O}C as is seen in the shaded area of the table. At the other extreme with $L_T = 0$, %, the table shows that at T_o = 35 ^{O}C, the *on-only* strategy would, as expected, use more conditioning energy than *on-off* (row 10, column 3) with 949 W. This particular situation or very low L_T is unlikely to arise however if only because for commercial viability $L_T \geq 70$ % is needed.

Significantly, these data show that as both ambient temperature and hotel occupancy rate increase above the threshold for commercial viability, so does the difference in energy between the two strategies. This increasingly makes the alternative *on-only* strategy practically optimal even with the minimum possible room traffic flow ($n = 1$).

As the number of room traffic flows increase ($n \geq 2$) it can be deduced from Eq. (5.10a), and can be seen in Table 5-3, that the predicted difference between the two conditioning energy strategies increases linearly for all commercially viable room occupancies, $L_T \geq 70$ %. It can be shown from the table that with each additional room inflow (and manual switching-on of the conditioner) the difference in energy used between the two strategies increases by about -1208 W.

The practical upshot is that at summer peak ambient temperatures with increased room occupancy rates and occupant room traffic flows, the energy savings that could be made by adopting the alternative *on-only* strategy for conditioning of the room air over the *on-off* are expected to increase significantly.

It is concluded therefore that the alternative *on-only* air-conditioning strategy is the economically elegant alternative in summer for all commercially viable occupancy rates and all room occupant traffic flows.

5.6.4 **Fr 13** ***framework and energy strategy failures***

Importantly, whilst the distributions fitted to the historical data for both ambient temperature and occupancy rate used in the simulations (respectively, Fig. 5-2 and 5-3) are a very useful guide for demonstration of the *Fr 13* simulations, it is acknowledged that these historical data cannot strictly logically, be used to predict precisely future values. However, for the present study of a comparison of two energy strategies, these derived theoretical distributions, limited to the range of values covering published values, are most reasonable (Zou and Davey, 2016; Vose, 2008; Law, 2011).

Notably, although the probabilistic computations of Table 5-4 show the value of the peak ambient temperature and occupancy rate are given to two (2) significant figures (respectively, rows 2 and 3, column 4), it is not implied these need to be measured to this accuracy. The values reported are for completeness and are those sampled in the r-MC simulations.

If all 319 failures of the *on-only* energy strategy for conditioning of the room air in the 5,000 scenarios is thought of as a typical day (10 of these are shown in Table 5-5), then an unexpected failure with the *on-only* energy strategy would result in (319/5,000 =) 6.4 % of all cases averaged over the long term with the minimum practically possible room traffic flow $n = 1$. That is, the alternative *on-only* strategy would be expected to be successful with real gains made in savings of electrical energy to condition the room bulk air to the *auto-set* temperature 93.6 % of the time over the long term. Practically, this equates to 84 days in the 90 of summer that the alternative *on-only* conditioning of the room air would be the better strategy.

From a practical standpoint, the Spearman rank correlation coefficient – a measure of statistical dependence between two variables (Snedecor and Cochran, 1989) and readily available in *@Risk* –

can be used to highlight that the key model parameter for the energy strategy risk factor (*p*) for conditioning the air is the room occupancy rate L_T, Table 5-6.

The table shows a strong inverse correlation (-0.83) between L_T and the value of the dimensionless risk factor.

Applied, this means that random changes in occupancy rate will have a significant impact on the conditioning strategy, namely, as the room occupancy rate increases the value of the energy strategy risk factor decreases, and the chance of a failed *on-only* strategy lessens. Conversely, as occupancy rate decreases the value of the energy risk factor increases and the chance of a failed air-conditioning strategy using the alternative *on-only* increases. This trend overall can be readily seen in the values for ($q_{on\text{-}only}$ - $q_{on\text{-}off}$) of Table 5-2 for all $L_T \leq 60$ %. Significantly, these tabulated results highlight that the alternative *on-only* room air-conditioning strategy would be optimal for all occupancy rates for commercial viability of the hotel ($L_T \geq 70$ %).

Table 5-6 shows also that the overall impact of fluctuations in the peak ambient temperature on the energy strategy risk factor for air-conditioning is less than that for the room occupancy rate, but is itself also inverse (-0.30). This means that at elevated values of T_o i.e. the hotter summer days, the value of the energy risk factor decreases, and the risk of a failed *on-only* conditioning energy strategy lessens. Clearly, as T_o decreases i.e. cooler days, the value of the energy risk factor for the *on-only* strategy increases, until at $T_o = T_i$, the *auto-set* room temperature, where either energy strategy is equivalent. This is also evident in Table 5-2 (row 3) for $L_T \geq 0$.

Table 5-6: Spearman rank correlation coefficient (Snedecor and Cochran, 1989) for the air-conditioning model input parameters on the energy risk factor, *p*

Conditioning parameter	Coefficient
L_T (%)	-0.83
T_o (^{O}C)	-0.30

A failure of the alternative *on-only* energy strategy for conditioning of the room air will result in an increased electrical energy use, and, therefore, costs more than the current *on-off* to maintain an *auto-set* room temperature. There will however not be any disruption to operations, or any loss in capital outlays, as effectively there are none involved. There will be a (small) increase in GHG emissions however. It is important to note, there will not be an unrestrained use of conditioning energy with a failure of the *on-only* strategy because of the *auto-cycle* on the conditioner that will automatically switch-off once the room bulk air is at 22 ^{O}C.

It is concluded overall therefore that the widely believed and practised default *on-off* conditioning strategy is, from a quantitative chemical engineering heat transfer perspective, both misguided and costly. The reason that this less effective energy strategy widely persists appears to be because of a lack of quantitative modelling together with related insight by hotel operators and managers of conditioning energy use. The view that ‘If the air-conditioner is on, electrical energy is being used and if it is not on, then no cost for conditioning the room air can be incurred’, is revealed as circumscribed thinking. This is because it ignores that conditioning of the room bulk air is a whole-of-building process.

Given that the risk of failure of the alternative *on-only* strategy is predicted to be low, and to diminish with increasing L_T, especially near the threshold of ~70 to 75, % necessary for hotel commercial viability, application of this energy strategy appears to have low attendant risk of practical failure. It was thought therefore that this should be tested in at least a preliminary trial.

5.6.5 Preliminary trial and energy strategy validation

A preliminary test in a 10-day ‘proof-of-concept’ *in-situ* trial in an existing multi-room commercial hotel (CSGH) was carried out in summer with $24.2 \leq T_o \leq 40.5$, ^{O}C in the hot clime of S-E Australia (latitude -37.819708, longitude 144.959936). Results (Appendix F) showed conditioning energy cost savings overall of some 18.9 %, and some 20.7 % reduction in corresponding GHG emissions, for air-conditioning with an *on-only* energy strategy. This implied actual electrical cost savings of AUD $2.23 per suite (paired-room) per day. Although it is acknowledged these are limited data the results gave good reason for confidence in the alternate *on-only* conditioning hypothesis and strategy.

Therefore an extended commercial-scale experimental test of predictions covering a continuous period of summer-autumn-winter-spring was successfully negotiated with a large hotel chain in S-E Australia.

Because the present work is based on established unit-operations principles (Wankat, 2007; McCabe et al., 2001; Perry and Green, 1997; Foust et al., 1980) it is concluded that the demonstrated quantitative simulations could be readily generalized for winter and other seasons. Further, that extended simulations could be developed for multi-room, large commercial and public buildings of varying sizes, configurations and aspects.

An attraction of the alternative *on-only* energy strategy for conditioning of the room air, if realized, is that the returns would not need any capital investment or other outlays and all savings would reflect in profit. The concomitant reduction of GHG emissions could be used to obtain energy credit certificates and traded to add to profit (e.g. Anon., 2017 a; Anon., 2017 b). The commercial and monetary value of the GHG reduction has not been quantified.

Practical realization of this alternative conditioning strategy could be made based on readily available temperature data forecast (by a Bureau of Meteorology), together with consolidated room bookings, out to say 10 to 14 days to manage building air-conditioning operations. Ideally, this would be implemented using a simple *App*-driven (Anon., 2012 b; Davey, 2015 b) automatic technology. Additionally, the impact of unexpected events for e.g. transport disruptions restricting occupancy flow or sudden weather events, could be simulated and air-conditioning strategy adapted to minimise energy use.

5.7 Chapter summary and conclusions

1. Results from a newly synthesized convective-radiative heat transfer model for the conditioning of room air in summer as impacted by ambient temperature and traffic flow in the hot clime of S-E Australia has shown that an alternative *on-only* strategy will require less electrical energy to maintain an *auto-set* bulk air temperature of 22 ^{O}C with typical overall commercially viable occupancy rate of around 70 to 75, %

2. A new probabilistic assessment of this model which took account of naturally occurring fluctuations in the ambient peak temperature and room occupancy has shown that an *on-only* strategy is likely to use less electrical energy to condition room bulk air in 84 of the 90 days of summer, averaged over the long term

3. Because all scenarios that could exist practically, including failures, have been simulated, the *Fr 13* risk framework represents an advance over more traditional solution assessments

4. A limited ‘proof-of-concept’ experimental trial in a large commercial hotel confirmed the *on-only* strategy used less energy than the default *on-off*

5. However, to confirm these limited experimental findings it is concluded that a large-scale experimental study is needed.

In the next chapter, Chapter 6, a large-scale experiment validation and testing of the *on-only* energy strategy is presented for 77 contiguous summer days.

CHAPTER 6

LARGE-SCALE EXPERIMENTAL VALIDATION OF AN ENERGY STRATEGY TO MINIMIZE ENERGY USED IN CONDITIONING OF AIR IN SUMMER WITH FLUCTUATING AMBIENT AND ROOM OCCUPANCY RATE

Parts of this chapter have been published as:

Chu, J.Y.G., Davey, K.R., 2017 b. Results from a commercial-scale experimental validation of a quantitative strategy to minimize energy used in conditioning of air in buildings in summer with fluctuating ambient and room occupancy rate. Chemical Engineering Science – *submitted* (*May*.).

6.1 Introduction

In Chapter 5, a *Fr 13* probabilistic assessment solution of a convective-radiative whole-of-building process model showed that an alternative *on-only* energy strategy would use less electrical energy than the default *on-off*.

A limited ‘proof-of-concept’ *in-situ* (10 days) experimental test in a commercial hotel (Appendix F) confirmed the hypothesis. An acknowledged drawback however was that the experimental test was of limited duration and the findings could not be reliably extrapolated.

Therefore, a large-scale *in-situ* experimental validation over 77 contiguous days of summer (Jan. to Mar. 2016) [12] (n = 3,696) of the hypothesis was undertaken for the first time.

Results and analyses are presented in this chapter.

6.2 Materials and methods

6.2.1 Commercial site

The air-conditioner (8.1 kW) in each of two separate, but dimensionally-identical suites (each of two paired-rooms with a total floor plan 10.164 x 9.675, m) with similar furniture and fit-out in a large (169 room), 14 storey commercial hotel (latitude -37.819522, longitude 144.95949) with ‘smart’ electrical meters (National Meter Identification (NMI) 61024190331 and 61025490332) (Secure Meter Ltd., Model *i*-Credit 500). These were programmed (Silver Springs Networks, Aust.) to automatically transmit contiguous (24-7) electrical use at 30 min intervals from the suite to the public supply (*Origin Energy, Ltd*) utility.

The two identical paired-room suites (1321/1322 and 1421/1422) were directly above one another (i.e. one floor apart) and about 40 m above street level with identical S-E corner aspect, Fig. 6-1. As is seen in the figure the hotel was on a standard city-block intersection. Importantly, as highlighted by the figure, there was no shadowing from adjacent buildings at this level (or lower).

Each suite was *auto-set* to a bulk room air temperature of 22 ^{O}C. It was assumed the overriding electrical energy used was in conditioning of the bulk air, and not in the room lighting, refrigerator or in occupant metabolism with heat generation. Lighting and refrigeration were assumed similar for each suite and considered negligible to total daily electrical energy metered.

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[12] Strictly, summer in S-E Australia is Dec. through Feb., however because the hot clime has a long tail it is assumed Mar. can be considered summer for this study; 2016 was a leap year.

The suites were fitted with industry-standard, single-glazed pane windows with aluminium frames. The building was of a standard steel-frame with concrete exterior and brick interior (constructed mid 1990s). Both suites had identically-fitted internal fabric curtains for attenuation of incident radiant heat.

Daily ambient temperatures were supplied (in 30 min intervals) by the Australian Bureau of Meteorology (BoM) an Australian Government instrumentality (nearest automatic weather station at Olympic Park, ID 086338) located nearby the hotel at -37.83, 144.98.

Suite traffic flows and overall occupancy was provided by the hotel as detailed *check-in* and *check-out* times.

The scaled-schematic of Fig. 6-1 was created using commercial software (SketchUp 2015™ version 15.3.331, Trimble Navigation), and is based (mm scale) on the building architectural plan (Peddle Thorpe Architecture, 1996 for Yarraview Properties Pty Ltd). This figure is intended to show clearly the hotel as it is and the S-E aspect of the suites used in the experimental validation [13].

In suite 1321/1322 (*treated*) the air-conditioner was operated continuously i.e. *on-only*, whilst in the other 1421/1422 (*control*) it was left to wide-spread industry practice of *on-off* manual switching i.e. conditioning-on whilst the room is occupied, and conditioning-off, when un-occupied.

The hotel management was committed to the research study and agreed to practical protocols, and; to oversee these daily. Occupants (guests) checking into the *on-only* suite were informed of the experiment by the hotel management and given a letter (*see* Appendix C) stating the suite was being used in an energy management study and told the room air-conditioner could not be altered. If they were unhappy another room would be readily provided.

6.2.2 Preliminary validation trial

To establish the experimental protocols and to test possible suite-bias, preliminary studies were carried out. These involved the air-conditioning in suite 1321/1322 being operated as an *on-only* strategy (*treated*), and that in suite 1421/1422 *on-off* (*control*) for five (5) contiguous days (4 to 8 Dec. 2015). The conditioning strategy was then reversed for a further five (5) contiguous days (15 to 19 Dec. 2015).

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[13] An added advantage, because of its 3D nature, was that the computer model could be used longer-term to optimize room-architecture and directional aspect.

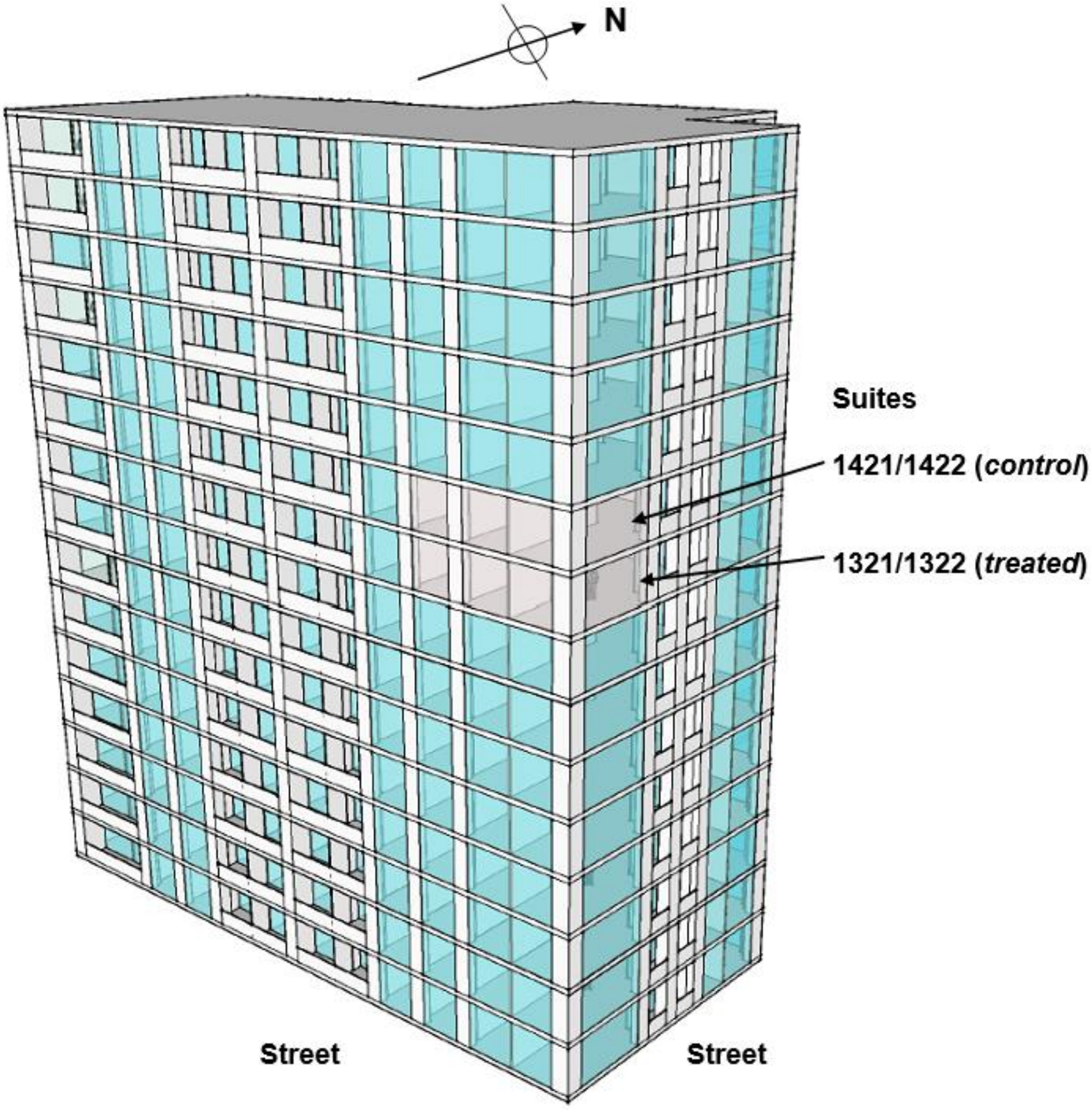

Fig. 6-1: 3D schematic of the hotel showing the two identical suites 1321/1322 (*treated*) and 1421/1422 (*control*)

A (research) workshop for hotel staff was conducted on the importance and objectives of the study by the author and hotel management. Staff were instructed to maintain normal daily cleaning and to switch-off of the conditioner in the *control* suite, and to not interfere with the continuous running of the conditioner in the *treated* suite.

Because a comparison of results of mean electrical use revealed that the alternative *on-only* strategy used less energy when was applied to either suite (*see* Appendix F) it was concluded there was no measurable suite-bias.

It was concluded also that management and hotel staff understood the experimental protocols and that these were sufficiently robust for an extended (large-scale) experimental validation test.

Generalized SOPs were written (*see* Appendix B) and used based on the proposed validation methodology.

Peak and off-peak (AUD cents per kWh) and daily supply (AUD $ per day) rates are also obtained from *Origin Energy Ltd* Australia, a public electricity supplier to the hotel.

GHG emissions (CO_2-e) were calculated based on factors and formula given in the July 2014 National Greenhouse Accounts Factors Report (Anon., 2014). The formula is replicated in Eq. (6.1)

$$Y = Q\frac{EF}{1000} \tag{6.1}$$

where Y is the GHG emissions measured in carbon dioxide equivalent, CO_2-e (t); Q is the quantity of electricity purchased (kWh);and EF is the emission factor, for the State, Territory or electricity grid in which the consumption occurs (kg CO_2-e per kWh). In Victoria, Australia the location of the hotel (CSGH) for the *in-situ* experimental validation the EF = 1.18 kg CO_2-e per kWh.

6.2.3 Large-scale validation

For 77 contiguous days (15 Jan. to 31 Mar.) suite 1321/1322 was conditioned with an *on-only* (*treated*) strategy whilst suite 1421/1422 with an *on-off* (*control*) strategy.

To maintain engagement of the hotel staff with the study, five (5) approximately equally-spaced, visits to the hotel were made by the author to oversee the experimental protocols. Hotel staff were reminded by hotel management at intervals not to alter the conditioner controls in the *treated* suite, 1321/1322.

Throughout therefore, it was assumed that for the *control* suite (1421/1422) staff would continue to manually turn the air-conditioner off (at around 10.00 to 12.00, h) following daily cleaning, and would leave the *treated* suite with *on-only* continuous conditioning.

Ambient temperature data for the period (at 30 min intervals) were obtained from the BoM (Anon., 2016 a). Electrical energy use (30 min intervals) for both suites was obtained from the public supply utility (*Origin Energy Ltd*, Australia). The electrical energy costs for the two suites were computed from the independent detailed energy data and the utility tariff provided by the public supply utility company. Concomitant GHG emissions were computed from an official conversion (Anon., 2014).

Suite overall occupancy rate as *check-in* and *check-out* times was provided by the hotel. A record of any refusals to *check-in* to 1321/1322 (the *treated* suite in which air-conditioning could not be altered) were made by the hotel.

The hotel management advised they expected 'typical' summer business and overall occupancy over the planned 77 days of the experimental test, that is, they did not foresee any disruption to normal business.

6.3 Results

6.3.1 Consent to treated *suite*

Most notably, in both the 10-day preliminary validation trial and in the larger-scale commercial trial of 77 contiguous days, no hotel occupants refused the treated suite at *check-in* i.e. all hotel occupants accepted that in the treated suite the air-conditioning could not be altered during their stay.

6.3.2 Preliminary validation trial

The overall conditioning electrical energy consumption for each day of the two 5-day preliminary trials is presented in Tables F-1 (a) and F-1 (b).

Inspection of Tables F-1 (a) and F-1 (b) show that the *on-only* energy strategy used less conditioning energy than *on-off* in 4 of the 5 contiguous days, respectively days 1 to 4, and 6 & 8 to 10 i.e. in 80 % of days overall.

It was concluded therefore that the larger-scale study should go ahead because the electrical meterage equipment and experimental protocols were proven reliable. This was agreed to by the commercial hotel management.

6.3.3 Large-scale validation

Overall data for the large-scale experimental validation are summarised in Table 6-1.

Table 6-1: Summary of raw and derived data for the 77 contiguous days experimental test (15 Jan. to 31 Mar. 2016 [*])

Day	**Raw Data**					**Derived Data**			
	T_o (^{O}C)	L_T (%)		Q (kWh)		**Energy Cost** ($)		**GHG Emissions**[&] (kg CO_2-e)	
		on-only[†] (*treated*)	*on-off*[††] (*control*)	*on-only* (*treated*)	*on-off* (*control*)	*on-only* (*treated*)	*on-off* (*control*)	*on-only* (*treated*)	*on-off* (*control*)
1	18.6	64.72	65.35	37.89	37.24	10.12	10.09	44.71	43.94
2	21.9	26.46	77.85	40.24	29.16	6.01	4.65	47.48	34.41
3	32.1	75.07	100.00	53.68	50.61	7.67	7.29	63.34	59.72
4	34.7	82.78	100.00	59.89	59.85	16.62	15.46	70.67	70.62
5	30.4	90.21	69.55	50.15	64.45	13.20	16.07	59.18	76.05
6	28.0	34.55	83.33	37.52	36.23	10.60	9.48	44.27	42.75
7	26.4	0.00	36.67	11.19	48.72	3.72	12.29	13.20	57.49
8	22.4	0.00	0.00	32.94	41.50	8.07	11.90	38.87	48.97
9	21.0	53.30	0.00	17.29	41.28	3.18	6.14	20.40	48.71
10	21.8	100.00	0.00	13.08	44.39	2.66	6.52	15.43	52.38
11	20.5	100.00	0.00	11.23	46.91	3.34	12.90	13.25	55.35
12	29.0	81.18	0.00	28.08	47.64	4.51	6.92	33.13	56.22
13	28.7	85.10	15.56	37.45	44.45	11.25	11.24	44.19	52.45
14	26.8	97.92	92.60	51.04	52.62	13.22	13.61	60.23	62.09
15	18.0	53.30	100.00	21.79	11.63	5.34	3.29	25.71	13.72
16	21.5	69.79	100.00	5.90	17.28	1.78	3.18	6.96	20.39
17[*]	**20.9**	**80.73**	**78.16**	**25.27**	**27.07**	**4.17**	**4.39**	**29.82**	**31.94**
18	23.3	100.00	82.47	33.91	32.55	9.16	9.23	40.01	38.41
19	31.0	83.06	100.00	54.97	14.78	14.58	4.72	64.86	17.44
20	21.1	83.30	56.81	34.86	7.41	8.31	2.72	41.13	8.74
21	20.4	79.76	75.51	37.13	9.28	9.81	2.95	43.81	10.95
22	29.1	100.00	84.65	49.21	31.12	12.74	8.97	58.07	36.72
23	32.4	73.23	100.00	63.66	49.32	10.05	8.02	75.12	58.20
24	27.1	37.67	79.51	36.23	47.95	6.17	7.83	42.75	56.58
25	22.4	19.83	91.22	8.00	40.02	2.85	10.11	9.44	47.22
26	22.5	25.97	44.31	24.62	5.88	6.84	2.35	29.05	6.94
27	22.6	75.38	57.81	23.15	23.96	6.35	6.94	27.32	28.27
28	23.6	38.75	86.88	33.47	33.23	9.08	8.33	39.49	39.21
29	24.1	17.53	67.50	24.76	31.01	7.22	8.89	29.22	36.59
30	29.6	100.00	100.00	41.54	50.88	6.92	8.24	49.02	60.04
31	23.8	74.44	100.00	33.57	40.37	5.79	6.75	39.61	47.64
32	25.5	84.44	100.00	35.09	38.65	9.34	9.91	41.41	45.61
33	18.8	74.51	100.00	12.89	14.03	3.71	3.63	15.21	16.56
34	20.6	100.00	76.18	7.14	12.56	2.66	3.97	8.43	14.82
35	21.9	100.00	81.74	5.76	24.24	2.30	6.37	6.80	28.60
36	21.6	78.99	76.53	12.73	19.69	3.95	5.64	15.02	23.23
37	19.8	94.44	100.00	10.97	23.42	2.58	4.35	12.94	27.64
38	24.2	95.17	45.63	27.92	50.54	4.99	8.19	32.95	59.64
39	27.0	100.00	7.92	40.03	58.93	10.37	14.74	47.24	69.54
40	39.1	91.70	74.24	44.54	41.62	12.24	11.57	52.56	49.11
41	25.3	100.00	100.00	35.82	45.18	9.61	11.66	42.27	53.31
42	26.3	74.55	88.96	33.40	44.76	9.01	12.29	39.41	52.82
43	22.7	69.03	100.00	38.90	34.48	10.40	9.61	45.90	40.69
44	21.6	66.18	94.44	25.98	23.80	4.71	4.40	30.66	28.08

Table 6-1 cont'd ...

