A PROBABILISTIC *FR 13* SIMULATION OF STRATEGIES FOR COOLING OF AIR IN BUILDINGS WITH UNPLANNED TRAFFIC FLOW DURING SUMMER

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ABSTRACT
Many buildings with varying traffic flow (i.e. occupancy), such as public buildings and hotels, do not have a quantitative strategy to manage energy use. Although seasonal, energy use is difficult to predict. A problem is to know the risk of failure of a postulated energy strategy used for cooling of the building interior air to an *auto-set* value (customarily 22 ^{O}C). A new probabilistic assessment of the proposed *on-only* cooling strategy of Chu et al. (2015) has shown that some 12 unexpected, or *Fr 13*, failures can occur each summer, averaged over a prolonged period. Simulations highlight the cooling strategy is actually highly dependent on traffic flow (as occupancy) in the buildings, and not on ambient summer temperatures. Because all occupancy scenarios that could practically exist have been simulated the *Fr 13* risk assessment is an advance over more traditional assessments.

Keywords: cooling of large buildings; cooling strategy; varying traffic impact on cooling; probabilistic risk modelling; Friday 13th risk modelling

1. INTRODUCTION

Modern buildings, including commercial hotels and public structures, commonly have a massive concrete-and-steel frame to provide strength, together with a façade(s) of glass panes to provide internal light and vista during the day. These panes however permit heat transfer to the interior from ambient. As a consequence, during summer months, large air conditioning systems are installed to cool-down and maintain an *auto-set* room interior air temperature (customarily 22 ^{O}C).

In an attempt to limit operating costs, an energy strategy that is widely used, particularly in hotels, is that cooling to the room is switched on only when the room is occupied and switched off immediately when the room is unoccupied (this is the *on-off* strategy); this is especially true of hotels and government office buildings. An alternative however is to leave the cooling continuously on (the *on-only* strategy). Oddly, research has generally focused on the design and calibration and measurement of energy parameters, using discrete and deterministic assessments (Coakley et al., 2012; Eisenhower et al., 2012) and not on which of these strategies to adopt under given circumstances.

Recently, Chu et al. (2015) synthesised a cooling unit-operations model (Foust et al., 1980; Wankat, 2007) and established, using simulations for a range of room traffic flows (occupancy) and ambient temperatures, that the *on-only* strategy would be more energy efficient long-term than the *on-off* in the hot summer months in areas of South Eastern Australia. A major reason identified was that the thermal 'sink' (i.e. mass) that the building's concrete-and-steel affords, has to be cooled repeatedly with the *on-off* strategy; however with the *on-only* strategy however this heat is removed from the sink only once.

They concluded that the *on-only* strategy should be adopted.

A drawback with this formative study, however, is that occupancy and ambient temperature will be impacted by naturally occurring fluctuations about their likely (mode) value and will not be either fixed or evolve predictably as assumed by Chu et al. (2015).

A problem is to recognize these naturally occurring fluctuations in occupancy (traffic arrival and departure) and ambient temperature and to determine quantitatively whether these will have a significant impact on which strategy is better.

To quantify the impact of these naturally occurring fluctuations in key parameters in otherwise well-designed and well-operated systems, Davey and co-workers (Davey 2015; Abdul-Halim and Davey, 2015; Davey et al., 2015) have developed a new, quantitative probabilistic methodology. Their thesis is predicated on the fact that random change in values can sometimes accumulate unexpectedly in one direction and leverage significant change in process or product. They titled this underlying risk of vulnerability to surprise failure due to random affects as *Fr 13*. They have demonstrated this work with a number of case studies including surprise shifts from: sterile to non-sterile milk (Davey and Cerf, 2003); stable to unstable (washout) operation of a fermenter (Patil et al., 2005); removal of protein deposits in Clean-In-Place (CIP) processing to failure to clean (Davey et al., 2013; Davey et al., 2015); potable to non-potable water using ultraviolet (UV) irradiation (Abdul-Halim and Davey, 2015); efficient to inefficient

fuel-to-steam conversion in a coal fired boiler (Davey, 2015), and; failure of raw milk pasteurization (Chandrakash, et al.; 2015).
A major practical advantage claimed for *Fr 13* analyses is that all operational scenarios that could exist, including energy strategy failures, would be evaluated and quantified.

1.1. This research
Here we simulate for the first time the *on-off* and *on-only* cooling strategies using the emerging methodology of Davey and co-workers to investigate the impact of fluctuations in occupancy (traffic arrival and departure) and ambient temperature on the validity of the *on-only* cooling energy strategy