45	21.8	47.95	61.11	13.54	18.49	2.95	3.65	15.98	21.82
46	23.4	42.47	42.43	14.75	22.49	4.68	6.67	17.41	26.54
47	33.2	100.00	61.56	47.81	53.03	12.72	14.26	56.42	62.58
48	33.4	48.85	77.19	60.37	64.48	14.80	15.95	71.24	76.09
49	23.2	15.97	90.52	52.44	41.01	12.86	11.03	61.88	48.39
50	32.8	0.00	84.03	30.53	42.47	8.78	11.08	36.03	50.11
51	23.2	0.00	95.97	22.67	45.46	4.24	7.47	26.75	53.64
52	24.2	17.33	39.24	15.59	41.52	3.24	6.92	18.40	48.99
53	24.7	55.83	0.00	35.84	11.25	9.94	3.66	42.29	13.28
54	38.6	68.06	0.00	69.09	76.39	17.16	18.26	81.53	90.14
55	30.8	71.94	0.00	39.91	73.24	9.98	17.25	47.09	86.42
56	21.3	85.28	35.49	19.62	31.26	5.51	8.58	23.15	36.89
57	25.9	72.22	100.00	31.46	46.17	8.55	12.20	37.12	54.48
58	22.2	100.00	100.00	19.32	46.50	3.77	7.62	22.80	54.87
59	22.9	100.00	100.00	24.80	34.79	4.54	5.96	29.26	41.05
60	20.5	100.00	100.00	23.35	24.46	4.34	4.50	27.55	28.86
61	26.2	65.83	79.41	37.76	30.52	10.30	8.87	44.56	36.01
62	30.3	57.26	69.86	52.66	51.79	13.99	13.79	62.14	61.11
63	31.9	47.40	54.72	57.82	82.08	15.35	19.91	68.23	96.85
64	28.0	87.67	82.95	29.61	61.66	7.74	14.28	34.94	72.76
65	17.8	96.70	91.74	31.21	39.55	5.45	6.64	36.83	46.67
66	22.4	100.00	83.33	24.35	20.29	4.48	3.91	28.73	23.94
67	22.8	81.49	100.00	31.69	36.34	8.26	10.18	37.39	42.88
68	24.1	59.24	78.33	32.28	27.03	8.69	7.73	38.09	31.90
69	28.5	50.21	100.00	31.66	35.16	8.58	9.13	37.36	41.49
70	20.9	100.00	82.36	20.94	18.43	5.86	4.81	24.71	21.75
71	19.9	100.00	97.26	21.82	19.09	4.12	3.73	25.75	22.53
72	19.9	93.33	97.08	25.04	15.04	4.58	3.16	29.55	17.75
73	19.0	100.00	86.11	31.30	21.06	5.47	4.01	36.93	24.85
74	19.0	91.81	73.16	36.62	17.85	6.22	3.56	43.21	21.06
75	17.8	43.47	53.65	24.56	8.04	6.55	2.92	28.98	9.49
76	18.0	53.19	100.00	22.49	6.32	5.84	2.41	26.54	7.46
77	22.0	77.29	77.36	14.00	25.28	4.45	7.33	16.52	29.83
Mean	**24.7**	**69.66**	**71.25**	**31.32**	**35.57**	**7.55**	**8.30**	**36.96**	**41.98**
Stdev	**4.9**	**29.13**	**31.97**	**14.62**	**17.19**	**3.77**	**4.20**	**17.25**	**20.28**
Max	**39.1**	**100.00**	**100.00**	**69.09**	**82.08**	**17.16**	**19.91**	**81.53**	**96.85**
Min	**17.8**	**0.00**	**0.00**	**5.76**	**5.88**	**1.78**	**2.35**	**6.80**	**6.94**
Total				**2411.78**	**2739.23**	**581.19**	**639.23**	**2845.90**	**3232.29**

[*] 2016 was a leap year.

[&] Conversion factor = 1.18 (Anon., 2014) such that GHG emissions (kg CO_2-e) = 1.18 x energy (kWh).

[†] Energy strategy for *treated* suite (1321/1322).

[††] Energy strategy for *control* suite (1421/1422).

[**] *see* text for sample computations from the applicable tiered tariffs, and details in Table 6-2.

The raw data for daily peak ambient temperature (T_o, ^{O}C), occupancy rate (L_T, %) and electrical energy used (Q, kWh) in both *on-only* (*treated*) and *on-off* (*control*) suites are presented in columns 2 through 6, and the derived [14] data for utility cost (AUD $) and GHG emissions (kg CO_2-e) [15] for both suites, in columns 7 through 10 of the table.

The ambient temperature is shown (column 2) as the daily peak, and is seen to have ranged from 39.1 to 17.8, ^{O}C (Anon., 2016 a) with a mean of 24.7 ^{O}C. The overall occupancy rate (columns 3 and 4), computed from hotel *check-in*, *check-out* times, was expressed as per cent of the 24-h day cycle. The raw electrical energy used is shown in column 5 and 6 for, respectively, the *treated* and *control* suites. The mean overall energy used is seen to be, respectively, 31.32 and 35.57, kWh per day (giving a sum, respectively, of 2,411.82 and 2,739.21, kWh). This is a difference of ~ 12 % between *control* and *treated* suite averaged over the 77 contiguous days for the electrical energy used to condition the room air.

The derived cost data for the electrical energy shown in columns 7 and 8 (Table 6-1) for the *treated* (1321/1322) and *control* (1421/1422) suites, respectively, were based on the tariffs from the public supply utility. The difference between the overall mean costs for the electrical energy used in the two strategies therefore for the suites is AUD $(7.55 - 8.30) = -AUD $0.75 per day or ~ 9 %.

Greenhouse gas emission (kg CO_2-e) (columns 9 and 10, Table 6-1) was computed from the conversion factor of 1:1.18 for indirect emissions from consumption of purchased electricity in S-E (Victoria) Australia (Anon., 2014). For example, the GHG for day 17 (**bolded text**) for 1421/1422 *control* suite, of 31.94 kg CO_2-e is computed from 27.07 kW used multiplied by 1.18.

The summary computations of Table 6-1 were all carried in standard Excel^{TM} spread sheeting, and a careful check was made to substantiate these.

6.4 Discussion

6.4.1 Occupant consent

The need to offer an alternative to the *treated* suite (1321/1322) to hotel occupants did not arise during the experimental validation.

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[14] From applicable -peak, off-peak and tariffs supplied by the electrical utility. Peak time is 07.00 to 23.00, h and off-peak 23.00 to 07.00, h, Monday to Friday, and all of Saturday and Sunday. Greenhouse gas emission is computed from the conversion 1:1.18 (Anon., 2014).

[15] kg CO_2-equivalent.

This is not thought remarkable however because occupants benefit, of course, from a more-controlled room air in having the air-conditioner on continuously. It is generally the hotel management that would turn this off during daily housekeeping – in the misguided belief that they are saving money. This is misguided because it ignores that conditioning of the room bulk air is a whole-of-building process.

The agreed experimental protocols for the period of the experimental trials however prevented management from doing this.

6.4.2 Preliminary validation trials

Overall data from these two 5-day preliminary validation trials demonstrated (Table F-1) that when ambient temperature was greater than the room interior *auto-set* temperature ($T_o > T_i$, ^{O}C), the alternative *on-only* strategy used less conditioning electrical energy. For example, Table F-1 (a), day 2 (row 6), column 5 and 6, $Q_{on\text{-}only} = 29.19$ and $Q_{on\text{-}off} = 37.52$, kWh, a difference of -8.33 kWh (22.2 %).

These two 5-day preliminary validation trials were important to initially test the energy strategy hypothesis and establish experimental protocols and industry involvement. This was because results would be relied on to engage industry in the planned larger commercial-scale validation of the alternative energy strategy hypothesis.

From Table F-1 (a) the room occupancy rate is seen to be almost identical for the two suites, respectively, 51.83 and 61.64, % for the first 5-day trial but different (Table F-1 (b)) for the second 5-day trial, respectively, 58.40 and 81.83, %. Nevertheless overall the room occupancy rates were sufficiently similar to permit a reasonable conclusion that the protocols were good, methods working and hotel would engage in completing with the study.

Over the 10-day trial period the total conditioning energy can be shown from the data of Table F-1 to be respectively 394.35 and 497.69, kWh for the *treated* and *control* suites. That is, the alternative *on-only* strategy used ~ 20.8 % less electrical conditioning energy than that for the *on-off*.

This was seen to a significant reduction in electrical energy and therefore costs. It was clear however this was at the height of summer with greatest maximum daily peak ambient temperature and therefore difference in the two electrical energy strategies. These findings could therefore not be reliably extrapolated for other seasons.

It was concluded nevertheless based on these preliminary results together with proof of reliability of the experimental protocols to continue with the larger-scale trial. Hotel management were in strong agreement.

6.4.3 Large-scale validation and granularity of data

It is seen in Table 6-1 that there was no significant difference in the overall occupancy rate between the *treated* and *control* suites with each having a mean, respectively, of 69.66, and 71.25, %, and; stdev of 29.13 and 31.97, %.

It was concluded therefore that there was no meaningful difference overall between the occupancies of the two suites, and a direct comparison of data was therefore justified. Significantly this occupancy rate is similar to that of the 75 % (range 70 to 75, %) that is anecdotally accepted in the hotel industry to be necessary for a viable commercial business (Anon., 2015).

Importantly, it can be concluded that the validation trials coincided with a typical business period for the hotel.

These summary data of Table 6-1 however do not explicitly show that the granularity of the data was at 30 min intervals – for both ambient temperature and electrical energy used in conditioning of the room air.

For the 77 days therefore a total of n (= 77 x 48) = 3,696 actual energy data were recorded for each suite (available from the author) – and were used in computations for the daily energy and concomitant GHG emissions. The peak ambient temperature shown was readily selected (via spreadsheet) from the 48 data supplied by the BoM (Anon., 2016 a) for each day.

Inspection of Table 6-1 shows the ambient peak temperature was not always greater than that of the *auto-set* suite bulk temperature of 22 ^{O}C. From Table 6-1 for example, days 1 and 75 show a peak ambient temperature of, respectively, 18.6 and 17.8, ^{O}C. There were in fact 28 of the 77 days on which the peak ambient was ≤ 22 ^{O}C (days 1, 2, 9 to 11, 15 to 17, 20, 21, 33 to 37, 44, 45, 56, 60, 65, 70 to 77). Unusually, this period was (anecdotally) ‘cool’ for S-E Australia. On these occasions the conditioner would switch automatically from cooling- to heating-conditioning mode. It can be noted that the dead-band temperature for the installed thermostat make-and-model was 2 ^{O}C (Anon., 2016 b).

Despite the fine granularity of the trial data, it is acknowledged that the experimental protocols do not permit a direct knowledge of the integer number of times (n) the conditioner in the *control* suite was manually switched-on i.e. the number of occupant inflows into the suite.

Significantly however, these experimental data were collected over a sufficient period (77 contiguous days) within a typical business period for the hotel and therefore clearly reflect the impact overall of usual room traffic flows and occupancy rates in summer. Given this, it is seen the data show conclusively that the *on-only* energy strategy used less electrical energy, and therefore cost less and indirectly generated less GHG than the industry practice of *on-off* strategy.

The cost of the electrical energy in both strategies though is not linearly related to the actual energy used. This is because, as elsewhere, the particular electrical energy tariff is tiered and varies with the time of the day based on the peak, off-peak, and supply, tariffs. For example, for days 1 through 17 of the Table 6-1 (15 Jan. to 31 Jan.) the applicable peak, off-peak and supply tariff was, respectively, AUD 28.78 cents per kWh, AUD 12.33 cents per kWh, and 105.01 cent per day. For days 18 through 77 (1 Feb. [16] to 31 Mar.), the peak, off-peak and supply tariff was, respectively, 26.21 cent per kWh, 14.18 cent per kWh, and 102.79 cent per day. (Peak time is 07.00 to 23.00, h and off-peak is 23.00 to 07.00, h, Monday to Friday, and all of Saturday and Sunday). The cost of AUD $4.39 shown for day 17 of Table 6-1 (31 Jan., a Sunday) (**bolded text**) for the *control* suite (1421/1422), for example, was computed from off-peak energy use of 27.07 kW used multiplied by off-peak tariff (12.33 cent per kWh) plus an electrical energy supply charge of 105.01 cent per day.

In contrast, the energy cost of AUD $9.23 for the same suite for day 18 (1 Feb., a Monday) was computed from an off-peak (00.00 to 0.700, h and 23.00 to 00.00, h) use from the total of 32.55 kW made up of 2.75 kW (not shown) multiplied by off-peak tariff (14.18 cent per kWh) plus peak (0.700 to 23.00, h) 29.80 kW used (not shown) multiplied by peak tariff (26.21 cent per kWh) plus supply (102.79 cent per day). Overall therefore the electrical cost for a week-day is greater than that incurred on the weekend-days by some 50 %.

Significantly, as far as is known, the raw (and computed) data presented in Table 6-1 are the first that directly tie together corresponding daily peak ambient temperature, occupancy rate and energy (and billing) for a commercial hotel in summer. Fig. 6-2 presents a plot of the daily peak ambient temperature (column 2) for each of the 77 contiguous days of summer (column 1 (15 Jan. to 31 Mar.)). The figure usefully highlights clearly that, over the validation period, the daily peak temperature (T_o, ^{O}C) fluctuated between 39.1 and 17.8, ^{O}C as supplied by the BoM (Anon., 2016 a).

Not shown in Table 6-1 is that the ambient temperature (column 2) was recorded at contiguous 30 min intervals (Anon., 2016 a), and the electrical energy data (columns 5 to 10) are the aggregated of the daily electrical energy used in the contiguous 30 min intervals. Overall therefore each column summarises a total of n (= 24 h x 2 data) = 48 micro-data per day or (= 77 x 48) = 3,696 raw micro-data in total [17]. A typical example of these micro-data is presented in Table 6-2 for day 17 (31 Jan.). The table shows that the ambient temperature oscillated (diurnal cycle) from a peak temperature of 20.9 ^{O}C with a minimum 15.0 ^{O}C, recorded, respectively, at 12.30 h and 23.30 h. Similar diurnal cycles were observed and reported for all other days during the validation trials.

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[16] A change in tariff occurred on at 00.00 h on 1 Feb. 2016.

[17] These data are available from the author.

The aggregated data shown for occupancy (L_T, %) in Table 6-1 and also Table 6-2 (columns 3 and 4, respectively, in each), were computed based on the hotel *check-in* and *check-out* times (determined to 1 min intervals by the hotel).

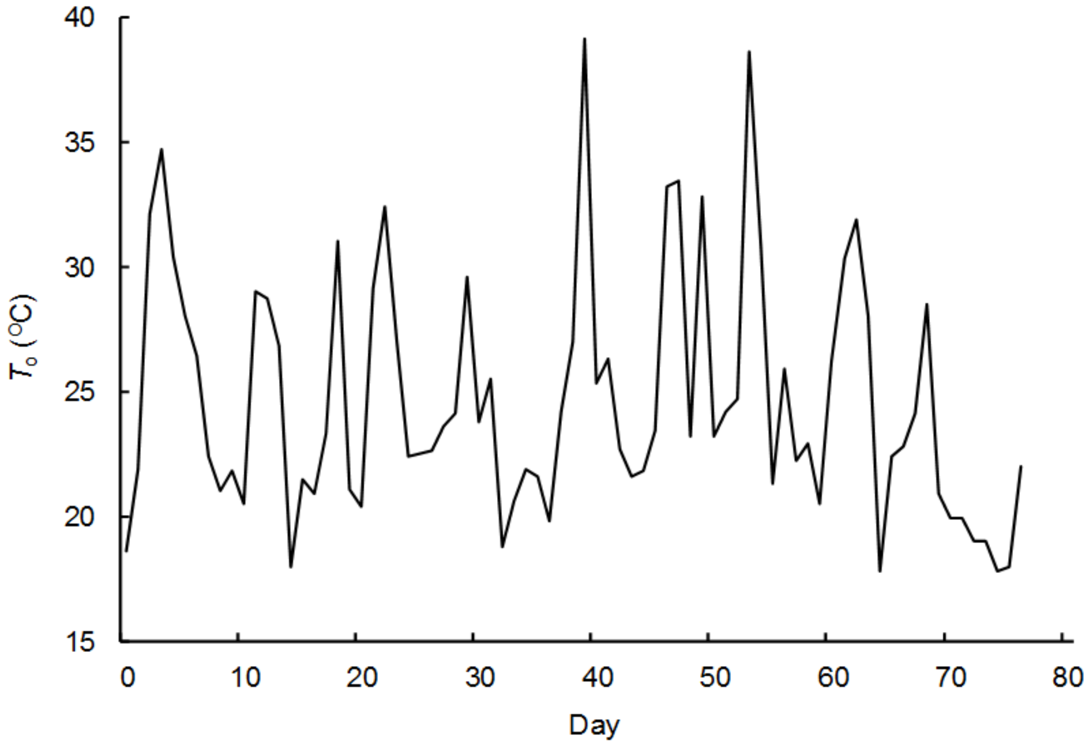

Fig. 6-2: Plot of daily peak ambient temperature (T_o, ^{O}C) supplied by BoM (Anon., 2016 a) about the room *auto-set* temperature (22 ^{O}C) for the 77 contiguous summer days

For example, for the micro-data of Table 6-2, hotel records showed occupants checked-out from the *treated* suite (column 3) at the interval nearest to 10.30 h (line 26, **bolded text**), and new occupants checked-in at the interval nearest to 15.00 h (line 35, **bolded text**). For this 2-room suite the actual c*heck-out* from the first of the two rooms was at 10.41 h and from the other at 10.46 h. The overall suite occupancy for the 10.30 h interval was computed therefore as (= (11/30 + 16/30)/2 x 100) = 45 % i.e. the mean of 11 mins and 16 mins past the 30-min interval. The actual *check-in* times for the two rooms were, 15.27 h and 15.15 h respectively, giving the overall suite occupancy of (= (3/30 + 15/30)/2 x 100) = 30 % that is shown for the interval at 15.00 h. Between *check-out* and *check-in*, the suite was unoccupied and the overall occupancy is shown in the table as zero percent (0 %). A value of L_T = 100 % highlights that occupants have checked-in but have not checked-out. An identical computation was used to determine overall occupancy of the *control* suite (column 4).

The summary occupancy data (L_T, %) in Table 6-1 were computed in the same way.

Table 6-2: Bulk ambient temperature fluctuation (at 30-min intervals) for day 17 (31 Jan. 2016)

Time	**Raw Data**					**Derived Data**			
	T_o	***L_T***		***Q***		**Energy Cost**[+]		**GHG Emissions**[&]	
(h)	(°C)	(%)		(kWh)		(cent)		(kg CO_2-e)	
		on-only[†] (*treated*)	*on-off*[††] (*control*)	*on-only* (*treated*)	*on-off* (*control*)	*on-only* (*treated*)	*on-off* (*control*)	*on-only* (*treated*)	*on-off* (*control*)
0.30	16.7	100.00	100.00	0.17	0.39	2.08	4.78	0.20	0.46
1.00	16.6	100.00	100.00	0.13	0.28	1.54	3.39	0.15	0.32
1.30	16.3	100.00	100.00	0.15	0.24	1.85	2.93	0.18	0.28
2.00	16.6	100.00	100.00	0.15	0.21	1.85	2.63	0.18	0.25
2.30	16.4	100.00	100.00	0.14	0.24	1.78	2.93	0.17	0.28
3.00	16.2	100.00	100.00	0.16	0.21	1.92	2.54	0.18	0.24
3.30	16.4	100.00	100.00	0.10	0.24	1.23	3.01	0.12	0.29
4.00	16.8	100.00	100.00	0.11	0.20	1.39	2.47	0.13	0.24
4.30	16.6	100.00	100.00	0.09	0.26	1.09	3.16	0.10	0.30
5.00	16.4	100.00	100.00	0.12	0.53	1.47	6.47	0.14	0.62
5.30	16.2	100.00	100.00	0.08	0.41	1.00	5.01	0.10	0.48
6.00	16.0	100.00	100.00	0.09	0.38	1.16	4.70	0.11	0.45
6.30	15.8	100.00	100.00	0.09	0.23	1.16	2.77	0.11	0.27
7.00	16.3	100.00	53.33	0.09	0.28	1.09	3.46	0.10	0.33
7.30	16.0	100.00	50.00	0.14	0.69	1.70	8.56	0.16	0.82
8.00	16.8	100.00	50.00	0.17	1.08	2.08	13.25	0.20	1.27
8.30	17.7	100.00	50.00	0.28	1.12	3.39	13.80	0.32	1.32
9.00	18.1	100.00	50.00	0.16	0.89	1.92	11.02	0.18	1.05
9.30	18.7	100.00	50.00	0.19	1.03	2.39	12.71	0.23	1.22
10.00	19.1	100.00	50.00	0.16	1.31	1.92	16.10	0.18	1.54
10.30[1]	**19.8**	**45.00**	**50.00**	**0.58**	**1.07**	**7.16**	**13.18**	**0.69**	**1.26**
11.00	19.4	0.00	50.00	1.81	0.98	22.35	12.10	2.14	1.16
11.30	19.2	0.00	50.00	1.25	0.78	15.41	9.63	1.48	0.92
12.00	20.4	0.00	50.00	1.03	0.82	12.64	10.10	1.21	0.97
12.30	20.9	0.00	50.00	0.98	0.88	12.02	10.86	1.15	1.04
13.00	20.6	0.00	50.00	1.01	0.60	12.40	7.40	1.19	0.71
13.30	20.1	0.00	50.00	1.01	0.58	12.40	7.16	1.19	0.69
14.00	19.1	0.00	50.00	0.97	0.66	11.95	8.17	1.14	0.78
14.30	18.5	0.00	50.00	1.40	0.84	17.26	10.33	1.65	0.99
15.00[2]	**20.6**	**30.00**	**50.00**	**1.26**	**0.71**	**15.57**	**8.79**	**1.49**	**0.84**
15.30	19.8	100.00	50.00	0.45	0.60	5.55	7.40	0.53	0.71
16.00	19.4	100.00	50.00	0.46	0.48	5.62	5.86	0.54	0.56
16.30	19.6	100.00	50.00	0.45	0.49	5.55	6.02	0.53	0.58
17.00	19.8	100.00	50.00	0.42	0.78	5.17	9.63	0.49	0.92
17.30	19.4	100.00	98.33	0.49	0.57	6.02	7.02	0.58	0.67
18.00	19.9	100.00	100.00	0.92	0.69	11.33	8.56	1.08	0.82
18.30	19.4	100.00	100.00	0.61	0.48	7.56	5.86	0.72	0.56
19.00	18.7	100.00	100.00	0.38	0.68	4.70	8.40	0.45	0.80
19.30	18.0	100.00	100.00	0.44	0.46	5.40	5.62	0.52	0.54
20.00	17.9	100.00	100.00	1.08	0.42	13.25	5.17	1.27	0.49
20.30	17.4	100.00	100.00	0.74	0.64	9.17	7.87	0.88	0.75
21.00	17.3	100.00	100.00	1.46	0.39	18.04	4.78	1.73	0.46
21.30	17.0	100.00	100.00	0.90	0.36	11.10	4.48	1.06	0.43
22.00	16.7	100.00	100.00	0.80	0.32	9.86	3.93	0.94	0.38
22.30	16.4	100.00	100.00	0.67	0.39	8.25	4.86	0.79	0.46

Table 6-2 cont'd …

23.00	16.0	100.00	100.00	0.33	0.44	4.08	5.40	0.39	0.52
23.30	15.0	100.00	100.00	0.31	0.42	3.77	5.17	0.36	0.49
0.00	15.8	100.00	100.00	0.33	0.36	4.01	4.39	0.38	0.42
Max	**20.9**	**100.00**	**100.00**	**1.81**	**1.31**	**22.35**	**16.10**	**2.14**	**1.54**
Min	**15.0**	**0.00**	**50.00**	**0.08**	**0.20**	**1.00**	**2.47**	**0.10**	**0.24**
Mean	**17.9**	**80.73**	**78.16**	**0.53**	**0.56**	**6.49**	**6.95**	**0.62**	**0.67**
Total				**25.27**	**27.07**	**416.61**[*]	**438.84**[*]	**29.82**	**31.95**

[&] Conversion factor = 1.18 (Anon., 2014) such that GHG emissions (kg CO_2-e) = 1.18 x energy (kWh).
[†] Energy strategy for *treated* suite (1321/1322).
[††] Energy strategy for *control* suite (1421/1422).
[+] Expressed as AUD cent (*cf* AUD $ in Table 6-1).
[*] Includes daily supply charge of AUD105.01 cent (AUD $1.05) per day.
[1] Occupant *check-out*.
[2] New occupant *check-in*.

Importantly, it is seen overall in the table there was no significant difference in occupancy between the *treated* and *control* suites – with a mean of 69.7, and 71.3, %, and; stdev of 29 and 32, % respectively. This overall occupancy rate is very nearly that of the 70 to 75, % required for a viable commercial hotel business (Anon., 2015) and, importantly, can be seen to underscore that the validation trial took place in period typical for the commercial hotel in a summer.

It is seen in the table that energy usage is not zero, for example, between 10.00 to 14.00 h, respectively, typical commercial *check-out*, and *check-in* times. This is because these suites have, at a minimum, the refrigerator (mini-bar) drawing electrical energy continuously 24/7 – and this had been captured by the accredited Smart Meter.

6.4.4 Outcomes, costs and benefits

Table 6-3 is a summary of the outcomes of electrical energy used in the experimental validation of *treated* and *control* suits (respectively, columns 2 and 3) for each of the 77 contiguous days. On any day when $Q_{on\text{-}only} > Q_{on\text{-}off}$ the alternative *on-only* energy strategy can be said to have failed i.e. the widely practiced *on-off* will have used less electrical energy in conditioning the room bulk air. A convenient, and strictly mathematical, means of stating failure however is offered through adaption of the dimensionless energy strategy risk factor (Chapters 4 and 5). Applied to the experimental data of Tables 6-1 and 6-2 this is defined as

$$p = \left(1 - \frac{Q_{on\text{-}off}}{Q_{on\text{-}only}} \right) 100 \qquad (6.2)$$

Eq. (6.2) is convenient because all $p > 0$ highlights a failure of the alternate *on-only* energy strategy. However, it must be noted that a failed *on-only* air-conditioning strategy ($p > 0$) does not mean a loss, but rather that no real savings is made in electrical energy to condition the room bulk air to the *auto-set* temperature over the *on-off* strategy (Chapter 5).

Table 6-3: Summary of energy strategy risk factor (*p*) for the contiguous 77 days of summer (15 Jan. to 31 Mar. 2016 *)

Day	***Q*** (kWh)		***p*** (%)
	on-only (*treated*)	*on-off* (*control*)	(1 - ($Q_{on\text{-}off}/Q_{on\text{-}only}$))*100
1	37.89	37.24	1.7
2	40.24	29.16	27.5
3	53.68	50.61	5.7
4	59.89	59.85	0.1
5	50.15	64.45	-28.5
6	37.52	36.23	3.4
7	11.19	48.72	-335.4
8	32.94	41.50	-26.0
9	17.29	41.28	-138.8
10	13.08	44.39	-239.4
11	11.23	46.91	-317.7
12	28.08	47.64	-69.7
13	37.45	44.45	-18.7
14	51.04	52.62	-3.1
15	21.79	11.63	46.6
16	5.90	17.28	-192.9
17 **	**25.27**	**27.07**	**-7.1**
18	33.91	32.55	4.0
19	54.97	14.78	73.1
20	34.86	7.41	78.7
21	37.13	9.28	75.0
22	49.21	31.12	36.8
23	63.66	49.32	22.5
24	36.23	47.95	-32.3
25	8.00	40.02	-400.3
26	24.62	5.88	76.1
27	23.15	23.96	-3.5
28	33.47	33.23	0.7
29	24.76	31.01	-25.2
30	41.54	50.88	-22.5
31	33.57	40.37	-20.3
32	35.09	38.65	-10.1
33	12.89	14.03	-8.8
34	7.14	12.56	-75.9
35	5.76	24.24	-320.8
36	12.73	19.69	-54.7
37	10.97	23.42	-113.5
38	27.92	50.54	-81.0
39	40.03	58.93	-47.2
40	44.54	41.62	6.6
41	35.82	45.18	-26.1
42	33.40	44.76	-34.0

Table 6-3 cont'd ...

43	38.90	34.48	11.4
44	25.98	23.80	8.4
45	13.54	18.49	-36.6
46	14.75	22.49	-52.5
47	47.81	53.03	-10.9
48	60.37	64.48	-6.8
49	52.44	41.01	21.8
50	30.53	42.47	-39.1
51	22.67	45.46	-100.5
52	15.59	41.52	-166.3
53	35.84	11.25	68.6
54	69.09	76.39	-10.6
55	39.91	73.24	-83.5
56	19.62	31.26	-59.3
57	31.46	46.17	-46.8
58	19.32	46.50	-140.7
59	24.80	34.79	-40.3
60	23.35	24.46	-4.8
61	37.76	30.52	19.2
62	52.66	51.79	1.7
63	57.82	82.08	-42.0
64	29.61	61.66	-108.2
65	31.21	39.55	-26.7
66	24.35	20.29	16.7
67	31.69	36.34	-14.7
68	32.28	27.03	16.3
69	31.66	35.16	-11.1
70	20.94	18.43	12.0
71	21.82	19.09	12.5
72	25.04	15.04	39.9
73	31.30	21.06	32.7
74	36.62	17.85	51.3
75	24.56	8.04	67.3
76	22.49	6.32	71.9
77	14.00	25.28	-80.6
		Number of $p > 0$	**30**

* 2016 was a leap year.
** *see* text for discussion.

It can be seen from column 4 of the table that there was, therefore, a failure of the alternative *on-only* strategy in 30 of the 77 contiguous days i.e. overall 39 %. These failures are all highlighted by positive values of the energy risk factor, p.

Alternatively stated, there was a success of the alternative energy strategy on 47 days (61 %) in the extended experimental validation. These are highlighted by the negative values of p.

For example, day 17 (**bolded text**) shows p = -7.1 %. It can be seen from the table that the savings in electrical conditioning energy for this day is (= 25.27 - 27.07) -1.8 kWh. (The maximum saving shown is for day 7 (-37.53 kWh) as indicated by the maximum p = -335.4 %).

However a simple accounting of the number of failures (or successes) of adoption of the alternative energy is not sufficient. What is principally important is the aggregate quantum in the difference in conditioning electrical energy used in the two strategies. A practical utility of the energy risk factor is that it can be used to illustrate this. A plot of the value of the daily energy risk factor (dimensionless) is presented as Fig. 6-3.

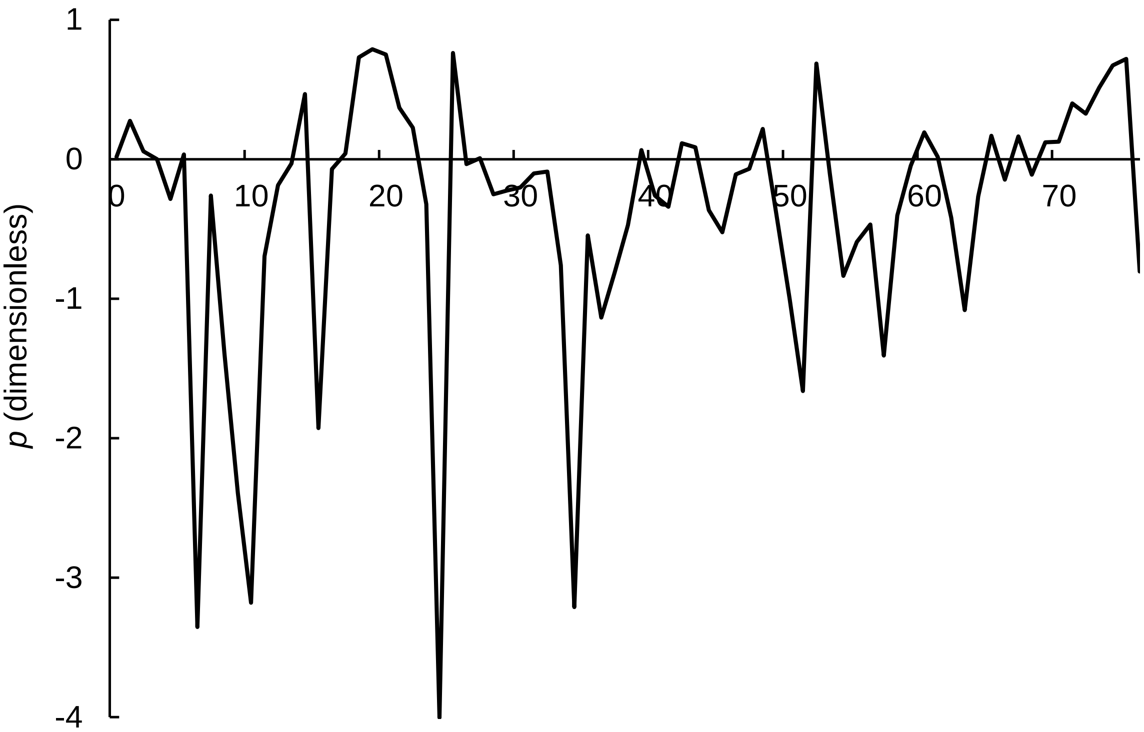

Fig. 6-3: Plot of energy strategy risk factor (p) for the 77 contiguous summer days

As is immediately highlighted in the figure there are more peaks (47) below the x-axis (daily operation) than there are peaks (30) above. Importantly, also readily apparent is that the value of the peaks below the x-axis are significantly greater than those values above. This highlights that that the quantum of electrical energy savings in successes is significantly greater than the quantum in losses with the *on-only* energy strategy. The area under the curve for the peaks is therefore a direct measure of the outcome behaviour of the two strategies. At a glance the figure conveys the aggregate area below the *x*-axis is significantly greater than that above and underscores the aggregate success of the *on-only* energy strategy for conditioning the room bulk air.

The actual overall mean of the aggregate daily electrical energy used in the two energy strategies over the 77 contiguous days is highlighted in Table 6-1 (columns 5 and 6) as respectively 31.3 and 35.6, kWh for the *treated* (*on-only*) and *control* (*on-off*) suites – a difference of -4.3 kWh per day. This resulted in the overall mean savings with the *on-only* strategy of AUD $0.75 (9 %) per day (the difference in columns 7 and 8 of the table).

Because these data are based on direct invoices from the electrical supply utility and not predictions or other indirect methods it is concluded the findings can be confidently extrapolated. Therefore if the 169 rooms of the hotel were used as some 85 two paired-room suites, a mean saving per year in electrical energy costs of (= AUD $0.75 per day x 85 x 365.25 day) AUD $23,285 would be expected for the hotel; or a mean net profit gain of ~ 9 % on the hotel's operating profit to be reflected in the profit and loss statement. This needs to be balanced however with the fact that the experimental data are based on the *treated* and *control* suites facing S-E (*see* Fig. 6-1). Those hotel suites facing W will, reasonably, be expected to have greater savings in electrical energy with adoption of the continuous *on-only* energy strategy than experimentally demonstrated here.

Importantly, these are real cost savings, if conservative, that are experimentally demonstrated with independent data. A major benefit is that these have been practically obtained without any capital outlay or increased maintenance of conditioners, and will therefore significantly increase company operating net profit indefinitely. Fears of breakdown of the conditioner in the *treated* suite because of 'abnormally' extended use (expressed by hotel management) were not realized. In any event, it can be shown the demonstrated yearly saving of AUD $23,285, would be sufficient to readily replaced a conditioner (at a quoted cost from the manufacturer of AUD $12,000 and warranty of 5 years with normal *on-off* (*control*) use).

Clearly, the *on-only* energy strategy can readily be used in other buildings, and should be particularly advantageous, for example, if used across hotel chains.

6.4.5 Reduced GHG emissions

As is seen in Table 6-1 (columns 5 and 6), with reduced electrical energy used in conditioning the room bulk air with the alternative *on-only* strategy, a major advantage is that there is a concomitant reduction in the mean emission of GHG of (41.98 - 36.96 =) 5.02 kg CO_2-e per day averaged over the 77 day contiguous period (columns 9 and 10 respectively). That is, with the alternative *on-only* conditioning strategy there is a (5.02/41.98 x 100 ~) 12 % reduction in unwanted GHG averaged over the experimental period – this is significant.

Advantageously, grants or credit certificates [18] can be obtained from clean energy regulators (e.g. Anon., 2017 a; Anon., 2017 b) for demonstrated reductions in GHG.

These can be used commercially to further increase real savings with the alternative *on-only* energy strategy for conditioning of the bulk air.

6.4.6 Results overview

It can be seen that the observed heat losses from the commercial-scale experimental validation are larger than those calculated in Chapter 5 – by about 22 %. For example, in Table 5-1 the mean predicted convective and radiative energy used, from Eq. (5.9), is 1.21 kW, or 1.21 x 24 = 29.04 kWh per day, whereas in Table 6-1 the mean metered-energy used using the same *on-off* strategy is 35.57 kWh per day.

This is because in the commercial-scale experimental validation the heat loss is metered every 30 min and is aggregated for the 24 h period and therefore takes account of the diurnal cycle and includes any and all electrical energy use, whereas, in the calculations in Chapter 5 it was assumed that room lighting, refrigerator or moderation of occupant metabolism was negligible. This has resulted in the greater overall actual heat loss in the experiments (35.57 kWh) compared to that calculated in the scoping study (29.04 kWh).

Overall it can be concluded the *on-only* hypothesis described in Chapters 3 to 5 has been quantitatively validated in a commercial environment. Importantly, the probative finding for this conclusion is based on independent and direct invoices for electrical energy used, and not on indirect methods such as prediction. Significantly, the savings validated in electrical energy with the alternative *on-only* strategy resulted in 12 % real savings in GHG.

It is interesting to note that the practical validation of the *on-only* energy strategy revealed a mix of success (61 %) and failure (39 %). This finding underscores the impact that uncontrolled, naturally occurring fluctuations can have on practical outcome behaviour, and; highlights the utility of the *Fr 13* probability risk framework, especially as it was used in the initial analysis in Chapters 4 and 5. It is satisfying that the validation results, and general trends, agree well with the predictive model. For example, in these chapters the author predicted a theoretical 87 % success compared with the experimentally determined 61 %. The model however was highly simplified and was based on

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[18] The commercial and monetary value of the GHG reduction has not been quantified.

limited historical data. Its overriding importance was to show for the first time how a clearly articulated energy strategy could be synthesized using the *Fr 13* probabilistic risk framework.

Results however are not considered conclusive for all buildings and seasons. It is concluded therefore the experimental validation trials should continue in a large-scale venue for an extended period beyond 77 contiguous days.

It is concluded overall that the widely practised *on-off* conditioning strategy in industry is in practice circumscribed thinking, because it ignores that conditioning is a whole-of-building process.

6.5 Chapter summary and conclusions

1. An alternative *on-only* energy strategy has been experimentally validated using independent data for conditioning of room air in a large-scale commercial hotel in summer in S-E Australia (latitude -37.819708, longitude 144.959936) – a hot clime. With a room *auto-set* bulk temperature of 22 ^{O}C and occupancy rate of 70 %, results showed overall savings (gains) in electrical cost of AUD $0.75 (9 %) per suite per day when compared with the widely practised *on-off* conditioning energy strategy. For the ~ 85 hotel suites, this equated to AUD $23,285 per year. Importantly, the trials coincided with a typical business period for the hotel

2. Ambient peak temperature ranged from 17.8 to 39.1, ^{O}C with 32 days recorded with rainfall over the validation period of 77 contiguous days. The alternative *on-only* strategy was successful in using less energy for conditioning on 47 days (61 %)

3. A concomitant overall reduction of 12 % in GHG emissions resulted for the period

4. Significantly, implementation of the alternative *on-only* energy strategy did not require capital investment or additional maintenance of the room conditioners

5. The widely practised *on-off* conditioning energy strategy appears to persist because room air-conditioning in industry is not understood as a whole-of-building process

6. A present shortcoming however is that the experimental data are limited to a summer period. This restricts generalization of findings to other seasons.

In the next chapter, Chapter 7, new data and analyses from an extended large-scale commercial experimental validation to cover four consecutive seasons is presented to address this limitation.

CHAPTER 7

EXTENDED LARGE-SCALE COMMERCIAL VALIDATION OF AN ALTERNATIVE ENERGY STRATEGY TO MINIMIZE ENERGY USED IN CONDITIONING OF AIR WITH FLUCTUATING AMBIENT AND ROOM OCCUPANCY

Parts of this chapter have been published as:

Chu, J.Y.G., Davey, K.R., 2017 c. An extended experimental validation of daily electrical energy used in conditioning of air in a commercial building with fluctuating ambient and room occupancy over four seasons. Chemical Engineering Science – *in preparation*.

7.1 Introduction

The 77 contiguous days experimental study reported in Chapter 6 showed that the alternative *on-only* energy strategy used significantly less electrical energy, therefore cost less, and; gave a concomitant reduction in GHG emissions, when compared with the industry default *on-off* strategy. However it was acknowledged these data were limited to a summer period that, therefore, restricted generalization of findings to other seasons.

Therefore an extensive experimental validation (n = 13,008) to determine the electrical energy used in conditioning of room air in identical suites in a commercial hotel over 271 (nearly contiguous) days and all four seasons was carried out for the first time and is reported in this chapter. The overall aim was to provide sufficient data that covered four consecutive seasons with which to test the generalizability of the *on-only* energy hypothesis in a commercial setting.

The methods described in Chapter 6 are used, together with extensive analyses to compare consumption of electrical energy in the two strategies.

7.2 Materials and methods

7.2.1 Commercial site and experimental protocols

The two separate and dimensionally-identical suites (each of two paired-room suites with a total floor plan 10.164 x 9.675, m and labelled *treated* or *control*) with identical furniture and fit-out in a large (169 room) as described in Chapter 6 were used. Both suites had identically-fitted internal fabric curtains for attenuation of incident radiant heat.

Each suite was *auto-set* to a bulk room air temperature of 22 ^{O}C. It was again assumed that the overriding electrical energy used would be in conditioning of the air and not in room lighting, refrigerator or moderating occupant metabolism. Electrical lighting and refrigeration energy were therefore assumed similar for each suite over the long term.

Suite overall occupancy rate was provided by the hotel as detailed *check-in* and *check-out* times and expressed as %-daily overall occupancy rate. Occupants checking into the *on-only* suite were informed of the experiment and given a letter (Appendix C) stating the suite was being used in an energy management study and told the room air-conditioner could not be altered. (If they were unhappy, another room was readily provided and a record kept by the hotel).

Hotel management did not anticipate any change to ‘typical’ seasonal business and overall occupancy rates over the planned 271 days of the experimental validation.

7.2.2 Extended validation and computations

Electrical energy cost was computed from independent invoices for each of the 30-min interval data over the 271 days (Dec. 2015 to Oct. 2016 [19]) together with the appropriate utility tariff [20] as provided by the electrical company (*Origin Energy Ltd* or *Simply Energy Ltd*, Australia [21]). Concomitant GHG emissions were computed from the Australian Government (Department of Environment) official conversions [22].

A convenient energy strategy risk factor (p) was defined (Chapter 6) as

$$p=\left(1-\frac{Q_{on\text{-}off}}{Q_{on\text{-}only}}\right)100 \qquad (6.2)$$

where all $p > 0$ highlights a failure of the alternate *on-only* energy strategy. Most importantly, a failed *on-only* air-conditioning strategy ($p > 0$) does not mean a loss but rather that a no real gain is made in savings over the default *on-off* strategy.

Daily ambient temperature (at 30 min intervals) data together with occurrence of rainfall were obtained from the Australian Bureau of Meteorology (BoM), an Australian Government instrumentality (ID 086338) located nearby the hotel (at -37.83, 144.98) (Anon., 2016 a).

7.3 Results

Experimental data for the 271 days validation are summarised in Table 7-1 [23]. It is seen in this table that the raw data for daily peak ambient temperature (T_o, ^{O}C), occupancy rate (L_T, %) and energy used (Q, kWh) in both the *treated* and *control* suites are presented in columns 2 through 6, and; the computed data for utility cost (AUD \$) and GHG emissions (kg CO_2-e) for both suites, in columns 7 through 10. The computations were carried in standard Excel^{TM} spread sheeting, and a careful check was made to substantiate these. The daily ambient peak temperature is seen (column 2) to have mean of 19.2, with a range from 40.5 (max) to 9.8 (min), and a stdev of 5.9, ^{O}C.

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[19] 2016 was a leap year.

[20] From the applicable peak, off-peak and supply tiered tariffs. Peak time is 07.00 to 23.00, h and off-peak 23.00 to 07.00, h, Monday to Friday, and all of Saturday and Sunday.

[21] The hotel changed utility supplier in June 2016.

[22] From the official conversion of 1:1.18 (Anon., 2014).

[23] The data shown for day 1 to 87 (inclusive) of the 271 are those reported in Chapter 6.

Table 7-1: Summary of raw and derived data for the 271 days experimental validation (4 Dec. 2015 to 31 Oct. 2016 [*])

Day[**]	**Raw Data**					**Derived Data**			
	T_o (°C)	***L_T*** (%)		***Q*** (kWh)		**Energy Cost** ($)		**GHG Emissions**[&] (kg CO$_2$-e)	
		on-only[†] (*treated*)	*on-off*[††] (*control*)	*on-only* (*treated*)	*on-off* (*control*)	*on-only* (*treated*)	*on-off* (*control*)	*on-only* (*treated*)	*on-off* (*control*)
1	30.6	13.33	63.88	23.41	31.59	7.18	9.93	27.62	37.28
2	25.3	57.96	65.29	29.19	37.52	4.65	5.68	34.44	44.27
3	29.1	68.00	62.83	26.41	38.28	4.31	5.78	31.16	45.17
4	27.3	72.63	69.00	29.02	49.48	8.04	13.07	34.24	58.39
5	35.0	47.21	47.21	51.19	50.29	14.47	14.80	60.40	59.34
6	24.2	56.50	100.00	6.05	37.52	2.46	10.78	7.14	44.27
7	26.7	88.54	100.00	37.41	25.89	11.19	8.02	44.14	30.55
8	36.8	40.42	68.96	53.03	64.80	15.53	18.26	62.58	76.46
9	34.1	36.79	69.63	71.71	81.48	18.54	20.66	84.62	96.15
10	40.5	69.75	70.54	66.93	80.84	9.31	11.02	78.98	95.39
11	18.6	64.72	65.35	37.89	37.24	10.12	10.09	44.71	43.94
12	21.9	26.46	77.85	40.24	29.16	6.01	4.65	47.48	34.41
13	32.1	75.07	100.00	53.68	50.61	7.67	7.29	63.34	59.72
14	34.7	82.78	100.00	59.89	59.85	16.62	15.46	70.67	70.62
15	30.4	90.21	69.55	50.15	64.45	13.20	16.07	59.18	76.05
16	28.0	34.55	83.33	37.52	36.23	10.60	9.48	44.27	42.75
17	26.4	0.00	36.67	11.19	48.72	3.72	12.29	13.20	57.49
18	22.4	0.00	0.00	32.94	41.50	8.07	11.90	38.87	48.97
19	21.0	53.30	0.00	17.29	41.28	3.18	6.14	20.40	48.71
20	21.8	100.00	0.00	13.08	44.39	2.66	6.52	15.43	52.38
21	20.5	100.00	0.00	11.23	46.91	3.34	12.90	13.25	55.35
22	29.0	81.18	0.00	28.08	47.64	4.51	6.92	33.13	56.22
23	28.7	85.10	15.56	37.45	44.45	11.25	11.24	44.19	52.45
24	26.8	97.92	92.60	51.04	52.62	13.22	13.61	60.23	62.09
25	18.0	53.30	100.00	21.79	11.63	5.34	3.29	25.71	13.72
26	21.5	69.79	100.00	5.90	17.28	1.78	3.18	6.96	20.39
27	20.9	80.73	78.16	25.27	27.07	4.17	4.39	29.82	31.94
28	23.3	100.00	82.47	33.91	32.55	9.16	9.23	40.01	38.41
29	31.0	83.06	100.00	54.97	14.78	14.58	4.72	64.86	17.44
30	21.1	83.30	56.81	34.86	7.41	8.31	2.72	41.13	8.74
31	20.4	79.76	75.51	37.13	9.28	9.81	2.95	43.81	10.95
32	29.1	100.00[†]	84.65	49.21	31.12	12.75	8.97	58.07	36.72
33	32.4	73.23	100.00	63.66	49.32	10.06	8.02	75.12	58.20
34	27.1	37.67	79.51	36.23	47.95	6.17	7.83	42.75	56.58
35	22.4	19.83	91.22	8.00	40.02	2.85	10.12	9.44	47.22
36	22.5	25.97	44.31	24.62	5.88	6.85	2.35	29.05	6.94
37	22.6	75.38	57.81	23.15	23.96	6.35	6.94	27.32	28.27
38	23.6	38.75	86.88	33.47	33.23	9.08	8.33	39.49	39.21
39	24.1	17.53	67.50	24.76	31.01	7.22	8.89	29.22	36.59
40	29.6	100.00	100.00	41.54	50.88	6.92	8.24	49.02	60.04
41	23.8	74.44	100.00	33.57	40.37	5.79	6.75	39.61	47.64
42	25.5	84.44	100.00	35.09	38.65	9.34	9.91	41.41	45.61

Table 7-1 cont'd ...

43	18.8	74.51	100.00	12.89	14.03	3.71	3.63	15.21	16.56
44	20.6	100.00	76.18	7.14	12.56	2.66	3.97	8.43	14.82
45	21.9	100.00	81.74	5.76	24.24	2.30	6.37	6.80	28.60
46	21.6	78.99	76.53	12.73	19.69	3.95	5.64	15.02	23.23
47	19.8	94.44	100.00	10.97	23.42	2.58	4.35	12.94	27.64
48	24.2	95.17	45.63	27.92	50.54	4.99	8.19	32.95	59.64
49	27.0	100.00	7.92	40.03	58.93	10.37	14.74	47.24	69.54
50	39.1	91.70	74.24	44.54	41.62	12.24	11.57	52.56	49.11
51	25.3	100.00	100.00	35.82	45.18	9.61	11.66	42.27	53.31
52	26.3	74.55	88.96	33.40	44.76	9.01	12.29	39.41	52.82
53	22.7	69.03	100.00	38.90	34.48	10.40	9.61	45.90	40.69
54	21.6	66.18	94.44	25.98	23.80	4.71	4.40	30.66	28.08
55	21.8	47.95	61.11	13.54	18.49	2.95	3.65	15.98	21.82
56	23.4	42.47	42.43	14.75	22.49	4.68	6.67	17.41	26.54
57	33.2	100.00	61.56	47.81	53.03	12.72	14.26	56.42	62.58
58	33.4	48.85	77.19	60.37	64.48	14.80	15.95	71.24	76.09
59	23.2	15.97	90.52	52.44	41.01	12.86	11.03	61.88	48.39
60	32.8	0.00	84.03	30.53	42.47	8.78	11.09	36.03	50.11
61	23.2	0.00	95.97	22.67	45.46	4.24	7.47	26.75	53.64
62	24.2	17.33	39.24	15.59	41.52	3.24	6.92	18.40	48.99
63	24.7	55.83	0.00	35.84	11.25	9.94	3.66	42.29	13.28
64	38.6	68.06	0.00	69.09	76.39	17.16	18.26	81.53	90.14
65	30.8	71.94	0.00	39.91	73.24	9.98	17.25	47.09	86.42
66	21.3	85.28	35.49	19.62	31.26	5.51	8.58	23.15	36.89
67	25.9	72.22	100.00	31.46	46.17	8.55	12.20	37.12	54.48
68	22.2	100.00	100.00	19.32	46.50	3.77	7.62	22.80	54.87
69	22.9	100.00	100.00	24.80	34.79	4.54	5.96	29.26	41.05
70	20.5	100.00	100.00	23.35	24.46	4.34	4.50	27.55	28.86
71	26.2	65.83	79.41	37.76	30.52	10.30	8.87	44.56	36.01
72	30.3	57.26	69.86	52.66	51.79	13.99	13.79	62.14	61.11
73	31.9	47.40	54.72	57.82	82.08	15.35	19.91	68.23	96.85
74	28.0	87.67	82.95	29.61	61.66	7.74	14.28	34.94	72.76
75	17.8	96.70	91.74	31.21	39.55	5.45	6.64	36.83	46.67
76	22.4	100.00	83.33	24.35	20.29	4.48	3.91	28.73	23.94
77	22.8	81.49	100.00	31.69	36.34	8.27	10.18	37.39	42.88
78	24.1	59.24	78.33	32.28	27.03	8.69	7.73	38.09	31.90
79	28.5	50.21	100.00	31.66	35.16	8.58	9.13	37.36	41.49
80	20.9	100.00	82.36	20.94	18.43	5.86	4.81	24.71	21.75
81	19.9	100.00	97.26	21.82	19.09	4.12	3.73	25.75	22.53
82	19.9	93.33	97.08	25.04	15.04	4.58	3.16	29.55	17.75
83	19.0	100.00	86.11	31.30	21.06	5.47	4.01	36.93	24.85
84	19.0	91.81	73.16	36.62	17.85	6.22	3.56	43.21	21.06
85	17.8	43.47	53.65	24.56	8.04	6.55	2.92	28.98	9.49
86	18.0	53.19	100.00	22.49	6.32	5.84	2.41	26.54	7.46
87	22.0	77.29	77.36	14.00	25.28	4.45	7.33	16.52	29.83
88	20.8	18.47	100.00	31.16	19.36	5.45	3.77	36.77	22.84
89	18.0	100.00	70.63	11.64	12.50	3.92	3.82	13.74	14.75
90	19.8	93.26	43.23	9.55	6.41	3.35	2.52	11.27	7.56
91	17.5	100.00	83.33	14.82	16.31	4.64	5.01	17.49	19.25
92	20.3	94.83	75.87	16.19	9.78	4.94	3.05	19.10	11.54
93	24.3	78.33	72.60	19.42	32.46	5.78	8.23	22.92	38.30
94	25.1	100.00	68.02	38.23	23.32	6.45	4.34	45.11	27.52

Table 7-1 cont'd ...

95	19.1	42.08	14.90	15.12	2.59	3.17	1.40	17.84	3.06
96	22.2	33.75	0.00	15.49	3.09	4.77	1.74	18.28	3.65
97	17.5	100.00	0.00	5.45	2.85	2.27	1.66	6.43	3.36
98	17.0	100.00	0.00	10.51	2.77	3.56	1.64	12.40	3.27
99	21.2	100.00	27.50	8.67	4.03	3.08	1.97	10.23	4.76
100	21.3	70.38	32.95	6.96	4.29	2.65	2.05	8.21	5.06
101	21.5	46.46	13.78	10.36	23.62	2.50	4.38	12.22	27.87
102	20.8	71.42	74.72	7.62	24.43	2.11	4.49	8.99	28.83
103	19.3	31.32	61.81	4.38	16.57	2.06	5.06	5.17	19.55
104	17.0	83.85	87.26	7.72	9.40	2.87	3.13	9.11	11.09
105	18.8	95.69	68.06	7.60	4.92	2.73	2.16	8.97	5.81
106	18.1	88.89	100.00	5.60	60.63	2.33	14.46	6.61	71.54
107	17.1	75.07	52.12	4.62	28.89	2.08	6.09	5.45	34.09
108	18.0	81.43	85.71	9.67	8.30	2.40	2.21	11.41	9.79
109	22.1	100.00	100.00	22.19	16.30	4.17	3.34	26.18	19.23
110	19.6	44.06	70.38	16.27	20.70	4.51	5.64	19.20	24.43
111	15.7	94.13	37.19	11.84	9.83	3.51	3.14	13.97	11.60
112	15.5	83.06	14.86	5.53	10.44	2.32	3.68	6.53	12.32
113	12.5	76.39	16.77	8.51	53.49	3.06	14.19	10.04	63.12
114	13.9	65.73	57.43	19.57	43.26	5.65	9.67	23.09	51.05
115	13.2	100.00	100.00	17.74	51.95	3.54	8.39	20.93	61.30
116	13.5	100.00	79.79	24.27	31.58	4.47	5.51	28.64	37.26
117	14.8	79.65	87.57	33.60	34.43	8.92	9.88	39.65	40.63
118	17.0	85.21	85.90	44.96	30.34	10.75	8.56	53.05	35.80
119	16.9	100.00	79.20	39.61	45.85	9.75	11.03	46.74	54.10
120	12.5	68.47	87.29	42.29	51.51	10.44	13.20	49.90	60.78
121	13.6	68.77	40.80	33.20	28.20	8.11	6.18	39.18	33.28
122	13.3	100.00	51.22	11.35	23.13	2.64	4.68	13.39	27.29
123	14.0	66.01	83.75	5.32	30.16	1.78	5.84	6.28	35.59
124	13.9	68.23	100.00	33.87	33.80	9.62	9.01	39.97	39.88
125	15.2	100.00	83.99	10.20	5.39	3.30	2.19	12.04	6.36
126	14.6	100.00	99.93	30.88	23.04	8.11	6.84	36.44	27.19
127	17.0	100.00	90.24	17.93	15.31	4.79	4.75	21.16	18.07
128	15.5	80.14	95.14	35.56	41.38	9.65	12.04	41.96	48.83
129	13.2	70.00	100.00	38.82	64.45	6.53	11.45	45.81	76.05
130	13.4	91.56	100.00	20.89	68.33	3.99	12.09	24.65	80.63
131	13.2	74.31	100.00	5.85	72.63	1.86	18.44	6.90	85.70
132	15.2	79.51	92.53	15.37	67.49	4.71	16.83	18.14	79.64
133	17.6	68.40	80.24	23.93	57.05	6.69	15.20	28.24	67.32
134	14.0	100.00	82.22	50.87	54.75	11.81	14.72	60.03	64.61
135	15.1	75.17	69.48	20.82	47.30	4.69	12.68	24.57	55.81
136	12.6	82.85	100.00	20.00	57.95	3.86	10.39	23.60	68.38
137	13.2	77.40	100.00	26.41	61.16	4.77	10.92	31.16	72.17
138	13.5	100.00	87.67	22.34	34.56	6.20	9.20	26.36	40.78
139	14.6	100.00	80.10	21.68	38.82	6.07	11.37	25.58	45.81
140	15.0	100.00	81.88	25.96	27.24	7.17	6.81	30.63	32.14
141	14.3	54.44	77.71	16.37	43.76	4.67	12.72	19.32	51.64
142	9.8	100.00	93.54	43.54	60.11	10.69	15.49	51.38	70.93
143	12.6	100.00	100.00	43.98	44.33	7.26	8.16	51.90	52.31
144	10.7	81.91	72.36	33.33	20.14	4.73	4.19	39.33	23.77
145	10.4	78.85	41.49	52.09	30.48	13.01	9.01	61.47	35.97
146	16.1	84.36	84.55	66.93	56.39	16.52	14.81	78.98	66.54

Table 7-1 cont'd ...

147	15.2	76.49	75.80	46.87	16.43	12.29	4.87	55.31	19.39
148	11.5	68.02	64.55	39.05	69.22	11.64	17.65	46.08	81.68
149	13.5	0.00	56.35	21.12	28.88	6.59	6.50	24.92	34.08
150	16.3	63.51	100.00	6.02	18.85	1.88	3.98	7.10	22.24
151	16.4	67.50	38.40	7.87	27.06	2.18	5.33	9.29	31.93
152	12.6	100.00	34.34	16.23	35.83	5.25	8.66	19.15	42.28
153	12.3	100.00	76.60	16.63	44.08	5.30	10.60	19.62	52.01
154	12.8	74.65	79.48	11.46	29.39	3.85	7.05	13.52	34.68
155	13.6	69.20	83.06	15.84	19.31	4.90	6.16	18.69	22.79
156	15.0	88.02	77.67	37.37	24.71	9.68	7.22	44.10	29.16
157	14.6	100.00	89.55	43.05	36.65	7.95	6.90	50.80	43.25
158	14.0	100.00	83.16	40.97	23.68	7.61	4.77	48.34	27.94
159	15.5	96.49	100.00	32.39	33.77	8.36	9.09	38.22	39.85
160	13.4	65.28	90.56	24.95	31.26	7.28	9.11	29.44	36.89
161	11.9	100.00	100.00	46.97	41.23	12.82	10.08	55.42	48.65
162	13.6	77.19	100.00	45.07	65.65	12.79	17.10	53.18	77.47
163	13.9	50.24	67.22	19.29	37.13	4.88	10.00	22.76	43.81
164	13.4	100.00	21.39	7.10	47.84	2.06	8.73	8.38	56.45
165	15.9	42.43	4.13	5.97	22.17	1.87	4.53	7.04	26.16
166	17.3	41.01	52.08	16.92	13.29	5.50	3.59	19.97	15.68
167	15.7	77.64	70.97	12.58	5.93	3.99	2.38	14.84	7.00
168	15.4	73.61	100.00	22.97	5.37	6.26	2.25	27.10	6.34
169	18.0	78.78	97.29	29.24	31.31	8.38	9.21	34.50	36.95
170	17.9	90.07	94.06	42.29	53.87	11.75	14.45	49.90	63.57
171	11.2	92.71	96.32	17.52	22.60	3.76	4.60	20.67	26.67
172	11.0	56.81	100.00	19.83	28.05	4.14	5.49	23.40	33.10
173	13.9	36.15	69.97	25.85	63.46	6.54	16.22	30.50	74.88
174	10.8	38.40	66.25	33.76	47.66	8.27	11.79	39.84	56.24
175	12.3	100.00	63.99	47.55	32.84	12.11	7.71	56.11	38.75
176	15.1	51.25	100.00	34.71	21.11	8.80	6.50	40.96	24.91
177	15.2	40.56	83.92	6.77	35.54	2.41	10.42	7.99	41.94
178	13.6	81.08	100.00	43.66	24.05	8.05	4.83	51.52	28.38
179	16.6	46.77	73.44	23.26	16.54	4.70	3.60	27.45	19.52
180	14.3	27.19	34.51	8.56	14.65	3.14	4.54	10.10	17.29
181	12.9	100.00	100.00	15.23	67.98	4.81	17.41	17.97	80.22
182	11.7	100.00	47.01	41.34	24.05	10.84	9.66	48.78	28.38
183	14.5	80.73	61.46	32.75	38.53	8.39	9.93	38.65	45.47
184	13.9	100.00	88.47	30.62	37.95	7.94	9.25	36.13	44.78
185	13.9	78.85	100.00	40.91	21.38	7.60	4.40	48.27	25.23
186	15.6	65.10	63.47	28.03	11.72	5.49	2.81	33.08	13.83
187	13.7	34.06	50.00	10.95	16.08	3.81	4.74	12.92	18.97
188	18.5	50.00	50.00	12.84	14.71	4.33	4.49	15.15	17.36
189	14.9	80.03	47.43	9.18	4.79	3.31	2.09	10.83	5.65
190	15.3	66.49	60.45	8.93	17.34	2.96	5.49	10.54	20.46
191	13.8	68.75	87.53	29.97	44.72	9.01	12.06	35.36	52.77
192	14.7	80.31	82.22	29.27	31.30	5.69	6.02	34.54	36.93
193	18.4	72.05	90.45	15.70	7.04	3.46	2.05	18.53	8.31
194	17.6	45.24	100.00	7.50	6.49	2.80	2.51	8.85	7.66
195	17.8	83.09	83.58	20.20	9.44	6.11	3.30	23.84	11.14
196	16.1	78.68	80.87	31.92	19.70	8.52	6.10	37.67	23.25
197	20.8	34.83	100.00	43.90	31.15	11.69	8.47	51.80	36.76
198	19.1	0.00	69.17	47.34	23.82	13.22	7.11	55.86	28.11

Table 7-1 cont'd ...

199	13.4	0.00	84.44	46.85	21.45	8.57	4.41	55.28	25.31
200	14.4	0.00	0.00	58.38	10.18	10.46	2.56	68.89	12.01
201	15.7	26.04	0.00	39.24	11.28	10.56	3.87	46.30	13.31
202	12.9	80.56	0.00	26.25	22.00	7.50	6.89	30.98	25.96
203	12.2	100.00	34.72	28.27	21.39	7.67	6.59	33.36	25.24
204	13.0	75.35	89.44	19.58	38.57	5.29	10.33	23.10	45.51
205	13.6	100.00	0.00	9.31	30.65	3.22	8.19	10.99	36.17
206	15.5	92.05	19.20	7.93	25.38	2.19	5.05	9.36	29.95
207	18.6	100.00	17.29	6.97	23.98	2.03	4.82	8.22	28.30
208	19.7	82.81	30.10	19.49	10.41	6.04	3.17	23.00	12.28
209	16.7	44.62	22.88	26.99	10.49	7.40	3.49	31.85	12.38
210	19.5	50.00	59.17	42.91	26.45	11.19	7.50	50.63	31.21
211	15.2	41.70	87.95	32.53	17.72	8.78	4.40	38.39	20.91
212	14.7	92.60	74.31	26.24	7.76	8.01	2.78	30.96	9.16
213	15.5	100.00	53.65	32.52	6.48	6.22	1.95	38.37	7.65
214	16.6	100.00	73.13	12.81	19.63	2.99	4.11	15.12	23.16
215	17.9	53.19	61.94	7.56	7.65	2.79	2.81	8.92	9.03
216	20.6	77.26	68.19	5.70	10.87	2.28	3.53	6.73	12.83
217	20.9	96.01	67.60	20.36	11.01	6.33	3.77	24.02	12.99
218	22.4	100.00	89.86	28.67	8.48	8.36	2.98	33.83	10.01
219	20.0	50.73	76.11	38.92	10.41	10.58	3.56	45.93	12.28
220	13.9	55.00	92.12	24.92	6.82	4.98	2.01	29.41	8.05
221	16.1	100.00	80.14	20.89	9.46	4.32	2.44	24.65	11.16
222	13.5	100.00	80.42	28.08	7.05	7.94	2.51	33.13	8.32
223	13.1	77.64	87.85	29.16	23.29	7.80	7.06	34.41	27.48
224	15.3	80.45	100.00	18.15	28.82	5.51	8.42	21.42	34.01
225	14.1	71.18	100.00	24.62	12.13	5.95	3.97	29.05	14.31
226	15.5	91.56	56.32	30.66	12.24	7.76	3.80	36.18	14.44
227	19.4	27.40	68.99	7.02	23.83	2.04	4.80	8.28	28.12
228	15.9	39.10	80.56	12.63	10.60	2.96	2.63	14.90	12.51
229	15.8	100.00	90.73	35.01	5.97	9.62	2.41	41.31	7.04
230	18.2	71.25	53.02	55.13	6.75	14.81	2.55	65.05	7.97
231	14.8	90.35	100.00	44.20	23.13	11.55	6.86	52.16	27.29
232	13.2	70.07	93.44	51.68	32.84	12.65	7.52	60.98	38.75
233	16.3	34.97	75.03	32.23	17.59	7.75	4.76	38.03	20.76
234	19.5	65.83	96.81	9.30	33.60	2.42	6.40	10.97	39.65
235	13.9	84.34	98.99	21.30	40.30	4.38	7.50	25.13	47.55
236	16.4	80.21	94.96	24.88	19.51	6.44	6.11	29.36	23.02
237	14.4	59.83	76.15	10.93	19.80	3.80	5.99	12.90	23.36
238	18.5	50.00	60.10	18.22	18.62	5.64	5.56	21.50	21.97
239	15.9	70.07	71.04	10.24	17.05	3.45	4.11	12.08	20.12
240	15.8	46.11	64.86	10.73	6.01	3.41	2.38	12.66	7.09
241	18.4	50.00	92.29	23.39	5.71	4.72	1.83	27.60	6.74
242	23.5	50.00	77.01	20.77	5.00	4.30	1.71	24.51	5.90
243	15.6	50.00	41.04	13.86	12.03	4.33	4.06	16.35	14.20
244	16.3	59.10	84.20	14.78	31.82	4.27	9.19	17.44	37.55
245	16.9	82.64	78.51	15.54	40.79	3.92	10.36	18.34	48.13
246	26.4	85.17	43.47	13.90	21.98	4.49	5.64	16.40	25.94
247	22.3	56.91	50.03	12.67	13.48	3.80	4.15	14.95	15.91
248	15.8	80.69	83.02	19.54	30.01	4.09	5.81	23.06	35.41
249	21.7	66.53	87.19	25.95	7.93	5.15	2.19	30.62	9.36
250	16.2	40.14	100.00	27.74	6.43	7.44	2.42	32.73	7.59

Table 7-1 cont'd ...

251	14.2	92.43	100.00	17.85	7.60	4.84	2.63	21.06	8.97
252	15.0	85.76	100.00	13.85	8.54	4.17	3.00	16.34	10.08
253	14.1	82.99	86.74	30.13	7.56	8.29	2.77	35.55	8.92
254	22.4	77.99	58.33	35.23	19.54	9.30	6.14	41.57	23.06
255	24.7	64.86	85.59	26.31	30.31	5.20	5.86	31.05	35.77
256	22.6	96.04	100.00	22.65	20.92	4.60	4.32	26.73	24.69
257	18.5	96.25	51.94	41.20	25.09	10.74	7.65	48.62	29.61
258	15.7	100.00	65.10	13.54	11.49	4.12	3.59	15.98	13.56
259	15.9	76.81	100.00	18.90	11.15	4.75	3.60	22.30	13.16
260	21.4	79.20	84.72	36.26	29.56	9.63	8.62	42.79	34.88
261	20.0	94.41	85.42	6.62	20.42	2.56	6.29	7.81	24.10
262	12.3	74.79	100.00	27.64	42.14	5.42	7.80	32.62	49.73
263	13.1	68.72	55.45	41.62	11.78	7.71	2.82	49.11	13.90
264	16.6	79.97	56.46	15.56	35.14	4.31	10.19	18.36	41.47
265	25.1	94.72	80.14	11.79	25.62	3.95	5.88	13.91	30.23
266	20.8	100.00	80.63	22.10	6.37	6.44	2.49	26.08	7.52
267	15.0	100.00	91.04	17.40	7.73	4.68	2.86	20.53	9.12
268	16.3	46.98	88.26	29.34	5.19	7.01	2.17	34.62	6.12
269	24.6	50.00	90.24	15.93	5.55	3.50	1.80	18.80	6.55
270	27.4	50.00	90.87	17.70	24.82	3.79	4.96	20.89	29.29
271	16.4	14.44	53.82	20.83	44.47	5.20	11.15	24.58	52.47
Mean	**19.2**	**71.90**	**71.67**	**26.33**	**29.01**	**6.57**	**7.15**	**31.07**	**34.23**
Stdev	**5.91**	**25.75**	**27.95**	**14.57**	**18.10**	**3.49**	**4.21**	**17.19**	**21.36**
Max	**40.5**	**100.00**	**100.00**	**71.71**	**82.08**	**18.54**	**20.66**	**84.62**	**96.85**
Min	**9.8**	**0.00**	**0.00**	**4.38**	**2.59**	**1.78**	**1.40**	**5.17**	**3.06**
Total				**7135.10**	**7861.89**	**1781.40**	**1936.81**	**8419.42**	**9277.03**

[*] 2016 was a leap year.

[**] Data shown for day 1 to 87 (inclusive) are those reported in Chapter 6.

[&] Conversion factor =1.18 (Anon., 2014) such that GHG emissions (kg CO_2-e) = 1.18 x energy (kWh).

[†] Energy strategy for *treated* suite (1321/1322).

[††] Energy strategy for *control* suite (1421/1422).

The overall occupancy rate (shown in columns 3 and 4) was computed from hotel *check-in, check-out* times, and expressed as percent (%) of the 24-h day cycle. It can be seen from the table that the mean daily occupancy rate for the *treated* and *control* suites was respectively computed as 71.9 and 71.7, % and a stdev of 25.7 and 27.9, %. Importantly the occupancy rates of the suites are therefore not meaningfully different and are within the range of 70 to 75 % required (anecdotally) (Anon., 2015) for viable commercial business.

The raw electrical energy used is shown in column 5 and 6 for, respectively, the *treated* and *control* suites. The mean overall energy used is seen to be, respectively, 26.33 and 29.01, kWh with a stdev 14.6 and 18.1, kWh per day (giving a sum, respectively, of 7,135.10 and 7,861.89 kWh). This is a difference of ~ 9.2 % between *control* and *treated* suite averaged over the 271 days for the electrical energy used to condition the room air of the identical suites.

The derived cost data for the electrical energy shown in columns 7 and 8 (Table 7-1) for the *treated* (1321/1322) and *control* (1421/1422) suites, respectively, were based on the tariffs from the public supply utility. The difference between the overall mean costs for the electrical energy used in the two strategies therefore for the suites is AUD \$(7.15 - 6.57) = AUD \$0.58 per day or ~ 8.0 %. Greenhouse gas emission (kg CO_2-e) (columns 9 and 10, Table 7-1) was computed from the conversion factor of 1:1.18 for indirect emissions from consumption of purchased electricity in S-E (Victoria) Australia (Anon., 2014). For example the GHG for day 160 (column 1) for 1421/1422 *control* suite, of 36.89 kg CO_2-e (column 10) is computed from the 31.26 kWh (column 6) used multiplied by 1.18.

A plot of the peak ambient temperature for each of the 271 days is presented as Fig. 7-1. The L of the figure highlights the summer, and; the R of the figure the following spring. The figure usefully shows the fluctuations and seasonal trend in ambient peak temperature for the period of the validation trial. The room *auto-set* temperature ($T_i = 22\ ^{O}C$) is highlighted also.

Table 7-2 summarizes the value of the energy strategy risk factor, p, Eq. (6.2), for all 271 days. A value of the risk factor $p > 0$ underscores a failure of the *on-only* energy strategy for conditioning of the bulk room air. As is seen in the table, there are 124 days on which $p > 0$ i.e. (124/271 x 100 =) 46 % of the period, and; that the value of the daily risk factor ranges from -1141.5 to 87.8, %.

A plot of the value of the energy risk factor (%) is presented as Fig. 7-2. The figure illustrates more clearly than the table the 124 failures of the *on-only* energy strategy as values above the x-axis. It shows that the alternative *on-only* air-conditioning energy is a mix of successes and failures. The absolute values of peaks of the successes of the energy strategy ($p \leq 0$) are seen to be greater than those of the failures ($p > 0$).

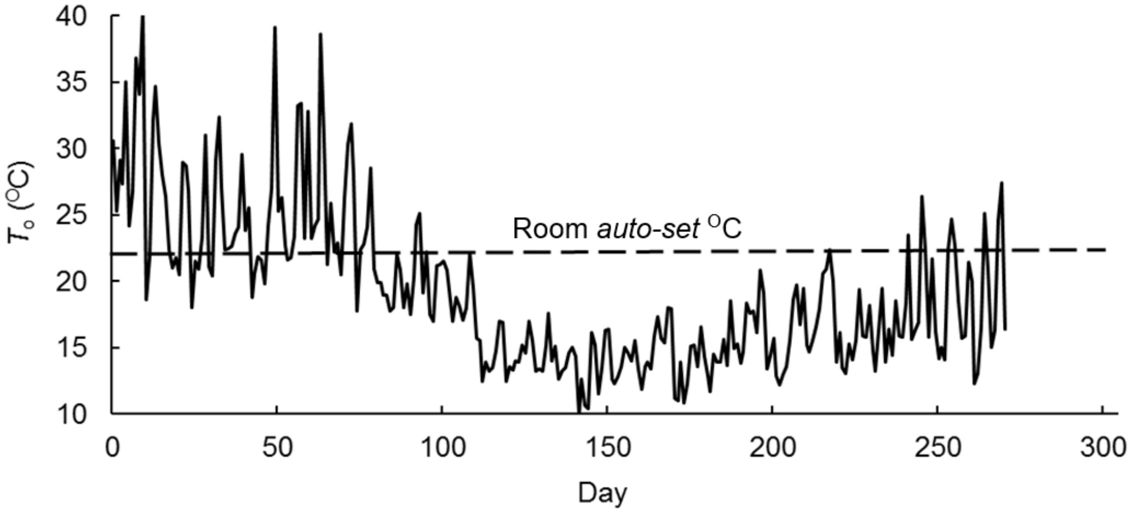

Fig. 7-1: Plot of bulk daily peak ambient temperature (T_o, ^{O}C) supplied by BoM (Anon., 2016 a) for the 271 days spanning four consecutive seasons

Table 7-2: Summary of energy strategy risk factor (p) for the 271 days spanning four consecutive seasons (4 Dec. 2015 to 31 Oct. 2016 *)

Day**	***Q*** (kWh) *on-only* (*treated*)	*on-off* (*control*)	***p*** (%) (1 - ($Q_{on-off}/Q_{on-only}$))100
1	23.41	31.59	-34.9
2	29.19	37.52	-28.5
3	26.41	38.28	-44.9
4	29.02	49.48	-70.5
5	51.19	50.29	1.8
6	6.05	37.52	-520.2
7	37.41	25.89	30.8
8	53.03	64.80	-22.2
9	71.71	81.48	-13.6
10	66.93	80.84	-20.8
11	37.89	37.24	1.7
12	40.24	29.16	27.5
13	53.68	50.61	5.7
14	59.89	59.85	0.1
15	50.15	64.45	-28.5
16	37.52	36.23	3.4

Table 7-2 cont'd ...

17	11.19	48.72	-335.4
18	32.94	41.50	-26.0
19	17.29	41.28	-138.8
20	13.08	44.39	-239.4
21	11.23	46.91	-317.7
22	28.08	47.64	-69.7
23	37.45	44.45	-18.7
24	51.04	52.62	-3.1
25	21.79	11.63	46.6
26	5.90	17.28	-192.9
27	25.27	27.07	-7.1
28	33.91	32.55	4.0
29	54.97	14.78	73.1
30	34.86	7.41	78.7
31	37.13	9.28	75.0
32	49.21	31.12	36.8
33	63.66	49.32	22.5
34	36.23	47.95	-32.3
35	8.00	40.02	-400.3
36	24.62	5.88	76.1
37	23.15	23.96	-3.5
38	33.47	33.23	0.7
39	24.76	31.01	-25.2
40	41.54	50.88	-22.5
41	33.57	40.37	-20.3
42	35.09	38.65	-10.1
43	12.89	14.03	-8.8
44	7.14	12.56	-75.9
45	5.76	24.24	-320.8
46	12.73	19.69	-54.7
47	10.97	23.42	-113.5
48	27.92	50.54	-81.0
49	40.03	58.93	-47.2
50	44.54	41.62	6.6
51	35.82	45.18	-26.1
52	33.40	44.76	-34.0
53	38.90	34.48	11.4
54	25.98	23.80	8.4
55	13.54	18.49	-36.6
56	14.75	22.49	-52.5
57	47.81	53.03	-10.9
58	60.37	64.48	-6.8
59	52.44	41.01	21.8
60	30.53	42.47	-39.1
61	22.67	45.46	-100.5

Table 7-2 cont'd ...

62	15.59	41.52	-166.3
63	35.84	11.25	68.6
64	69.09	76.39	-10.6
65	39.91	73.24	-83.5
66	19.62	31.26	-59.3
67	31.46	46.17	-46.8
68	19.32	46.50	-140.7
69	24.80	34.79	-40.3
70	23.35	24.46	-4.8
71	37.76	30.52	19.2
72	52.66	51.79	1.7
73	57.82	82.08	-42.0
74	29.61	61.66	-108.2
75	31.21	39.55	-26.7
76	24.35	20.29	16.7
77	31.69	36.34	-14.7
78	32.28	27.03	16.3
79	31.66	35.16	-11.1
80	20.94	18.43	12.0
81	21.82	19.09	12.5
82	25.04	15.04	39.9
83	31.30	21.06	32.7
84	36.62	17.85	51.3
85	24.56	8.04	67.3
86	22.49	6.32	71.9
87	14.00	25.28	-80.6
88	31.16	19.36	37.9
89	11.64	12.50	-7.4
90	9.55	6.41	32.9
91	14.82	16.31	-10.1
92	16.19	9.78	39.6
93	19.42	32.46	-67.1
94	38.23	23.32	39.0
95	15.12	2.59	82.9
96	15.49	3.09	80.1
97	5.45	2.85	47.7
98	10.51	2.77	73.6
99	8.67	4.03	53.5
100	6.96	4.29	38.4
101	10.36	23.62	-128.0
102	7.62	24.43	-220.6
103	4.38	16.57	-278.3
104	7.72	9.40	-21.8
105	7.60	4.92	35.3
106	5.60	60.63	-982.7

Table 7-2 cont'd ...

107	4.62	28.89	-525.3
108	9.67	8.30	14.2
109	22.19	16.30	26.5
110	16.27	20.70	-27.2
111	11.84	9.83	17.0
112	5.53	10.44	-88.8
113	8.51	53.49	-528.6
114	19.57	43.26	-121.1
115	17.74	51.95	-192.8
116	24.27	31.58	-30.1
117	33.60	34.43	-2.5
118	44.96	30.34	32.5
119	39.61	45.85	-15.8
120	42.29	51.51	-21.8
121	33.20	28.20	15.1
122	11.35	23.13	-103.8
123	5.32	30.16	-466.9
124	33.87	33.80	0.2
125	10.20	5.39	47.2
126	30.88	23.04	25.4
127	17.93	15.31	14.6
128	35.56	41.38	-16.4
129	38.82	64.45	-66.0
130	20.89	68.33	-227.1
131	5.85	72.63	-1141.5
132	15.37	67.49	-339.1
133	23.93	57.05	-138.4
134	50.87	54.75	-7.6
135	20.82	47.30	-127.2
136	20.00	57.95	-189.8
137	26.41	61.16	-131.6
138	22.34	34.56	-54.7
139	21.68	38.82	-79.1
140	25.96	27.24	-4.9
141	16.37	43.76	-167.3
142	43.54	60.11	-38.1
143	43.98	44.33	-0.8
144	33.33	20.14	39.6
145	52.09	30.48	41.5
146	66.93	56.39	15.7
147	46.87	16.43	64.9
148	39.05	69.22	-77.3
149	21.12	28.88	-36.7
150	6.02	18.85	-213.1
151	7.87	27.06	-243.8

Table 7-2 cont'd ...

152	16.23	35.83	-120.8
153	16.63	44.08	-165.1
154	11.46	29.39	-156.5
155	15.84	19.31	-21.9
156	37.37	24.71	33.9
157	43.05	36.65	14.9
158	40.97	23.68	42.2
159	32.39	33.77	-4.3
160	24.95	31.26	-25.3
161	46.97	41.23	12.2
162	45.07	65.65	-45.7
163	19.29	37.13	-92.5
164	7.10	47.84	-573.8
165	5.97	22.17	-271.4
166	16.92	13.29	21.5
167	12.58	5.93	52.9
168	22.97	5.37	76.6
169	29.24	31.31	-7.1
170	42.29	53.87	-27.4
171	17.52	22.60	-29.0
172	19.83	28.05	-41.5
173	25.85	63.46	-145.5
174	33.76	47.66	-41.2
175	47.55	32.84	30.9
176	34.71	21.11	39.2
177	6.77	35.54	-425.0
178	43.66	24.05	44.9
179	23.26	16.54	28.9
180	8.56	14.65	-71.1
181	15.23	67.98	-346.4
182	41.34	24.05	41.8
183	32.75	38.53	-17.6
184	30.62	37.95	-23.9
185	40.91	21.38	47.7
186	28.03	11.72	58.2
187	10.95	16.08	-46.8
188	12.84	14.71	-14.6
189	9.18	4.79	47.8
190	8.93	17.34	-94.2
191	29.97	44.72	-49.2
192	29.27	31.30	-6.9
193	15.70	7.04	55.2
194	7.50	6.49	13.5
195	20.20	9.44	53.3
196	31.92	19.70	38.3

Table 7-2 cont'd ...

197	43.90	31.15	29.0
198	47.34	23.82	49.7
199	46.85	21.45	54.2
200	58.38	10.18	82.6
201	39.24	11.28	71.3
202	26.25	22.00	16.2
203	28.27	21.39	24.3
204	19.58	38.57	-97.0
205	9.31	30.65	-229.2
206	7.93	25.38	-220.1
207	6.97	23.98	-244.0
208	19.49	10.41	46.6
209	26.99	10.49	61.1
210	42.91	26.45	38.4
211	32.53	17.72	45.5
212	26.24	7.76	70.4
213	32.52	6.48	80.1
214	12.81	19.63	-53.2
215	7.56	7.65	-1.2
216	5.70	10.87	-90.7
217	20.36	11.01	45.9
218	28.67	8.48	70.4
219	38.92	10.41	73.3
220	24.92	6.82	72.6
221	20.89	9.46	54.7
222	28.08	7.05	74.9
223	29.16	23.29	20.1
224	18.15	28.82	-58.8
225	24.62	12.13	50.7
226	30.66	12.24	60.1
227	7.02	23.83	-239.5
228	12.63	10.60	16.1
229	35.01	5.97	82.9
230	55.13	6.75	87.8
231	44.20	23.13	47.7
232	51.68	32.84	36.5
233	32.23	17.59	45.4
234	9.30	33.60	-261.3
235	21.30	40.30	-89.2
236	24.88	19.51	21.6
237	10.93	19.80	-81.2
238	18.22	18.62	-2.2
239	10.24	17.05	-66.5
240	10.73	6.01	44.0
241	23.39	5.71	75.6

Table 7-2 cont'd …

242	20.77	5.00	75.9
243	13.86	12.03	13.2
244	14.78	31.82	-115.3
245	15.54	40.79	-162.5
246	13.90	21.98	-58.1
247	12.67	13.48	-6.4
248	19.54	30.01	-53.6
249	25.95	7.93	69.4
250	27.74	6.43	76.8
251	17.85	7.60	57.4
252	13.85	8.54	38.3
253	30.13	7.56	74.9
254	35.23	19.54	44.5
255	26.31	30.31	-15.2
256	22.65	20.92	7.6
257	41.20	25.09	39.1
258	13.54	11.49	15.1
259	18.90	11.15	41.0
260	36.26	29.56	18.5
261	6.62	20.42	-208.5
262	27.64	42.14	-52.5
263	41.62	11.78	71.7
264	15.56	35.14	-125.8
265	11.79	25.62	-117.3
266	22.10	6.37	71.2
267	17.40	7.73	55.6
268	29.34	5.19	82.3
269	15.93	5.55	65.2
270	17.70	24.82	-40.2
271	20.83	44.47	-113.5
		Number of $p > 0$	**124**

[*] 2016 was a leap year.

[**] Data shown for day 1 to 87 (inclusive) are those reported in Chapter 6.

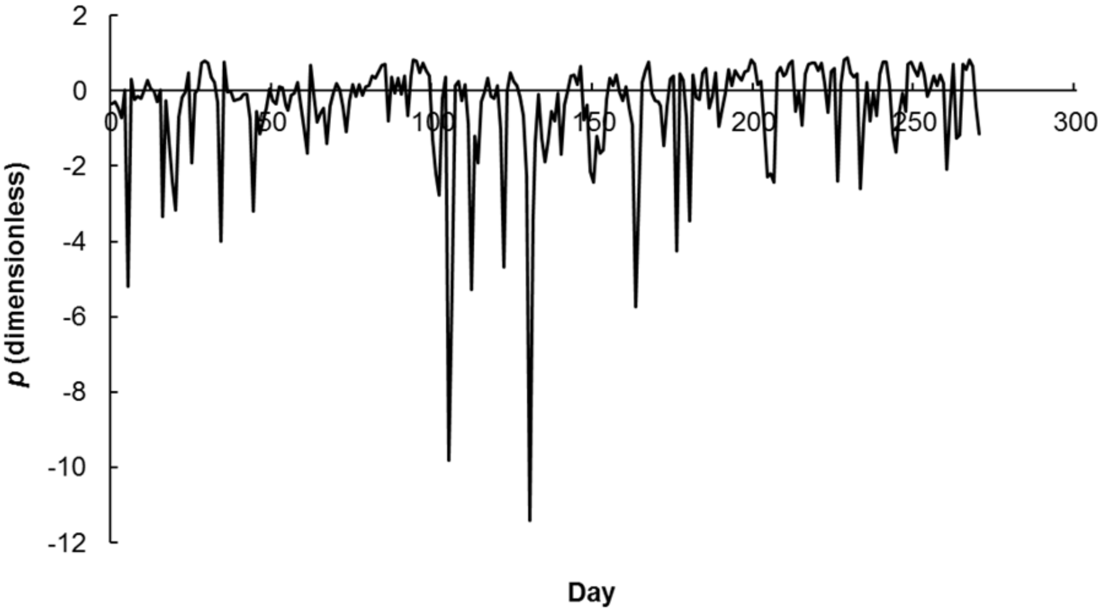

Fig. 7-2: Plot of energy strategy risk factor (p dimensionless) for *on-only* air-conditioning strategy during the extended experimental validation of 271 days for four consecutive seasons

7.4 Discussion

Notably, for all 271 days, all occupants accepted that the air-conditioning could not be altered during their stay in the *treated* (1321/1322) suite i.e. no occupants requested an alternative room. Although the agreed experimental protocols with hotel management prevented the conditioner from being switched-off in the *treated* suite, occupants in any case benefited from a more-controlled room air in having the air-conditioner on continuously.

7.4.1 Reliability of extended data

Importantly, the experimental data of Table 7-1 are seen to cover all four consecutive seasons. Because the electrical energy used and peak ambient temperature were independently recorded with a granularity of 30-min intervals, there are a total of (271 x 24 x 2) n = 13,008 sets of data [24]. This can be said to be sufficiently extensive.

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[24] These micro-data are available from the author.

It can be seen from the table that the maximum and minimum energy used for the *treated* and *control* suites was, respectively, 71.71, 4.38 and 82.08, 2.59, kWh. There is therefore a significant variation during the validation period.

Because the mean room occupancy rates (columns 3 and 4), respectively, for the *treated* and *control* suite, 71.9 and 71.7, %, are not meaningfully different, they therefore permit a direct comparison. Further, these occupancies are very close to that required for commercial viability of ≥ 70 % over the long term (Anon., 2015). The peak ambient temperature covers a wide range (40.5 to 9.8, ^{O}C) and there is every reason to regard this as typical seasonal behaviour over the long term.

It can be concluded that: 1) the period of the extended validation trial coincided with that for typical business, and; 2) the resulting data are sufficiently extensive to test the generalizability of the alternative *on-only* energy hypothesis in a commercial setting.

7.4.2 Generalizability of **on-only** *hypothesis*

Because the extensive and independent data for the identical suites matched a typical period of commercial business, together with typical seasonal impacts of fluctuations in ambient temperature and room occupancy, it is concluded that the difference in electrical energy used and greenhouse gas (GHG) emissions between the identical suites is a true measure. That is, a saving of AUD $0.58 per day per suite (8.0 %) and a reduction of 3.16 kg CO_2-e (9.2 %) in indirect GHG were practically realized with the simple adoption of the alternative *on-only* conditioning.

7.4.3 Savings and benefits

Extrapolated to the ~ 85 paired-room suites of the hotel, there is a real annual savings in electrical costs for conditioning of air of (AUD $0.58 x 85 x 365.25 =) AUD $18,006 per annum i.e. an increase of 3 % net profit margin (*see* Appendix G), together with a concomitant GHG reduction of (3.16 x 85 x 365.25/1,000 =) 98 t. Additionally, credit certificates for these GHG reductions can be used to increase savings (Anon., 2017 a; Anon., 2017 b).

Most importantly, these savings and benefits are achieved without recourse to capital outlays or increased maintenance costs. Significantly, further savings in electrical energy might be expected to be made for suites facing directly W.

Critically, there was no failure of the conditioning unit in the *treated* suite. Initially, fears have been expressed by hotel management that the continuous *on-only* conditioning might result in breakdown and consequent replacement with cost.

Because there are no apparent barriers to experimental protocols it is concluded the *on-only* energy strategy could be applied to a range of room geometries.

Given the overall net profit in the hotel industry is about 5 % (Anon., 2017 f; Anon., 2017 g), it can be readily shown (*see* Appendix G) that the demonstrated AUD $0.58 saving per day in electrical energy costs for conditioning of the room air with the *on-only* energy strategy would increase this to 5.15 %.

7.4.4 Overall review

Fig. 7-3 is a plot of p versus the temperature difference ($T_i - T_o$, ^{O}C) for all 271 days. The figure is presented as four, L to R clockwise, quadrants. Quadrants I and IV are those days on which the ambient peak temperature (T_o, ^{O}C) is greater than the *auto-set* room bulk temperature (T_i, ^{O}C), indicating cooling overall for conditioning of the room air was needed. Similarly, quadrants II and III are those days on which T_o is less than T_i, indicating heating overall for conditioning of the room air. This presentation usefully highlights the overall data.

For example, quadrants III and IV are those days (147) for which $p < 0$, indicating a real gain in savings of electrical energy over the industry default of *on-off* energy strategy. Quadrants I and II are those (124) days on which there was no advantage of the *on-only* energy strategy over the *on-off*. Notably, the spread of the p-data is seen to be greatest in quadrant III, days on which conditioning heating of the room air was needed with $T_o < T_i$.

It can be readily seen in the figure that there are 198 days in quadrant II and III (73 %) i.e. with ambient temperature (T_o, ^{O}C) less than the *auto-set* (T_i = 22 ^{O}C), and; 73 data (27 %) in quadrant I and IV ($T_o > T_i$, ^{O}C), highlighting that most days were cool and heating conditioning of the room air was required.

Significantly the data is independent and limited by any underlying heat-model.

Taking Fig. 7-3 and Fig. 7-2 together, it can be seen that by ‘moving’ the values for $p > 0$ to below the x-axis, an optimization of the *on-only* energy strategy would be achieved. Practically, this could be done predictively based on a knowledge of future ambient temperature and room occupancy and traffic flows. Chu and Davey (2017 a) (Chapter 5) suggested such optimization through an *App* (Anon., 2012 b) built around BoM predictions and forward hotel bookings to say 10 to 14 days out.

The *App* would be used as a quantitative predictive tool to a (simple) change of tactics for the days when the forecast peak ambient temperature was $T_i \pm 2$, ^{O}C (~ 18 to < 24, ^{O}C) or when the occupancy rate was low ($L_T < 70$ %). On such days the conditioning strategy should tactically be the industry default *on-off*.

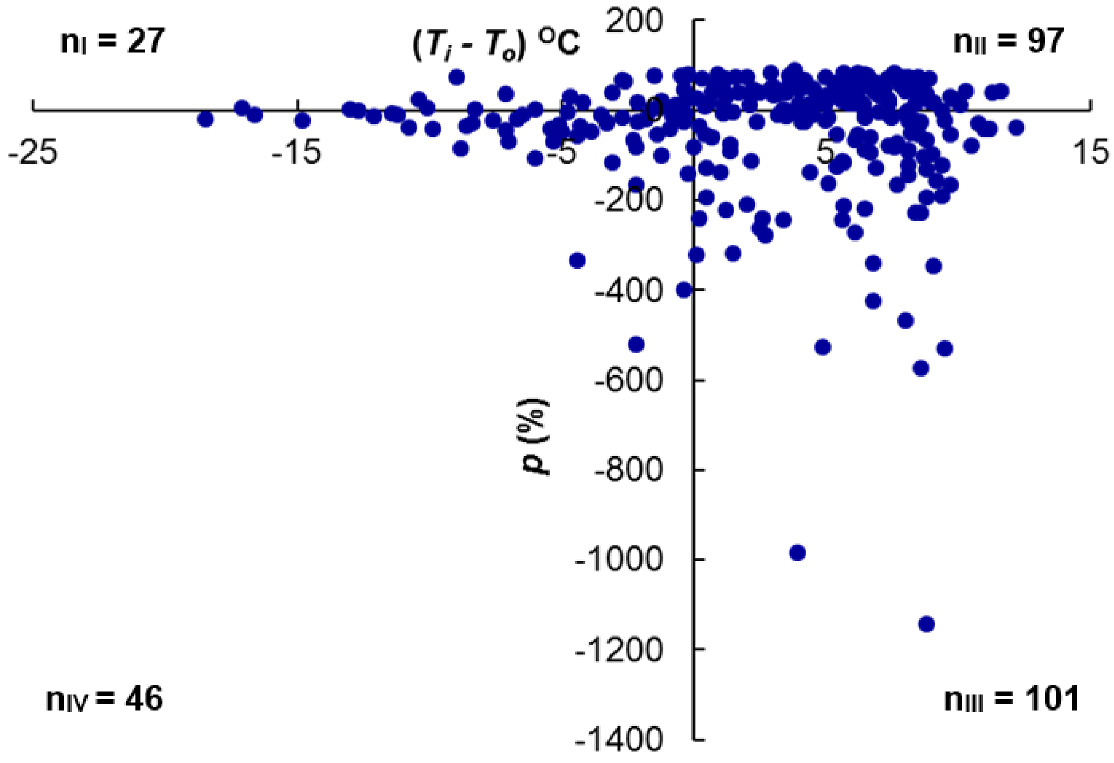

Fig. 7-3: Plot of energy strategy risk factor (*p* %) versus (T_i - T_o) (^{O}C) spanning four consecutive seasons with room *auto set* T_i = 22 ^{O}C

With a successful *App* to optimize the conditioning energy strategy, potential savings can be estimated as follows. For example, for the 143 days in which *on-only* made real savings over *on-off* (Table 7-1) the cost realized is AUD $320.58 per suite for the 271 days. Therefore it is possible to potentially realize an additional mean savings of (= AUD $320.58/128) AUD $2.50 per suite per day averaged over the long term and four consecutive seasons. The additional cost saving realized is then (AUD $2.50 x 85 x 365.25 ~) AUD $77,700 per annum.

This is significant at (AUD $2.50/AUD $19.00 x 100 ~) 13.2 % of net profit margin (*see* Appendix G for a methodology of calculating net profit).

It is concluded an *App* should be developed to realize these gains, and; the extensive data reported here should be sufficient for its development. A quantitative applied *App* is being developed.

7.5 Chapter summary and conclusions

1. Extensive data from a 271 day experimental study in a large-scale commercial hotel (latitude -37.819708, longitude 144.959936) demonstrate for the first time the generalizability of the alternative *on-only* electrical energy strategy for conditioning of room air to all four (and consecutive) seasons

2. An overall real saving in electrical energy cost of AUD $0.58 (8 %) per suite per day was demonstrated with the alternative *on-only* energy strategy. Extrapolated for the ~ 85 hotel suites this equates to AUD $18,006 per year

3. There was a concomitant 9.2 % (3.16 kg CO_2-e per day) reduction in indirect GHG emission with the alternative strategy. This could be converted to credit certificates and be used to increase savings

4. An adoption industry-wide of the *on-only* conditioning energy strategy could result in a 3 % (*see* Appendix G) increase in net profit margin. Significantly, this is achieved without additional capital or maintenance outlays on existing air-conditioners.

It is concluded overall that the data reported in this chapter could be used to assist operators in conditioning. This could, conveniently, be in the form of a new algorithm or *App* (Anon., 2012).

In the following chapter, Chapter 8, a computational *App* is synthesized for the first time to assist large-scale conditioning energy strategy.

CHAPTER 8

SYNTHESIS AND DEMONSTRATION OF A QUANTITATIVE *APP* TO MINIMIZE HEAT ENERGY USED IN CONDITIONING OF BULK ROOM AIR

Parts of this chapter have been published as:

Chu, J.Y.G., Davey, K.R., 2017 d. Synthesis and demonstration of a quantitative *App* to minimize heat energy used in conditioning of bulk room air. Chemical Engineering Science – *in preparation*.

8.1 Introduction

It was concluded that the extensive experimental data presented in Chapter 7 could be used to develop a quantitative algorithm to assist operators of conditioning in large buildings.

In this chapter a quantitative predictive algorithm is synthesized for the first time in the form of an *App*. Its utility, performance and limitations are discussed. Significantly, the *App* is not limited by any underlying heat-model.

Importantly, it is shown the *App* can be readily be applied without capital outlays or additional maintenance cost. It requires locally forecast T_o and L_T, both of which are generally available at least a few days in advance via major government agencies.

Results will be of immediate benefit to a wide range of risk and energy analysts, heat-design engineers, and owners and operators of large buildings.

8.2 Materials and methods

8.2.1 Conditioning heat-transfer data

The extensive experimental data (n = 13,008) presented in Chapter 7 are based on maintaining an *auto-set* bulk room temperature of 22 ^{O}C – a ‘standard’ value used almost globally in the conditioning of air in buildings (Tom, 2008) – in a large (85 paired-room suites) commercial hotel in S-E Australia for 271 (nearly contiguous) days over the four consecutive seasons.

For two identically fitted suites, with identical geometry and aspect, the data were summarised as daily peak ambient day temperature (T_o, ^{O}C), room occupancy (L_T, %) and resulting heat transfer for the alternative *on-only* (*treated*) and default *on-off* (*control*), energy strategy, respectively, $Q_{on\text{-}only}$ and $Q_{on\text{-}off}$ (kWh) to condition the room. Actual energy data were invoiced from an independent electrical utility (*Origin Energy Ltd*, or *Simply Energy Ltd*, Australia) at 30 min intervals and T_o was supplied by Bureau of Meteorology (Anon., 2016 a); L_T was computed from hotel (Anon., 2015) bookings and records.

Daily peak ambient ranged from $9.8 \leq T_o \leq 40.5$, ^{O}C and daily occupancy $0 \leq L_T \leq 100$, % to give concomitant energy used from $4.4 \leq Q_{on\text{-}only} \leq 71.7$ and $2.6 \leq Q_{on\text{-}off} \leq 82.1$, kWh.

Importantly, these are actual data and do not rely on assumptions for the *treated* (*on-only*) and *control* (*on-off*) strategies or a heat-model.

8.2.2 **App** ***synthesis and strategy risk factor***

A practical *App* is one in which forecast T_o and L_T can be reliably used to compute and compare the heat transfers required for each of the two energy strategies, together with a quantitative estimate of the risk in adopting a predicted future strategy. For the particular conditioning data, a model for both $Q_{on\text{-}only}$ and $Q_{on\text{-}off}$ (kWh) can be readily determined using commercially available software (*Statistica*© *v. 13*, StatSoft Inc.), respectively [25], as

$$Q_{on-only} = 81.7999 - 5.4763T_O - 0.2504L_{T,on-only} + 0.1335(T_O)^2 + 0.0049T_O L_{T,on-only} + 0.0012(L_{T,on\text{-}only})^2 \tag{8.1}$$

and

$$Q_{on-off} = 67.965 - 5.5106T_O + 0.0768L_{T,on-off} + 0.1636(T_O)^2 - 0.0127T_O L_{T,on-off} + 0.0021(L_{T,on\text{-}off})^2 \tag{8.2}$$

A justification for these quadratic model forms is that they account for curvature in both parameters. A (minor) drawback is that the surface plot is symmetrical. Other model forms based on more extensive data could be used however.

Fig. 8-A1 (Annex 8-A) is a 3D visualization of the surface function of the algorithm for the *App* generated using the software *Statistica*© *version 13*. Fig. 8-A1 (a) and Fig. 8-A1 (b) respectively is an illustrative representation of the surface function of Eqs. (8.1) and (8.2).

From Eqs. (8.1) and (8.2) an energy strategy risk factor (%) can be defined as

$$p = \left(1 - \frac{Q_{on\text{-}off}}{Q_{on\text{-}only}}\right)100 \tag{6.2}$$

This is computationally convenient both because it is dimensionless and because for all $p \leq 0$ the alternative *on-only* conditioning strategy will use less electrical heat-energy than the default *on-off* and should therefore be used. (Conversely, for all $p > 0$ the *on-only* conditioning strategy will use more energy than the default *on-off* and, therefore, fail).

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[25] The significant figures shown in Eqs. (8.1) and (8.2) for the respective surface function are generated by the software and have been applied without modification.

8.2.3 Application

Practically applied, the independently forecast daily T_o and L_T are used to compute both $Q_{on\text{-}only}$ and $Q_{on\text{-}off}$ (kWh) from Eqs. (8.1) and (8.2), respectively, for the two energy strategies. These are used to compute the energy strategy risk factor, p, from Eq. (6.2). For all $p \leq 0$ the alternative *on-only* energy strategy should be adopted for that day.

These computations can be automatically done daily in advance, when the accuracy of forecast T_o and L_T is greatest, or for a period of say some 5 days. The accuracy of the forecast will of course diminish with increased future time and impact the performance of the *App*.

8.3 Results

Table 8-1 summarizes the *App* predictions for the energy strategy risk factor (p) based on the extensive historical data presented in Chapter 7 for 271 (nearly contiguous) days and consecutive seasons (4 Dec. 2015 to 31 Oct. 2016 [26]) for a large commercial hotel in S-E Australia (latitude -37.819708, longitude 144.959936).

The shaded rows of the table highlight all $p > 0$, n = 85, that is, the number of time the *on-only* energy strategy is predicted to fail to minimize energy used in conditioning the room bulk air to the *auto-set* 22 ^{O}C.

It can be seen from the table that the ambient peak temperature ranged from $9.8 \leq T_o \leq 40.5$, ^{O}C (mean = 19.2), $0 \leq L_{T,on\text{-}only} \leq 100$, % (mean = 71.90), and; $0 \leq L_{T,on\text{-}off} \leq 100$, % (mean = 71.67). There is, therefore, no meaningful difference in the room occupancy rate.

The predicted energy transfer for the two strategies are, respectively, $20.78 \leq Q_{on\text{-}only} \leq 81.20$ (kWh) (mean = 26.16), and; $19.35 \leq Q_{on\text{-}off} \leq 99.01$, (kWh) (mean = 28.77). This has resulted in a range of values for the energy strategy risk $-40.04 \leq p \leq 26.41$ (%) (mean = -9.63). Notably however, in the present stage of development of the *Fr 13* framework an absolute value of the risk factor is not used (*pers. comm.*, K.R. Davey).

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[26] 2016 was a leap year.

Table 8-1: *App* predictions for the energy strategy risk factor (p) using the extensive historical data presented in Chapter 7 for 271 contiguous days and consecutive seasons (4 Dec. 2015 to 31 Oct. 2016 *) for a large commercial hotel in S-E Australia (latitude -37.819708, longitude 144.959936)

Day	**Forecast data**			**Predicted**		
				Energy transfer		**Risk factor**
	T_o **(°C)**	L_T **(%)**		Q **(kWh)**		p **%**
		on-only (treated)	*on-off (control)*	*on-only (treated)*	*on-off (control)*	
1	30.6	13.33	63.88	38.10	41.18	-8.07
2	25.3	57.96	65.29	25.40	26.25	-3.34
3	29.1	68	62.83	33.71	36.04	-6.92
4	27.3	72.63	69	29.65	30.83	-3.97
5	35	47.21	47.21	52.62	62.83	-19.40
6	24.2	56.5	100	23.84	28.37	-18.99
7	26.7	88.54	100	29.57	32.23	-8.99
8	36.8	40.42	68.96	60.19	69.78	-15.93
9	34.1	36.79	69.63	48.85	55.66	-13.94
10	40.5	69.75	70.54	81.20	92.72	-14.18
11†	18.6	64.72	65.35	20.85	20.62	1.10†
12	21.9	26.46	77.85	22.95	22.80	0.65
13	32.1	75.07	100	43.34	47.56	-9.74
14	34.7	82.78	100	54.09	58.35	-7.87
15	30.4	90.21	69.55	39.31	40.28	-2.47
16	28	34.55	83.33	30.65	33.28	-8.59
17	26.4	0	36.67	30.27	29.85	1.38
18	22.4	0	0	26.12	26.62	-1.91
19	21	53.3	0	21.22	24.39	-14.95
20	21.8	100	0	23.50	25.58	-8.85
21	20.5	100	0	22.64	23.75	-4.89
22	29	81.18	0	34.38	45.75	-33.07
23	28.7	85.1	15.56	33.94	40.60	-19.61
24	26.8	97.92	92.6	30.77	31.39	-2.02
25	18	53.3	100	21.24	27.60	-29.92
26	21.5	69.79	100	21.49	26.49	-23.24
27	20.9	80.73	78.16	21.53	22.34	-3.75
28	23.3	100	82.47	25.05	24.60	1.83
29	31	83.06	100	40.43	43.67	-8.02
30	21.1	83.3	56.81	21.77	20.44	6.07
31	20.4	79.76	75.51	21.28	21.84	-2.66
32	29.1	100	84.65	36.71	36.41	0.81
33	32.4	73.23	100	44.24	48.69	-10.08
34	27.1	37.67	79.51	28.71	30.79	-7.27

Table 8-1 cont'd ...

35	22.4	19.83	91.22	23.80	25.15	-5.66
36	22.5	25.97	44.31	23.34	21.66	7.17
37	22.6	75.38	57.81	22.51	21.85	2.94
38	23.6	38.75	86.88	23.49	25.52	-8.62
39	24.1	17.53	67.5	25.41	24.27	4.47
40	29.6	100	100	38.13	39.28	-3.01
41	23.8	74.44	100	23.77	27.94	-17.50
42	25.5	84.44	100	26.93	30.12	-11.87
43	18.8	74.51	100	20.90	26.99	-29.16
44	20.6	100	76.18	22.69	21.98	3.15
45	21.9	100	81.74	23.59	23.32	1.13
46	21.6	78.99	76.53	21.87	22.45	-2.66
47	19.8	94.44	100	21.92	26.53	-20.99
48	24.2	95.17	45.63	25.78	24.27	5.85
49	27	100	7.92	31.45	36.47	-15.95
50	39.1	91.7	74.24	76.47	83.02	-8.57
51	25.3	100	100	28.06	29.81	-6.26
52	26.3	74.55	88.96	27.72	29.93	-7.98
53	22.7	69.03	100	22.39	27.03	-20.71
54	21.6	66.18	94.44	21.49	25.34	-17.94
55	21.8	47.95	61.11	21.74	21.20	2.46
56	23.4	42.47	42.43	23.15	23.03	0.54
57	33.2	100	61.56	50.36	52.07	-3.39
58	33.4	48.85	77.19	46.45	52.11	-12.21
59	23.2	15.97	90.52	24.73	25.66	-3.79
60	32.8	0	84.03	45.80	49.50	-8.08
61	23.2	0	95.97	26.60	26.61	-0.02
62	24.2	17.33	39.24	25.53	24.61	3.63
63	24.7	55.83	0	24.50	31.66	-29.24
64	38.6	68.06	0	70.71	99.01	-40.02
65	30.8	71.94	0	38.83	53.44	-37.63
66	21.3	85.28	35.49	22.00	20.58	6.42
67	25.9	72.22	100	26.86	30.77	-14.58
68	22.2	100	100	23.86	26.74	-12.10
69	22.9	100	100	24.58	27.16	-10.50
70	20.5	100	100	22.64	26.40	-16.57
71	26.2	65.83	79.41	27.13	28.81	-6.19
72	30.3	57.26	69.86	36.53	39.92	-9.29
73	31.9	47.4	54.72	41.19	46.98	-14.05
74	28	87.67	82.95	32.43	33.25	-2.55
75	17.8	96.7	91.74	22.06	25.69	-16.46
76	22.4	100	83.33	24.05	23.89	0.67
77	22.8	81.49	100	23.01	27.09	-17.76
78	24.1	59.24	78.33	23.73	25.11	-5.79
79	28.5	50.21	100	31.63	36.28	-14.72
80	20.9	100	82.36	22.86	22.96	-0.46

Table 8-1 cont'd ...

81	19.9	100	97.26	22.40	25.85	-15.38
82	19.9	93.33	97.08	21.87	25.80	-17.97
83	19	100	86.11	22.21	23.73	-6.82
84	19	91.81	73.16	21.62	21.53	0.41
85	17.8	43.47	53.65	21.79	19.75	9.39
86	18	53.19	100	21.25	27.60	-29.90
87	22	77.29	77.36	22.08	22.81	-3.29
88	20.8	18.47	100	23.32	26.39	-13.17
89	18	100	70.63	22.26	21.54	3.26
90	19.8	93.26	43.23	21.84	19.37	11.32
91	17.5	100	83.33	22.38	24.09	-7.64
92	20.3	94.83	75.87	22.12	21.87	1.13
93	24.3	78.33	72.6	24.63	24.90	-1.09
94	25.1	100	68.02	27.71	25.98	6.26
95	19.1	42.08	14.9	21.43	20.39	4.85
96	22.2	33.75	0	22.61	26.26	-16.15
97	17.5	100	0	22.38	21.63	3.36
98	17	100	0	22.57	21.57	4.47
99	21.2	100	27.5	23.05	20.96	9.05
100	21.3	70.38	32.95	21.39	20.71	3.17
101	21.5	46.46	13.78	21.62	22.81	-5.48
102	20.8	71.42	74.72	21.17	21.85	-3.22
103	19.3	31.32	61.81	22.13	20.17	8.86
104	17	83.85	87.26	21.71	25.42	-17.08
105	18.8	95.69	68.06	21.87	20.89	4.47
106	18.1	88.89	100	21.52	27.51	-27.84
107	17.1	75.07	52.12	21.45	19.96	6.93
108	18	81.43	85.71	21.23	24.20	-13.98
109	22.1	100	100	23.77	26.70	-12.34
110	19.6	44.06	70.38	21.28	21.09	0.87
111	15.7	94.13	37.19	23.03	20.12	12.65
112	15.5	83.06	14.86	22.78	20.54	9.85
113	12.5	76.39	16.77	26.76	23.86	10.83
114	13.9	65.73	57.43	24.68	24.18	2.03
115	13.2	100	100	26.20	35.65	-36.05
116	13.5	100	79.79	25.78	29.21	-13.31
117	14.8	79.65	87.57	23.44	28.61	-22.08
118	17	85.21	85.9	21.76	25.11	-15.41
119	16.9	100	79.2	22.62	23.82	-5.29
120	12.5	68.47	87.29	26.88	33.49	-24.60
121	13.6	68.77	40.8	25.05	22.86	8.74
122	13.3	100	51.22	26.06	24.40	6.34
123	14	66.01	83.75	24.53	29.15	-18.87
124	13.9	68.23	100	24.62	34.00	-38.11
125	15.2	100	83.99	23.81	27.05	-13.61
126	14.6	100	99.93	24.42	32.50	-33.10

Table 8-1 cont'd ...

127	17	100	90.24	22.57	26.11	-15.68
128	15.5	80.14	95.14	22.72	29.44	-29.60
129	13.2	70	100	25.65	35.65	-38.96
130	13.4	91.56	100	25.53	35.16	-37.70
131	13.2	74.31	100	25.60	35.65	-39.25
132	15.2	79.51	92.53	23.00	29.23	-27.05
133	17.6	68.4	80.24	21.16	23.40	-10.62
134	14	100	82.22	25.12	28.77	-14.56
135	15.1	75.17	69.48	23.07	24.21	-4.94
136	12.6	82.85	100	26.60	37.18	-39.79
137	13.2	77.4	100	25.59	35.65	-39.31
138	13.5	100	87.67	25.78	31.23	-21.17
139	14.6	100	80.1	24.42	27.16	-11.22
140	15	100	81.88	24.00	26.89	-12.01
141	14.3	54.44	77.71	24.53	27.15	-10.71
142	9.8	100	93.54	32.72	43.59	-33.24
143	12.6	100	100	27.13	37.18	-37.07
144	10.7	81.91	72.36	30.32	34.45	-13.62
145	10.4	78.85	41.49	31.02	29.67	4.35
146	16.1	84.36	84.55	22.31	25.87	-15.97
147	15.2	76.49	75.8	22.97	25.26	-9.96
148	11.5	68.02	64.55	28.83	30.51	-5.82
149	13.5	0	56.35	32.20	24.72	23.22
150	16.3	63.51	100	22.02	29.59	-34.40
151	16.4	67.5	38.4	21.88	19.64	10.25
152	12.6	100	34.34	27.13	24.12	11.07
153	12.3	100	76.6	27.63	31.17	-12.85
154	12.8	74.65	79.48	26.25	30.68	-16.88
155	13.6	69.2	83.06	25.04	29.80	-18.99
156	15	88.02	77.67	23.42	25.95	-10.82
157	14.6	100	89.55	24.42	29.50	-20.80
158	14	100	83.16	25.12	29.01	-15.48
159	15.5	96.49	100	23.33	30.85	-32.23
160	13.4	65.28	90.56	25.44	32.26	-26.81
161	11.9	100	100	28.33	39.12	-38.11
162	13.6	77.19	100	24.98	34.69	-38.86
163	13.9	50.24	67.22	25.34	25.76	-1.65
164	13.4	100	21.39	25.91	22.46	13.32
165	15.9	42.43	4.13	23.32	21.23	8.98
166	17.3	41.01	52.08	22.24	19.85	10.76
167	15.7	77.64	70.97	22.49	23.65	-5.15
168	15.4	73.61	100	22.75	31.02	-36.36
169	18	78.78	97.29	21.15	26.89	-27.14
170	17.9	90.07	94.06	21.63	26.16	-20.96
171	11.2	92.71	96.32	29.40	39.95	-35.88

Table 8-1 cont'd …

172	11	56.81	100	30.42	41.85	-37.57
173	13.9	36.15	69.97	26.45	26.28	0.65
174	10.8	38.4	66.25	32.41	32.75	-1.04
175	12.3	100	63.99	27.63	28.45	-3.00
176	15.1	51.25	100	23.66	31.56	-33.40
177	15.2	40.56	83.92	24.24	27.04	-11.52
178	13.6	81.08	100	25.00	34.69	-38.73
179	16.6	46.77	73.44	22.40	23.05	-2.93
180	14.3	27.19	34.51	26.77	21.50	19.69
181	12.9	100	100	26.65	36.40	-36.57
182	11.7	100	47.01	28.70	27.15	5.38
183	14.5	80.73	61.46	23.80	23.79	0.05
184	13.9	100	88.47	25.24	30.59	-21.18
185	13.9	78.85	100	24.56	34.00	-38.45
186	15.6	65.1	63.47	22.62	22.57	0.20
187	13.7	34.06	50	26.98	23.57	12.66
188	18.5	50	50	21.19	19.35	8.67
189	14.9	80.03	47.43	23.33	21.57	7.55
190	15.3	66.49	60.45	22.90	22.52	1.68
191	13.8	68.75	87.53	24.76	30.55	-23.38
192	14.7	80.31	82.22	23.56	27.47	-16.60
193	18.4	72.05	90.45	20.92	24.95	-19.27
194	17.6	45.24	100	21.80	27.98	-28.37
195	17.8	83.09	83.58	21.35	23.91	-11.99
196	16.1	78.68	80.87	22.17	25.06	-13.04
197	20.8	34.83	100	21.93	26.39	-20.31
198	19.1	0	69.17	25.90	20.98	19.02
199	13.4	0	84.44	32.39	30.59	5.56
200	14.4	0	0	30.62	22.54	26.41
201	15.7	26.04	0	25.02	21.77	12.99
202	12.9	80.56	0	26.08	24.10	7.58
203	12.2	100	34.72	27.80	24.90	10.41
204	13	75.35	89.44	25.91	32.88	-26.87
205	13.6	100	0	25.64	23.28	9.20
206	15.5	92.05	19.2	23.10	20.32	12.02
207	18.6	100	17.29	22.20	19.94	10.19
208	19.7	82.81	30.1	21.21	19.58	7.70
209	16.7	44.62	22.88	22.45	19.57	12.82
210	19.5	50	59.17	21.03	19.96	5.10
211	15.2	41.7	87.95	24.15	28.02	-16.01
212	14.7	92.6	74.31	23.92	25.74	-7.62
213	15.5	100	53.65	23.55	21.46	8.86
214	16.6	100	73.13	22.77	23.00	-0.99
215	17.9	53.19	61.94	21.29	20.48	3.82
216	20.6	77.26	68.19	21.26	21.03	1.04
217	20.9	96.01	67.6	22.51	21.10	6.27

Table 8-1 cont’d …

218	22.4	100	89.86	24.05	24.91	-3.57
219	20	50.73	76.11	21.03	21.87	-3.99
220	13.9	55	92.12	25.08	31.61	-26.05
221	16.1	100	80.14	23.09	24.91	-7.89
222	13.5	100	80.42	25.78	29.36	-13.90
223	13.1	77.64	87.85	25.75	32.19	-25.03
224	15.3	80.45	100	22.92	31.20	-36.14
225	14.1	71.18	100	24.30	33.56	-38.13
226	15.5	91.56	56.32	23.08	21.76	5.73
227	19.4	27.4	68.99	22.45	20.93	6.77
228	15.9	39.1	80.56	23.57	25.25	-7.16
229	15.8	100	90.73	23.30	27.79	-19.24
230	18.2	71.25	53.02	20.96	19.58	6.55
231	14.8	90.35	100	23.72	32.13	-35.46
232	13.2	70.07	93.44	25.65	33.58	-30.90
233	16.3	34.97	75.03	23.51	23.66	-0.64
234	19.5	65.83	96.81	20.78	25.86	-24.43
235	13.9	84.34	98.99	24.63	33.68	-36.73
236	16.4	80.21	94.96	21.98	28.04	-27.61
237	14.4	59.83	76.15	24.16	26.64	-10.25
238	18.5	50	60.1	21.19	20.09	5.19
239	15.9	70.07	71.04	22.28	23.41	-5.08
240	15.8	46.11	64.86	23.18	22.54	2.75
241	18.4	50	92.29	21.22	25.37	-19.53
242	23.5	50	77.01	23.07	24.20	-4.89
243	15.6	50	41.04	23.16	20.37	12.04
244	16.3	59.1	84.2	22.12	25.53	-15.44
245	16.9	82.64	78.51	21.72	23.68	-9.02
246	26.4	85.17	43.47	28.67	29.24	-2.00
247	22.3	56.91	50.03	21.92	21.36	2.54
248	15.8	80.69	83.02	22.46	25.93	-15.47
249	21.7	66.53	87.19	21.55	24.05	-11.60
250	16.2	40.14	100	23.19	29.73	-28.23
251	14.2	92.43	100	24.49	33.35	-36.15
252	15	85.76	100	23.35	31.75	-35.97
253	14.1	82.99	86.74	24.34	29.72	-22.09
254	22.4	77.99	58.33	22.45	21.65	3.56
255	24.7	64.86	85.59	24.64	26.77	-8.66
256	22.6	96.04	100	23.88	26.96	-12.93
257	18.5	96.25	51.94	21.92	19.46	11.21
258	15.7	100	65.1	23.38	22.69	2.94
259	15.9	76.81	100	22.31	30.19	-35.35
260	21.4	79.2	84.72	21.75	23.51	-8.14
261	20	94.41	85.42	21.98	23.38	-6.36
262	12.3	74.79	100	27.13	37.99	-40.04
263	13.1	68.72	55.45	25.84	25.34	1.93

Table 8-1 cont'd ...

264	16.6	79.97	56.46	21.84	20.70	5.21
265	25.1	94.72	80.14	27.15	26.81	1.23
266	20.8	100	80.63	22.80	22.67	0.58
267	15	100	91.04	24.00	29.17	-21.53
268	16.3	46.98	88.26	22.64	26.48	-16.93
269	24.6	50	90.24	24.38	27.25	-11.76
270	27.4	50	90.87	29.17	32.50	-11.41
271	16.4	14.44	53.82	25.69	20.60	19.81
Mean	**19.2**	**71.90**	**71.67**	**26.16**	**28.77**	**-9.63**
Stdev	**5.9**	**25.75**	**27.95**	**7.91**	**10.17**	**14.92**
Max	**40.5**	**100.00**	**100.00**	**81.20**	**99.01**	**26.41**
Min	**9.8**	**0.00**	**0.00**	**20.78**	**19.35**	**-40.04**
Total				**7088.3**	**7797.7**	

[*] 2016 was a leap year.

[†] Shaded rows highlight $p > 0$, n = 85.

8.4 Discussion

8.4.1 App *application*

Fig. 8-B1 is a flowchart for predictions using the newly synthesized *App*. The inputs are T_i and the forecast T_o and L_T. Depending on the value of the risk factor (p) the output prediction is either to adopt the alternative *on-only* or the maintain the industry default *on-off*.

It is likely the *App* could be practically applied automatically – although there is scope for the conditioning to be manually changed daily if needed.

A limitation however with the present surface functions used in the *App* (Eqs. (8.1) and (8.2)) is that these apply only for the particular paired-rooms and orientation (S-E corner) and particular hotel and location (latitude -37.819708, longitude 144.959936).

However, it is reasonable to expect other identically-fitted paired-rooms of the hotel would be linearly related to these functions, for example, those rooms facing W would need additional energy to both heat and cool in this part of Australia.

It is reasonable also to assume using the protocols in Chapters 6 and 7 a number of further experiments could be carried out to determine refined surface functions for the heat transfers for both energy strategies. This could, ideally, also be done for any part of any hotel, globally. Accumulated data could be used to refine and improve the predictive accuracy of a particularized *App*.

8.4.2 Predictive accuracy

The predictive accuracy, and therefore utility, of the *App* is limited by the accuracy of forecast T_o and L_T (and the surface functions for heat transfers). This raises the general question of accuracy of weather forecasts for particular localities.

These forecasts are widely provided on a rolling, daily, next-day, 5-day and 10-day basis (Anon., 2016 a). The reliability of temperature forecasts vary however (Anon., 2017 c; d; e). Beyond 10 days the ability to forecast the weather reliably is problematic (Anon., 2017 d).

Many factors influence the weather, although overall, it appears reasonable to assume that for a 5-day forecast this is 77 % for T_o (Anon., 2017 e). Beyond 10 days, reliably becomes problematic because factors influencing weather can readily change (Anon., 2017 d). Stern (2008) in an analysis of the accuracy of weather forecasts for the environment of the hotel in Melbourne, S-E Australia showed that prediction fell away significantly after 7-days.

By way of contrast, advance hotel room bookings are more reliable at around 99 % certainty (Anon., 2015) averaged over a long term. Knowledge regarding transport strikes, traffic problems, and the impact these will have on overall room occupancy, and therefore conditioning energy strategy is more certain, and often more immediate, than data regarding T_o. Importantly however, occupancy rates $L_T < 70$ % will not be commercially viable if established long term (Anon., 2015).

If the *App* is applied automatically, changes to conditioning energy strategy could be done daily thereby aiding practical utility.

8.4.3 Utility

From Table 8-1 it can be seen that over the 271 days, *App* predictions are that the industry default *on-off* conditioning should be applied on only 85 days (31.4 %) (shaded rows e.g. days 11 and 258). This means that the alternative *on-only* continuous conditioning advocated should be applied 186 times (68.6 %) (e.g. days 4 and 262).

Overall therefore, given the actual, naturally occurring fluctuations in T_o together with those in L_T, the alternative *on-only* should be applied for some 70 % of the time.

Significantly, therefore if the default industry energy strategy of *on-off* was continued the opportunity for real gains is not realized.

These gains from application of the new *App* can be estimated from Table 8-1 as (= 7088.3 - 7797.7) -709.40 kWh per (paired-room) suite (~ 2.62 kWh per suite per day), or, reasonably extrapolated linearly for the particular 85 paired-room hotel of

(= 85 x 709.40/271 x 365.25) ~ 81,270 kWh per annum. Significantly this is achieved without any capital outlays or additional maintenance costs.

For example, based on a tiered-tariff for day 17 (Sunday, 31 Jan. 2016), the off-peak and peak electrical tariff are respectively AUD $0.1233 per kWh for the whole day, in addition to a supply charge of AUD $1.0501 per day. Similarly based on a tiered tariff for day 18 (Monday, 1 Feb.), the off-peak and peak electrical tariff are respectively AUD $0.1418 (23.00 to 07.00 h) and AUD $ 0.2621 (07.00 to 23.00, h), per kWh in addition to a supply charge of AUD $1.0279 per day. This tariff is applicable for weekdays. On average for the week, this equates to AUD $0.1938 per kWh and AUD $1.0342 per day, respectively, for electrical use and supply charge. Therefore a reduction of 2.62 kWh per suite per day translates to ~ AUD $47,870 per annum for the 85 paired-room hotel. This is significant.

A concomitant benefit is reduced greenhouse emissions of (= 1.18 [27] x 2.62) 3.1 kg CO_2-e per day per room (~ 1,128 kg CO_2-e per annum for the hotel).

These real gains underscore the practical utility of the generalizable new *App*.

8.4.4 Limitation

A limitation of the present *App* is that data for the heat transfer functions for the two conditioning energy strategies apply only for the particular rooms and hotel. A generalized *App* will be needed for particular room geometries, fit-outs and building type and global location. Data however could be readily accumulated using the protocols established in Chapters 6 and 7, and; these refined with time.

Significantly however is that the accuracy of a particular *App* is not limited by any underlying heat-model. This is because the heat transfer functions are built from independent and invoiced data for energy and will differ for building arrangement and from room to room even in the same building, and in differing global locations.

The predictive utility of the *App* will be greatest, for example, at locations distant from the Equator where variation in T_o is greatest in summer and winter compared with that nearer the Equator.

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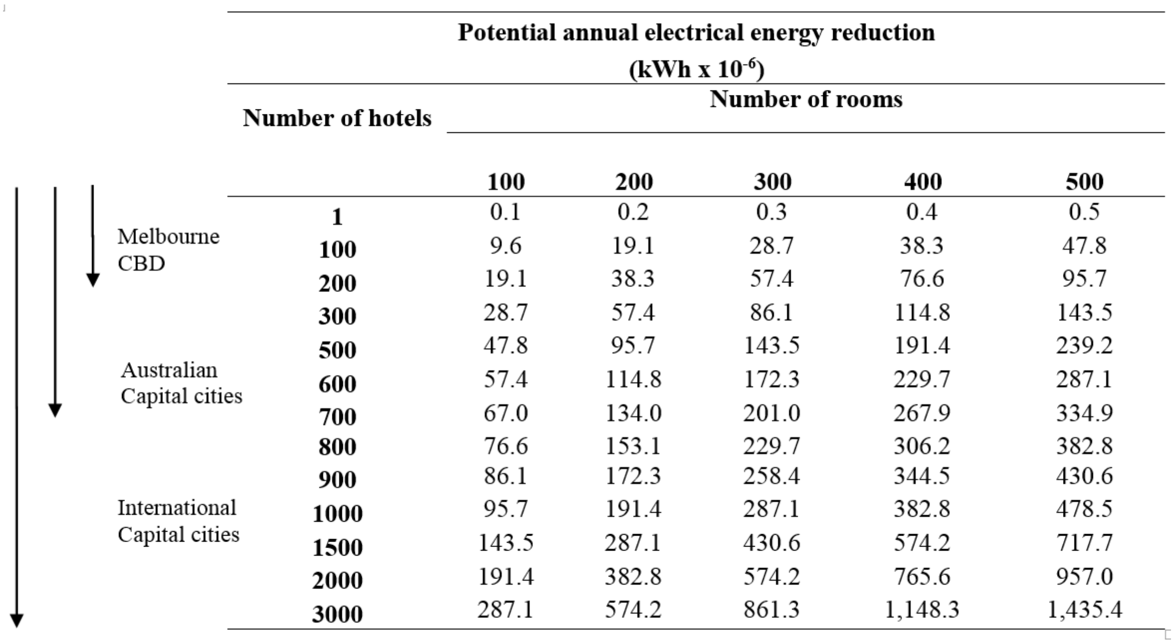
[27] Anon., (2014).

8.4.5 Potential reduction in energy use

Table 8-2 illustrates a potential reduction in energy use that could be achieved applying the *App* based on 2.62 kWh per room per day. Row 4 shows the number of rooms a hotel might have. Column 1 shows the number of 4- to 5-star hotels that could exist in the Melbourne CBD, Australian capital cities, and; internationally. For example, in Melbourne if there were 300 hotels each consisting of 200 rooms the annual potential reduction in energy use is (= 2.62 x 200 x 300 x 365.25) ~ 57.4 x 10^6 kWh. This is a significant amount of energy reduction.

As the *App* was synthesized for the specific rooms and hotel the potential heat transfer reductions achievable will vary from room to room in that hotel building and for different hotel geo-locations. However the trends will be similar.

Table 8-2: Summary of potential annual reduction in energy use with the application of an *App* based on an energy reduction of 2.62 kWh per room per day



	Number of hotels	**Potential annual electrical energy reduction (kWh x 10^{-6})**				
		Number of rooms				
		100	**200**	**300**	**400**	**500**
	1	0.1	0.2	0.3	0.4	0.5
Melbourne CBD	**100**	9.6	19.1	28.7	38.3	47.8
	200	19.1	38.3	57.4	76.6	95.7
	300	28.7	57.4	86.1	114.8	143.5
	500	47.8	95.7	143.5	191.4	239.2
Australian Capital cities	**600**	57.4	114.8	172.3	229.7	287.1
	700	67.0	134.0	201.0	267.9	334.9
	800	76.6	153.1	229.7	306.2	382.8
	900	86.1	172.3	258.4	344.5	430.6
International Capital cities	**1000**	95.7	191.4	287.1	382.8	478.5
	1500	143.5	287.1	430.6	574.2	717.7
	2000	191.4	382.8	574.2	765.6	957.0
	3000	287.1	574.2	861.3	1,148.3	1,435.4

8.5 Chapter summary and conclusions

1. A new predictive and quantitative *App* was synthesized and demonstrated for the first time. Significantly, the *App* is not limited by any underlying heat-model but is based on extensive independent experimental data

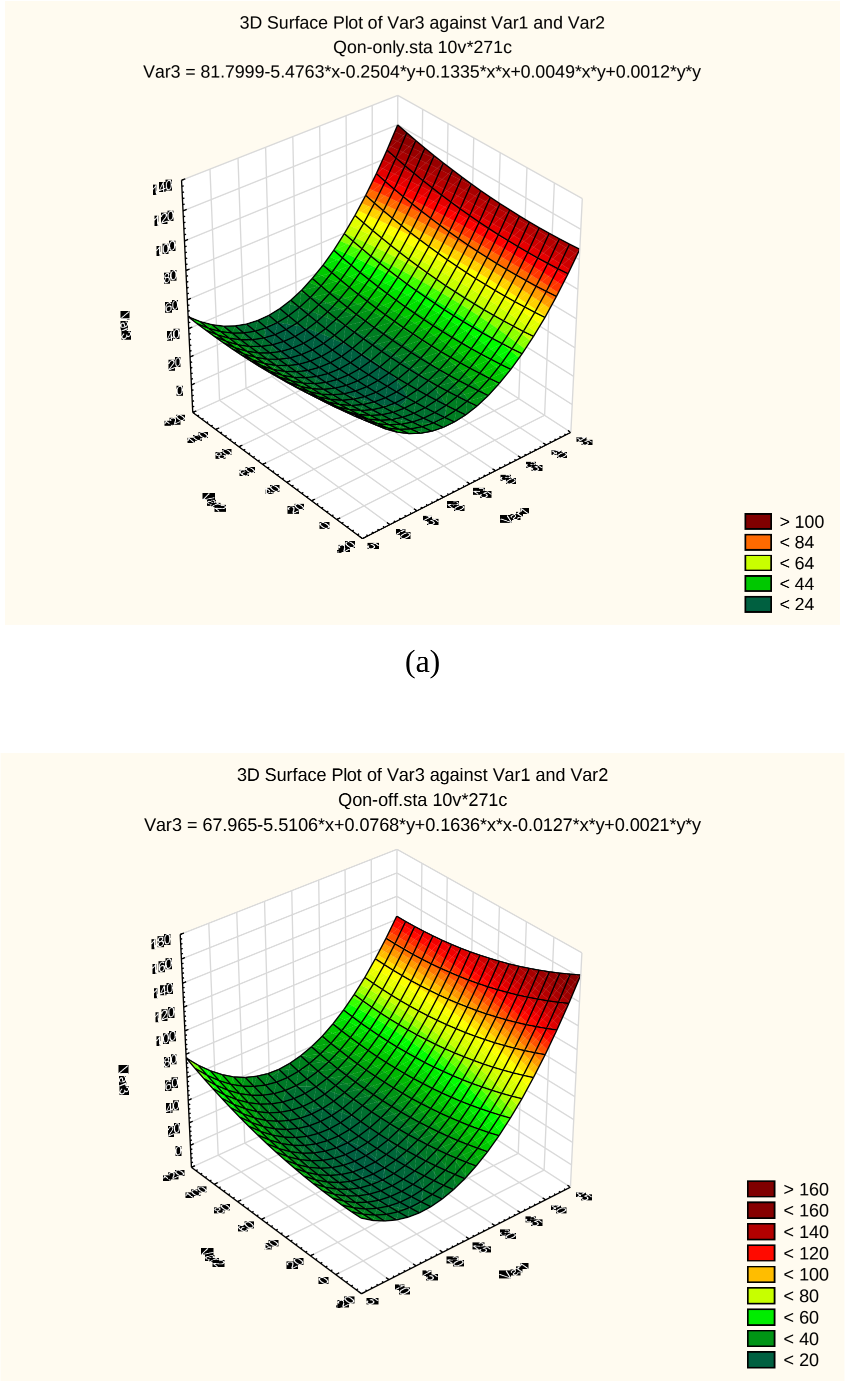
2. Practical utility is dependent on the accuracy of locally forecast T_o and L_T and correlation(s) for heat transfer(s). Applied to a large commercial hotel in S-E Australia (latitude -37.819708, longitude 144.959936) the *App* predicts a savings of 2.62 kWh per room per day based on historical and independent data from electrical invoices (271 days) in which the accuracy of forecast for T_o was 77 % and for L_T 99 %, averaged over the long term. A concomitant benefit is a predicted reduction in greenhouse emissions of 3.1 kg CO_2-e per day

3. The *App* is presently limited to a particular hotel and room(s). Further data is needed different aspects and buildings in different geographical locations

4. Results could be readily commercialized - and will be of immediate benefit to risk analysts, heat-design engineers, and owners and operators of large buildings.

In the following chapter, Chapter 9, the overall conclusions from this research are presented.

Annex 8-A: Surface functions of energy strategies $Q_{on\text{-}only}$ (a) and $Q_{on\text{-}off}$ (b) (W)



(a)

(b)

Fig. 8-A1: 3D surface functions plots for Eqs. (8.1) and (8.2) respectively

Annex 8-B: Flow chart for synthesizing of a new *App* for the prediction of energy use

This flowchart stepwise shows the methodology of applying the newly synthesized predictive *App*.

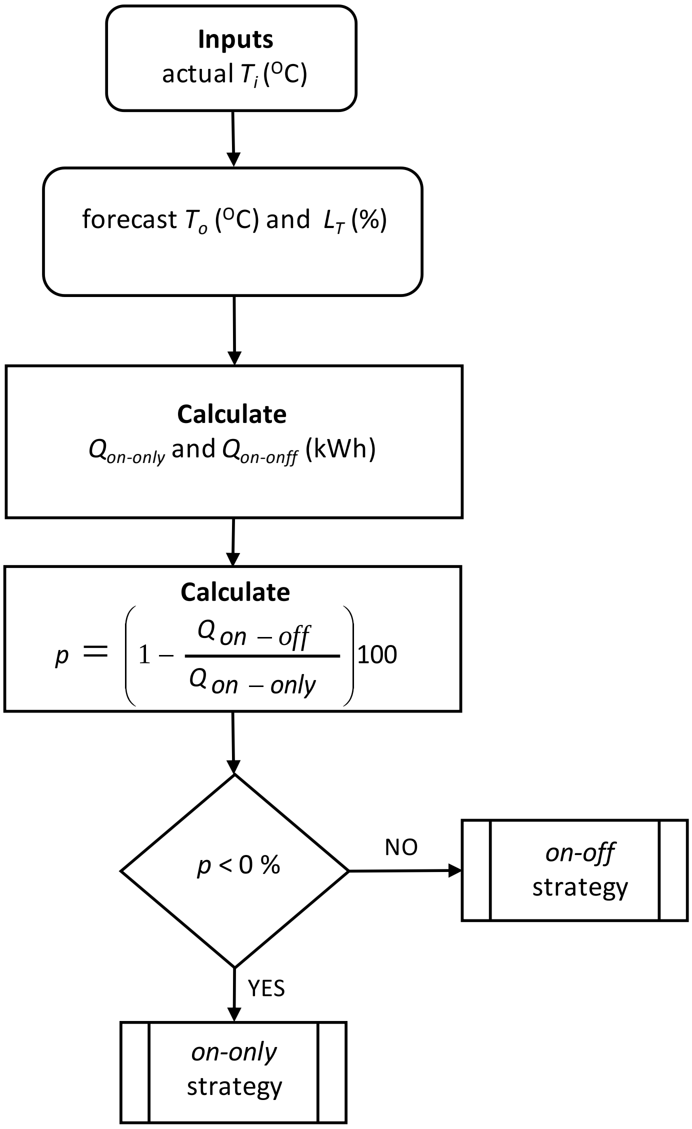


Fig. 8-B1: Flowchart (logic diagram) for the *App*

CHAPTER 9

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

9.1 Conclusions

The following can be concluded from this research:

1. Steady-state modelling is globally used in heat transfers. However, the impact of naturally occurring, random (stochastic) fluctuations in parameters is not addressed explicitly in traditional deterministic methods. The probabilistic *Fr 13* framework of Davey and co-workers is an advance because all outcome behaviours that can practically exist are simulated and quantified

2. Predictions from a newly synthesized *Fr 13* analysis of convective and radiative heat transfers in conditioning of room air as impacted by ambient temperature (T_o) and occupancy (room traffic flow) (L_T) showed that a continuous *on-only* strategy would use less energy in 87.2 % of summer days ($15 \leq T_o \leq 45$, ^{O}C) with commercially viable occupancies $L_T \geq 70$ % in S-E Australia (latitude -37.819708, longitude 144.959936), compared with present industry default of *on-off* conditioning i.e. conditioning on when the room is occupied, and off when un-occupied. Practically, the alternative energy strategy would be expected to fail 12 of the 90 days, averaged over the long term with minimum room traffic flow ($n = 1$) and a (widely used) *auto-set* room bulk temperature of 22 ^{O}C

3. Importantly, these new probabilistic predictions permitted practical and quantitative experimental validation

4. Experimental findings based on an *in-situ* commercial validation (n = 3,696) of the probabilistic predictions over 77 contiguous days ($17.8 \leq T_o \leq 39.1$, ^{O}C) in summer (Jan. to Mar., 2016 [28]) carried out in two, dimensionally-identical 2-room existing hotel suites (10.164 x 9.675, m floor plan), with the same fit-out and S-E aspect (-37.819708, 144.959936) together with identical air-conditioner (8.1 kW) and nationally registered meters, showed the *on-only* conditioning strategy used less energy on 47 days (61 %) of the experimental period. A reduction in cost of AUD $0.75 per day (9 %), averaged over the summer period, was demonstrated for the *on-only* strategy. Significantly, greenhouse gas emission (GHG) was reduced by 12 %

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[28] A leap year.

5. Because the alternate *on-only* conditioning hypothesis appeared generalizable, commercial–scale experimental validation (n = 13,008) was continued *in-situ* over 271 days to cover consecutive seasons. Peak ambient ranged from $9.8 \leq T_o \leq 40.5$, ^{O}C and there were 169 days (62 %) with rainfall. Results, based on independent electrical energy invoices, showed an overall mean energy saving of 2.68 kWh per day (AUD $0.58) with a concomitant reduction in indirect GHG of 3.16 kg CO_2-e. Extrapolated for the 85 x 2-room suites of the commercial hotel, this is a saving of ~ AUD $18,006 per annum (plus credit [29] certificates that could be used to increase savings)

6. A predictive new *App* synthesized from the extensive data highlights that a reduction of 2.62 kWh per 2-room suite per day could be gained where accuracy of forecast of T_o is 77 % and L_T is 99 %, together with a concomitant reduction in GHG of 3.1 kg CO_2-e per day, averaged over the long term. The *App* appears generalizable, and significantly, is not limited by any underlying heat-model. It appears it could be readily developed commercially [30]

7. Overall, it is concluded the *Fr 13* framework is applicable to heat transfers in conditioning of dry air in buildings, and; a mean saving in energy of ~ 8.5 % can be made using an *on-only* energy strategy compared with the present default of *on-off*. This translates to some 13 to 17, % profit gain. Importantly, the methodology and SOPs developed for the commercial validation can be readily applied to existing buildings without capital outlays or increase costs in maintenance.

This research is original and not incremental work.

The success of this research underscores the value of the risk framework to practical applications. Results will be of immediate benefit to risk analysts, heat-design engineers, and owners and operators of a range of large buildings that are conditioned for room air.

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[29] Commercial (monetary) value of the GHG reduction was not quantified.

[30] Indeed, following a final presentation (18 July 2017, Appendix G), the CSGH hotel management agreed to commercially trial the new *App* in a controlled-experiment using wireless-control to the conditioner thermostat in the *treated* suite – this work is outside the present research scope however.

9.2 Future research

Given the success of this research suggestions for future work include:

1. Collection of experimental data for a range of existing building-types in a range of global locations. An advantage is that this this can be done without capital outlays or increased maintenance costs. These data can be used to extend and generalize the *App*

2. Use of the *App* to control conditioning. It is expected that nearer the Equator the *on-only* strategy will be less cost-advantageous - because seasonal and diurnal affects are less when compared with northern and southern climes. However, because actual savings of 13 to 17, % have been highlighted, savings will be substantial in any large city

3. Investigation of means to quantitatively increase thermal capacitance of existing (*analysis*) or planned (*synthesis*) buildings. This will necessitate revised *Fr 13* model simulations. Building re-design (thermal insulation and materials) or new design (shape) might result.

APPENDICES

APPENDICES A – J

APPENDIX A – A definition of some important terms used in this research

Air-conditioner	Main heat transfer component of an air-conditioning system
Air-conditioning	Heat transfer process for conditioning of air for comfort
App	An *application*, especially as downloaded by a user to a mobile device (Anon., 2012 b; Davey, 2015 b)
Auto-set	Room *set-point* for automatic bulk air temperature (22 ^{O}C)
BoM	Bureau of Meteorology, an Australian Government Agency for weather data
Chance	*see* variability
control	Suite using the wide-spread default *on-off* air-conditioning energy strategy. See also *on-off*
CSGH	Clarion Suites Gateway Hotel (latitude -37.819708, longitude 144.959936) (Anon., 2015)
Curtain wall	An exterior building wall that carries no roof or floor loads and consists entirely of glass supported by a framework (*see* ASHRAE Handbook, Anon., 2013)
Fact	*see* uncertainty
Fenestration	An architectural term that refers to arrangement, proportion, and design of windows in a building (Anon., 2013)

Fr 13	A term coined by Davey and co-workers to address unexpected (surprise, or, Friday 13th Syndrome) failures due to impact of naturally occurring stochastic fluctuations in input parameters on output behaviours
GHG	Greenhouse gas
Hazard	Dormant or potential threat
Occupancy rate	Percentage of time (day) that a room is occupied. From a commercial perspective a room is occupied i.e. no longer available when a client has *checked-in*. It does not imply that client has to be present in the room at all times until *check-out*
NMI	National Meter Identification (Australia)
on-off	Operational energy strategy where conditioning is turned on only if the room is occupied – the default industry setting
on-only	Operational energy strategy where conditioning is on continuously regardless of occupancy – contrasts with industry default setting of *on-off*
Risk	Hazard plus vulnerability
SHG	Solar heat gain – a quantitative function of glass and solar radiation distribution
Single value assessment (SVA)	Assessment of a model output with a single value input (usually the mean)
Tolerance	Margin of safety

Traffic flow	*see* occupancy rate
treated	Suite with the alternative *on-only* air-conditioning energy strategy
Uncertainty	A lack of knowledge, or level of ignorance, about parameters that characterize the physical system. Uncertainty is sometimes reducible through further measurement or careful study, or through consulting more experts (Vose, 2008)
Unit-operation	An operation in which chemical as well as physical changes takes place e.g. mixing, drying, heating, distillation, evaporation
Variability	The effect of *chance* on an outcome. It is a function of the system. Variability is not reducible through further study or careful measurement. It can however be reduced through changing the physical system (Vose, 2008; *see* for a discussion Chandrakash and Davey, 2017 a)

APPENDIX B – Standard operating procedures (SOPs)

Introduction

The newly synthesized quantitative energy strategy model is experimentally validated at Clarion Suites Gateway Hotel (CSGH) (latitude -37.819708, longitude 144.959936) on a commercial-scale using the air-conditioning system in paired-room units 1302 (1321/1322) and comparing it with an identical Unit 1402 (1421/1422). This allows a comparative measure of the energy used by the suites (that are identical in all aspects except that they are located in the hotel one floor above the other).

Materials

The materials used in the commercial-scale validation include:

1. Two pairs of identical rooms units 1302 (consisting of rooms 1321/1322) and unit 1402 (consisting of rooms 1421/1422) each with separate air-conditioning systems

2. Independent electrical energy is supplied by *Origin Energy Ltd*, or *Simply Energy Ltd*, Australia each a public utility company contracted by the hotel to supply it will all electrical supply requirements. Each pairs of room have separate 'smart' electricity meter to automatically record energy consumptions remotely by *Origin Energy Ltd* or *Simply Energy Ltd*, Australia (the hotel changed electrical utility suppliers about June 2016)

3. Daily ambient temperature provided by the Australian Government Bureau of Meteorology (BoM) from the nearest automatic weather station at Olympic Park (ID 86338, latitude -37.83, longitude 144.98)

4. Daily occupancy rate computed from guest *check-in* and *check-out* times and dates provided by management of CSGH.

Methods

The following procedure is used for the duration of the 'proof-of-concept' (4 to 8, and; 15 to 19 Dec. 2015), summer (15 Jan. to 31 Mar. 2016) and extended (1 May to 31 Oct. 2016) large-scale commercial experimental validation *in-situ* in CSGH:

1. Unit 1302 (rooms 1321/1322) will be the '*treated*' suite with the air-conditioning controller temperature set to 22 ^{O}C and switched-on continuously (*on-only* strategy) for the duration of the test. Occupants checking in and allocated for this suite will be given a letter (*see* Appendix C) informing them an experimental test is being conducted and seeking their cooperation of leaving the air-conditioning on and not altering the set point for the days of their stay.

   House-keeping is also instructed not to turn off the air-conditioner after they finished servicing the rooms or when the guest checks out until experimentation is complete

2. Unit 1402 (rooms 1421/1422) will be the '*control*' suite used and serviced as usual with no change in hotel habit (*on-off* strategy)

3. Energy use data are automatically and remotely read by the public electrical utility supplier from smart electrical meters located inside hotel. These are recorded every 30 min and provided at the end of experimental validation trials. Electrical supply tariffs are provided in the invoices about every 90 days

4. Ambient temperature data supplied by BoM are recorded every 10 min but for consistency with electrical energy use is provided every 30 mins

5. Occupancy rate (guest *check-in* and *check-out* times and dates) is provided by the hotel management at the completion of the validation trials

6. Hotel management agree to oversee the day-to-day management of the procedure and these SOPs for the duration of the experimental validation.

APPENDIX C – Copy of explanatory letter to guests regarding the commercial experiments

CLARION SUITES GATEWAY

Dear Guest

Welcome to the Clarion Suites Gateway, it is a pleasure to have you stay with us.

We seek your help and cooperation whilst you are staying in this room as we are assisting a client who is conducting Ph.D. research regarding energy consumption patterns. If possible, we request that the air conditioning not be turned off or altered from the 21 degrees it is set on.

If you would prefer to be able to control the settings, we would be happy to move you to another room.

Thank you in advance for your assistance, please enjoy the homemade cookies with our compliments.

Kind regards

Kelly Matthews

Business Development Manager

One William Street
Melbourne, Vic. 3000
AUSTRALIA
T (61-3) 9296 8888
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ABN 29 079 551 643

APPENDIX D – Photographs of CSGH hotel-room and air-conditioning system used in the experimental validation

Fig. D-1: Arrangement of one of the rooms in 2 x room suite in commercial-scale validation

Fig. D-2: Curtain and fenestration treatment

Fig. D-3: Individual air-conditioning unit and temperature controller

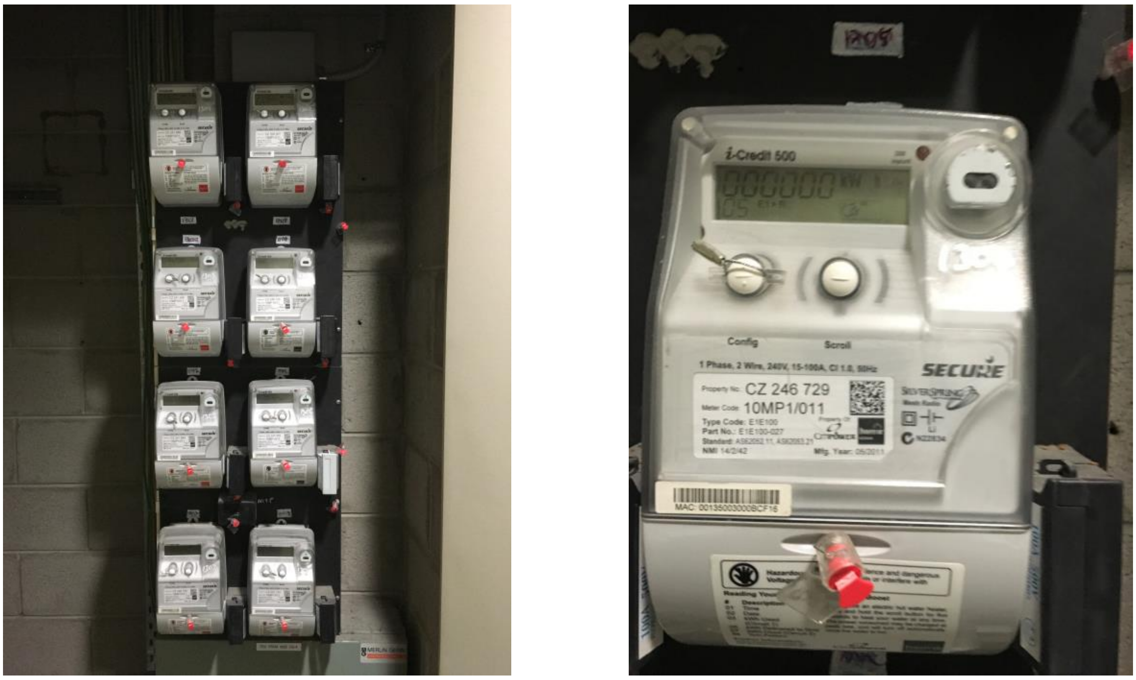


Fig. D-4: Individual suite smart-electricity meter

APPENDIX E – Effect of energy strategy as T_o approaches $T_i = 22$ ^{O}C

An example of micro-data of Table 5-2 showing the impact of refined granularity on energy strategy difference as T_o approaches $T_i = 22$ ^{O}C. It can be seen that as: 1) the occupancy rate (L_T) increases, and; 2) the value of temperature interval (T_o) decreases the *on-only* energy strategy uses less energy. This is highlighted by the shaded area in Table E-1.

Fig. E-1 is a graphical snapshot at $82 \leq L_T\ (\%) \leq 84$ % and for $20.0 \leq T_o \leq 23.0$, ^{O}C.

Both Table E-1 and Fig. E-1 show that at $T_o = T_i = 22$ ^{O}C the energy use of either strategy is the same, that is $q_{on\text{-}only} = q_{on\text{-}off} = 0$ W.

Table E-1: Micro-data showing the effects on $q_{on\text{-}only}$ - $q_{on\text{-}off}$ (W) at 0.2 ^{O}C interval in ambient peak temperature for $21.0 \leq T_o \leq 24.0$, ^{O}C and $L_T \sim \geq 75$ %

	T_o (^{O}C)	**($q_{on\text{-}only}$ - $q_{on\text{-}off}$) (W)**										
		L_T (%)										
(Row)		**82.0**	**82.2**	**82.4**	**82.6**	**82.8**	**83.0**	**83.2**	**83.4**	**83.6**	**83.8**	**84.0**
1	**21.0**	-13	-6	-6.2	-6.4	-6.7	-6.9	-7.2	-7.4	-7.7	-7.9	-8.2
2	**21.2**	-9.7	-3.8	-4.0	-4.2	-4.4	-4.6	-4.8	-5.0	-5.2	-5.4	-5.6
3	**21.4**	-6.4	-2.0	-2.2	-2.3	-2.5	-2.6	-2.7	-2.9	-3.0	-3.2	-3.3
4	**21.6**	-3.6	-0.6	-0.7	-0.8	-0.9	-1.0	-1.1	-1.2	-1.3	-1.4	-1.5
5	**21.8**	-1.2	0.2	0.2	0.1	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.2
6	**22.0**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	**22.2**	-1.2	0.2	0.2	0.1	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.1
8	**22.4**	-3.5	-0.6	-0.7	-0.8	-0.3	-1.0	-1.1	-1.2	-1.2	-1.3	-1.4
9	**22.6**	-6.4	-2	-2.1	-2.3	-2.4	-2.5	-2.7	-2.8	-3	-3.1	-3.3
10	**22.8**	-9.6	-3.73	-3.9	-4.1	-4.3	-4.5	-4.7	-4.9	-5.1	-5.3	-5.5
11	**23.0**	-13.1	-5.8	-6.0	-6.3	-6.5	-6.8	-7.0	-7.2	-7.5	-7.8	-8.0

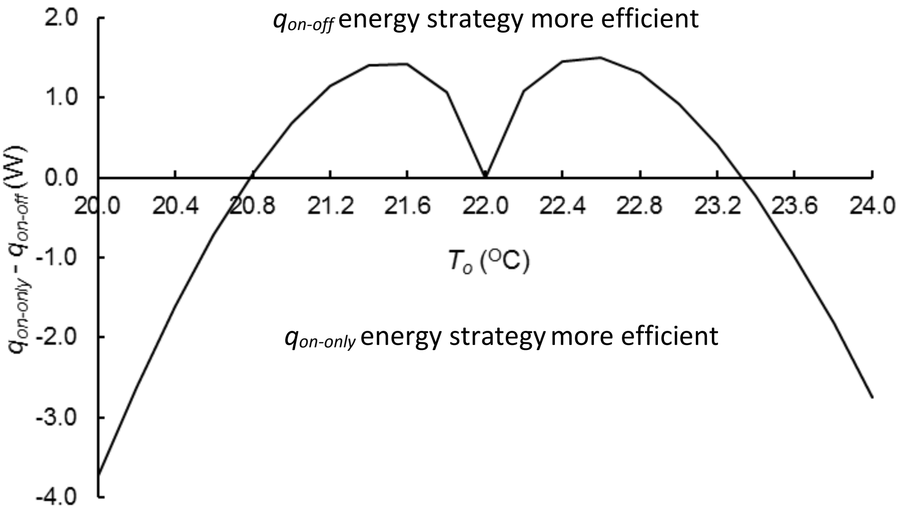


Fig. E-1: An example of a plot of micro-data of $q_{on\text{-}only}$ - $q_{on\text{-}off}$ (W) for $20.0 \leq T_o \leq 24.0$, ^{O}C and L_T = 65 % showing that as T_o approaches T_i = 22 ^{O}C $q_{on\text{-}only}$ - $q_{on\text{-}off}$ ≥ 0 W

APPENDIX F – Results of preliminary 'proof-of-concept' experimental trial

A preliminary 'proof-of-concept' *in-situ* study in CSGH (Anon., 2015) was carried out to establish the experimental protocols and to test possible suite-bias involved the air-conditioning in suite 1321/1322 being operated as *on-only* (*treated*), and that in suite 1421/1422 *on-off* (*control*), for 5 contiguous days; and, the conditioning strategy then being reversed for a further 5 contiguous days. The suites were *auto-set* to a bulk air temperature of 22 ^{O}C.

Raw data are presented in Table F-1 (a) and (b) respectively, days 1-5 and 6-10.

Because the mean electrical energy used in the *on-only* strategy for both tests is seen to be meaningfully less than that for the *on-off* it was concluded there was no measurable suite-bias.

Table F-1: Preliminary test for (a) suites 1321/1322 and 1421/1422 with, respectively, *on-only* and *on-off* strategy for days 1 through 5 (4 to 8 Dec.), and; (b) suites 1421/1422 and 1321/1322 with, respectively, *on-only* and *on-off* strategy for days 6 through 10 (15 to 19 Dec.). The *auto-set* bulk air temperature was 22 ^{O}C

(a)

Day	**Data**				
	T_o	L_T		Q	
	(^{O}C)	(%)		(kWh)	
		*on-only**	*on-off^*	*on-only*	*on-off*
1	30.6	13.33	63.88	23.41	31.59
2	25.3	57.96	65.29	29.19	37.52
3	29.1	68.00	62.83	26.41	38.28
4	27.3	72.63	69.00	29.02	49.48
5	35.0	47.21	47.21	51.19	50.29
Mean	**29.46**	**51.83**	**61.64**	**31.84**	**41.43**

* Energy strategy for 1321/1322.
^ Energy strategy for 1421/1422.

(b)

Day	**Data**				
	T_o (°C)	L_T (%)		Q (kWh)	
		on-only§	*on-off*‡	*on-only*	*on-off*
6	24.2	56.50	100.00	6.05	37.52
7	26.7	88.54	100.00	37.41	25.89
8	36.8	40.42	68.96	53.03	64.80
9	34.1	36.79	69.63	71.71	81.48
10	40.5	69.75	70.54	66.93	80.84
Mean	**32.46**	**58.40**	**81.83**	**47.03**	**58.11**

§ Energy strategy for 1421/1422.

‡ Energy strategy for 1321/1322.

APPENDIX G – Example calculation of net profit

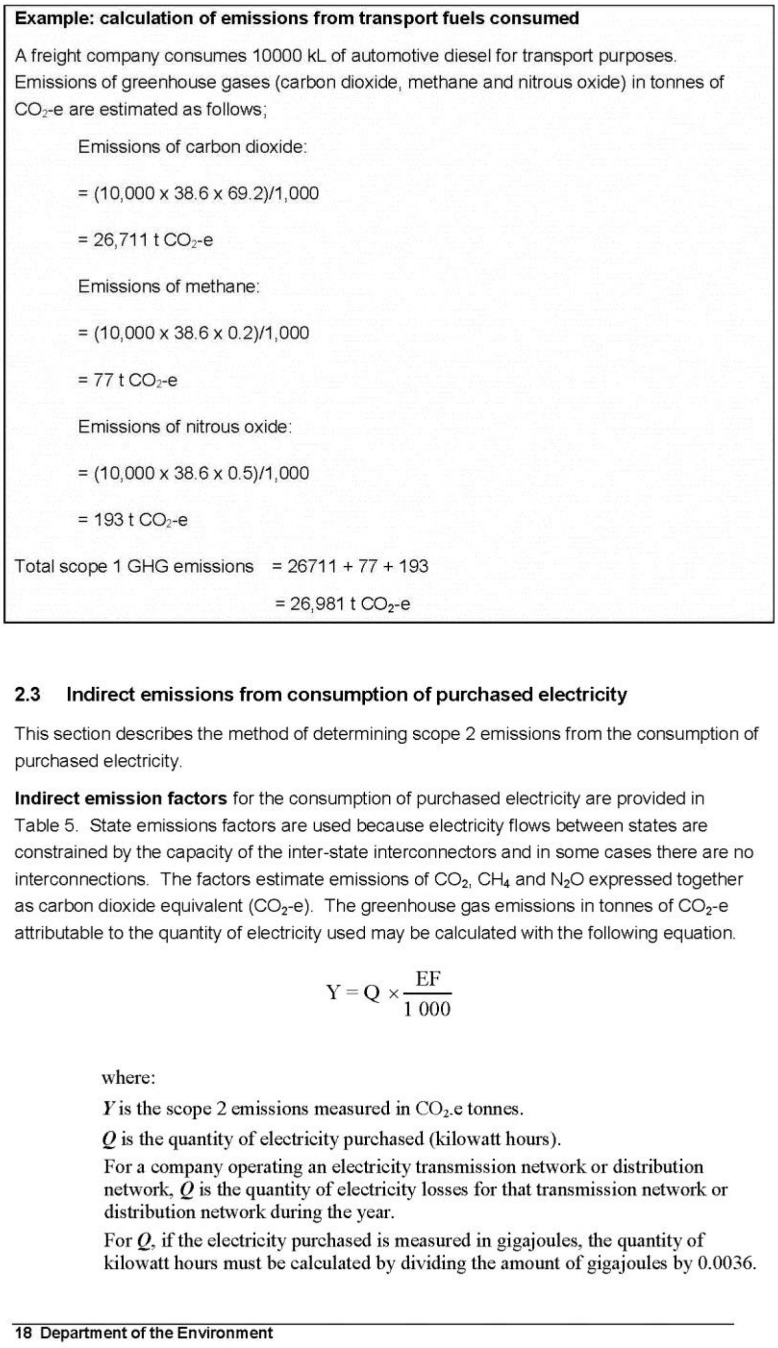
An example calculation of the normal net profit margin and additional gain in net profit margin as a result of using the alternate *on-only* air-conditioning energy strategy is summarized in Table G-1. From the table it can be concluded the increase in net profit margin above the normal is (0.05 + 0.03 x 0.05) x 100 =) 5.15 %.

Table G-1: An example calculation of net profit

Description	Value
Assume mean rate charged	AUD $190 per room per day
Assume mean gross profit margin (Anon., 2017 f)	30 %
Room gross profit	= 0.3 x AUD $190 = AUD $57 per day
Assume mean net profit margin (Anon., 2017 g)	5 %
Room net profit	= 0.05 x AUD $190 = AUD $9.50 per room per day
	= AUD $19.00 per suite (paired-room) per day
Actual mean electrical energy savings	= AUD $0.58 per suite (paired-room) per day
Therefore increase in net profit margin	= AUD $0.58 / AUD $19.00 x 100 = ~ 3 %
Overall profit margin using the *on-only* strategy	= (0.05 + 0.03 x 0.05) x 100 = 5.15 %

APPENDIX H – Extract from 2014 National Greenhouse Gas Accounts Factors

Extract of paragraph 2.3 from the 2014 National Greenhouse Gas Accounts Factors published by the Australian Government (Anon., 2014) showing the formula used to convert energy use (kWh) to GHG emissions in CO_2-e (tonnes); conversion factor applicable for the different Australian states (in Victoria the factor is 1.18 kg CO_2-e per kWh); and an example calculation.



Example: calculation of emissions from transport fuels consumed

A freight company consumes 10000 kL of automotive diesel for transport purposes. Emissions of greenhouse gases (carbon dioxide, methane and nitrous oxide) in tonnes of CO_2-e are estimated as follows;

Emissions of carbon dioxide:

= (10,000 x 38.6 x 69.2)/1,000

= 26,711 t CO_2-e

Emissions of methane:

= (10,000 x 38.6 x 0.2)/1,000

= 77 t CO_2-e

Emissions of nitrous oxide:

= (10,000 x 38.6 x 0.5)/1,000

= 193 t CO_2-e

Total scope 1 GHG emissions = 26711 + 77 + 193

= 26,981 t CO_2-e

2.3 Indirect emissions from consumption of purchased electricity

This section describes the method of determining scope 2 emissions from the consumption of purchased electricity.

Indirect emission factors for the consumption of purchased electricity are provided in Table 5. State emissions factors are used because electricity flows between states are constrained by the capacity of the inter-state interconnectors and in some cases there are no interconnections. The factors estimate emissions of CO_2, CH_4 and N_2O expressed together as carbon dioxide equivalent (CO_2-e). The greenhouse gas emissions in tonnes of CO_2-e attributable to the quantity of electricity used may be calculated with the following equation.

$$Y = Q \times \frac{EF}{1\,000}$$

where:

Y is the scope 2 emissions measured in CO_2-e tonnes.

Q is the quantity of electricity purchased (kilowatt hours).

For a company operating an electricity transmission network or distribution network, *Q* is the quantity of electricity losses for that transmission network or distribution network during the year.

For *Q*, if the electricity purchased is measured in gigajoules, the quantity of kilowatt hours must be calculated by dividing the amount of gigajoules by 0.0036.

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EF is the scope 2 emission factor, for the State, Territory or electricity grid in which the consumption occurs (kg CO_2-e per kilowatt hour). If the electricity is not sourced from the main electricity grid the emission factor can be either provided by the supplier of the electricity or, if that factor is not available, the emission factor for the Northern Territory may be used.

Table 5: Indirect (scope 2) emission factors for consumption of purchased electricity from the grid

State, Territory or grid description	Emission factor kg CO_2-e/kWh
New South Wales and Australian Capital Territory	0.86
Victoria	1.18
Queensland	0.81
South Australia	0.61
South West Interconnected System in Western Australia	0.76
Tasmania	0.20
Northern Territory	0.68

Sources: National Greenhouse and Energy Reporting (Measurement) Determination 2008 (Schedule 1)

Example: calculation of emissions from electricity consumption

A company in New South Wales consumes 100,000 kWh of purchased electricity from the grid.

Emissions of greenhouse gases (scope 2) in tonnes of CO_2-e are estimated as follows:

= 100,000 x (0.86 /1000)

= 86 tonnes.

Total scope 2 GHG emissions = 86 tonnes CO_2-e

2.4 Fugitive emissions from fuels

2.4.1 Coal Mining

2.4.1.1 Underground mines

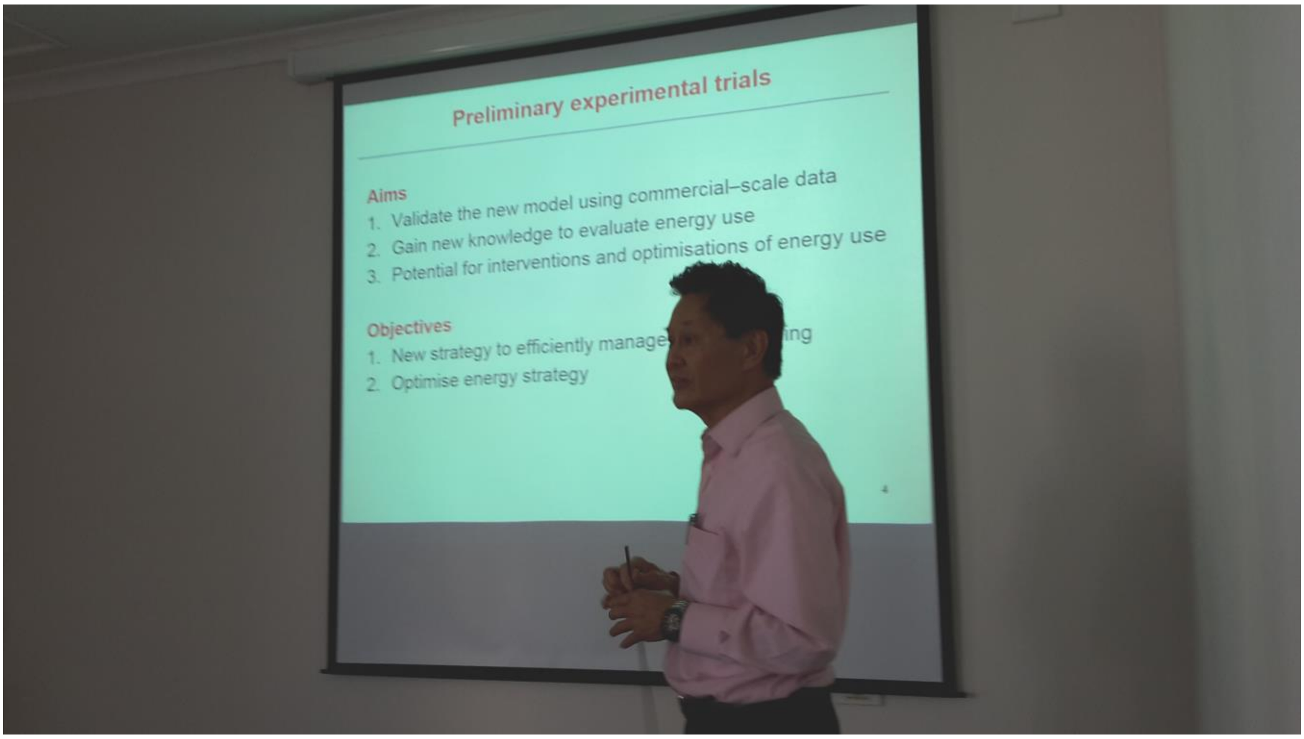
Fugitive emissions from underground mines involve the release of methane and carbon dioxide during the mining process due to the fracturing of coal seams, overburden and underburden strata. Emissions also arise from post mining activities such as transportation and stockpiling of coal from the release of residual gases not released during the mining process. Emissions will also occur when coal mine waste gas is flared.

Where the estimation of fugitive emissions from underground mining activities is for the purposes of NGER reporting, then direct measurement (method 4) under section 3.6 of Chapter 3 in the *National Greenhouse and Energy Reporting (Measurement) Determination 2008* must be used. As method 1 is no longer available for NGER reporting, it is also not reflected here in the NGA Factors publication. However a summary of the fugitive gas emission profile of Australian underground coal 2012 production by coalfield is provided for reference in section 3.8.2 of the National Inventory Report 2012 Volume 1.

APPENDIX I – Dates of summative presentations to Clarion Suites Gateway Hotel (CSGH)

Five (5) progressive summative presentations were made to CSGH Management and support staff to maintain active engagement, on progress and results obtained, on each of the following:

Presentation	Date
Introductory	3 Feb. 2016
Results of preliminary experimental trials for cooling of air in summer	8 Mar. 2016
Results of commercial-scale trials (77 days) for cooling of room air in summer	28 Jun. 2016
Results of commercial-scale trials (271 days) for conditioning of room air	15 Feb. 2017
Synthesis of a convenient predictive *App*	18 Jul. 2017



Preliminary experimental trials

Aims
1. Validate the new model using commercial–scale data
2. Gain new knowledge to evaluate energy use
3. Potential for interventions and optimisations of energy use

Objectives
1. New strategy to efficiently manage ing
2. Optimise energy strategy

4

Fig. I-1: Example of a presentation (by JYG Chu) of experimental progressive findings (8 Mar. 2016)

APPENDIX J – Refereed publications from this research

Refereed Engineering Journals

Chu, J.Y.G., Davey, K.R., 2017 a. Synthesis of a quantitative strategy to minimize energy used in conditioning of air in buildings in summer with fluctuating ambient and room occupancy rate. Chemical Engineering Science – *submitted* (*May*).

Chu, J.Y.G., Davey, K.R., 2017 b. Results from a commercial-scale experimental validation of a quantitative strategy to minimize energy used in conditioning of air in buildings in summer with fluctuating ambient and room occupancy rate. Chemical Engineering Science – *submitted* (*May*).

Refereed Conference Proceedings

Chu, J.Y.G., Davey, K.R., O'Neill, B.K., 2016. A preliminary simulation of strategies for cooling of air in buildings with unplanned traffic flow during summer. In: Proc. APCChE 2015 Congress (Asia-Pacific Century – Growth & Innovation) incorporating CHEMECA 2015, Sept. 27-Oct. 1, Melbourne, Australia. Paper 3135128, pp. 396-405. ISBN: 9781922107473

Chu, J.Y.G., Davey, K.R., 2015. A probabilistic *Fr 13* simulation of strategies for cooling of air in buildings with unplanned traffic flow during summer. In: Proc. 3rd Int. Workshop on Simulation for Energy, Sustainable Development & Environment-SESDE 2015, Sept. 21-23, Bergeggi, Italy, Paper 45, pp. P1, 51-59. ISBN: 9788897999614

Other Related

Collins, S.D., Davey, K.R., Chu, J.Y.G., O'Neill, B.K., 2016. A new quantitative risk assessment of Microbiologically Influenced Corrosion (MIC) of carbon steel pipes used in chemical engineering. In: Proc. CHEMECA 2016: Chemical Engineering - Regeneration, Recovery and Reinvention, Sept. 25-28, Adelaide, Australia. Paper 3386601, pp. 209 to 217. ISBN: 9781922107831

Manuscripts in Preparation

Chu, J.Y.G., Davey, K.R., 2017 c. An extended experimental validation of daily electrical energy used in conditioning of air in a commercial building with fluctuating ambient and room occupancy over four seasons. Chemical Engineering Science – *in preparation*.

Chu, J.Y.G., Davey, K.R., 2017 d. Synthesis and demonstration of a quantitative *App* to minimize heat energy used in conditioning of bulk room air. Chemical Engineering Science – *in preparation*.

NOMENCLATURE

The number in parentheses after description refers to the equation(s) in which the symbol is first used or defined.

A	area (m^2) (3.1)
A_{glass}	surface area of single-glazed glass pane wall (m^2) (3.2), (3.7), (5.6)
A_{brick}	surface area of brick wall (m^2) (3.3), (3.8)
Bi	Biot number (dimensionless)
Bi_{brick}	Biot number for brick walls (dimensionless) (3B.1)
c	specific heat of air at constant pressure (J kg^{-1} K^{-1}) (3.15), (5.4)
d_{glass}	thickness of single-glazed glass pane (0.01 m) (3.5)
d_{brick}	thickness of brick wall (0.11 m) (3.6)
D	depth of room (5 m) (3.8)
g	acceleration constant (9.81 m s^{-2}) (3.14)
Gr	Grashof number (dimensionless) (3.14)
h	heat transfer coefficient for air (W m^{-2} K^{-1}) (3.12)
h_o	heat transfer coefficient of outside air (W m^{-2} K^{-1}) (3.4)
$h_{o,glass}$	heat transfer coefficient of outside air adjacent glass pane (W m^{-2} K^{-1}) (3.5)
h_i	heat transfer coefficient of inside air (W m^{-2} K^{-1}) (3.4)
$h_{i,glass}$	heat transfer coefficient of inside air adjacent glass pane (W m^{-2} K^{-1}) (3.5)
$h_{i,brick}$	heat transfer coefficient of inside air adjacent brick wall (W m^{-2} K^{-1}) (3.6)
IAC	indoor solar attenuation coefficient (0.8 dimensionless) (3B3.12), (5.7)
k	thermal conductivity of air (W m^{-1} K^{-1}) (3.4), (5.5)
k_{glass}	thermal conductivity of glass (W m^{-1} K^{-1}) (3.5)
k_{brick}	thermal conductivity of brick (W m^{-1} K^{-1}) (3.6)
L	vertical length (height) of room (2.5 m) (3.7)

L_T	occupancy rate (days room is let per 100 days, or, h let per 24 h) (%) (5.9)
n	number of inflows per room (integer ≥ 1) (5.9)
Nu	Nusselt number (dimensionless) (3.12)
p	energy strategy risk factor (%) (4.1), (5.11), (6.2)
P	energy strategy risk factor (W) (5.11a)
Pr	Prandtl number (dimensionless) (3.12)
Q	quantity of electrical energy purchased or used (kWh) (6.1)
$q_{convection}$	convective heat transfer (W) (3.1)
$q_{convection\ and\ conduction}/A_{glass}$	heat flux for convection and conduction (W m^{-2}) (3B.10)
q_{glass}	convective heat transfer from glass (W) (3.2), (5.8)
q_{brick}	convective heat transfer from brick (W) (3.3), (5.8)
$q^*_{on\text{–}off}$	heat transfer for *on-off* strategy (W) (5.8)
$q_{on\text{–}off}$	heat transfer for *on-off* strategy with occupancy rate factor (W) (3.20), (5.9)
$q_{on\text{–}only}$	heat transfer for *on-only* strategy (W) (3.21), (5.10)
$q^*_{radiation}$	radiative heat transfer (W) (5.6)
$q_{radiation}$	radiative heat transfer through the glass pane wall (W) (5.7)
$q_{radiation}/A_{glass}$	heat flux for radiation (W m^{-2}) (3B.12)
q_{total}/A_{glass}	total heat flux due to convection, conduction and radiation (W m^{-2}) (3B.13)
R^2	correlation coefficient (dimensionless)
$R_{convection\ and\ conduction}$	resistance to heat transfer due to convection and conduction (K W^{-1}) (3B.3)
$R_{i,brick}$	convective resistance of the surface of the brick adjacent to the room interior (K W^{-1}) (3B.3), (3B.4)
$R_{i,air}$	conductive resistance of room interior air (K W^{-1}) (3B.3), (3B.5)
$R_{i,glass}$	convective resistance of inside of glass adjacent the room interior air (K W^{-1}) (3B.3), (3B.6)
$R_{o,glass}$	convective resistance of outside of glass adjacent the ambient air (K W^{-1}) (3B.3), (3B.7)

R_{glass}	conductive resistance of glass pane (K W^{-1}) (3B.3), (3B.8)
Ra	Rayleigh number (dimensionless) (3.12), (3.13)
Re	Reynolds number for a flat surface(dimensionless) (3A.1)
ΔT	temperature difference between outside and inside of room (K or ^{O}C) (3.1), (3.9), (3B.10)
$\delta T_{o,glass}$	temperature difference between glass wall and air film outside of room (K or ^{O}C) (3.16)
$\delta T_{i,glass}$	temperature difference between glass wall and air film inside of room (K or ^{O}C) (3.17)
δT_{brick}	temperature difference between brick wall and interior of room (K or ^{O}C) (3.18)
t	metric ton (6.1)
T	temperature (K) (^{O}C + 273.15) (3.1)
$T_{convection\ and\ conduction}$ $(d_{brick} = 0)$	surface temperature of the interior brick walls due to convective and conductive heat at a given time (K) (3B.11)
$T_{air,glass}$	average film temperature on glass pane (K) (3.10)
$T_{air,brick}$	average film temperature on brick wall (K) (3.11)
T_{brick}	average temperature of brick wall (^{O}C) (3.11)
T_i	*auto-set* bulk temperature of room interior air (K) (3.9), (5.6)
T_o	ambient bulk temperature (outside air) (K) (3.9), (5.6)
T_{total} $(d_{brick} = 0)$	surface temperature of the room interior brick walls due to convective, conductive and heat flux at a given time (K) (3B.14)
$U_{convection\ and\ conduction}$	overall heat transfer coefficient due to convection and conduction (W m^{-2} K^{-1}) (3B.9)
U_o	overall heat transfer coefficient (W m^{-2} K^{-1}) (3.1)
$U_{o,glass}$	overall heat transfer coefficient of glass (W m^{-2} K^{-1}) (3.4)
$U_{o,brick}$	overall heat transfer coefficient of brick (W m^{-2} K^{-1}) (3.5)
W	width of room (4.5 m) (3.7)
x	distance from glass pane (m) (3A.1)

Greek

α	shape factor for Betageneral distribution

α'	thermal diffusivity (m^{2} s^{-1})
α_{brick}'	thermal diffusivity of brick wall (m^{2} s^{-1}) (3B.2)
β	volumetric coefficient of expansion of air (K^{-1}) (5.1)
ε	emissivity of glass (0.8 dimensionless) (3B.12), (5.6)
Δ	difference between two parameter values (3.1)
ρ	density of air (kg m^{-3}) (3.14), (3A.1), (5.2)
μ	dynamic viscosity of air (N s m^{-2}or kg m^{-1} s^{-1}) (3A.1), (5.3)
σ	Stefan-Boltzmann constant (5.667 x 10^{-8} W m^{-2} K^{-4}) (3B.12), (5.6)
τ	time (s) (3B.11), (3B.14)
v	airspeed or wind velocity (m s^{-1}) (3A.1)

Subscripts

air	air film
brick	brick wall
glass	vertical glass pane
i	inside (interior)
o	outside (ambient)

Other

auto-set	room set-point for bulk air temperature (22 ^{O}C)
control	suite with *on-off* conditioning practice
EF	Emission factor (6.1)
on-off	energy strategy for air-conditioning switched-on by occupant inflow
on-only	energy strategy for air-conditioning on-continuously
treated	suite with alternative *on-only* conditioning practice
Y	GHG emission (CO_2-e (t)) (6.1)

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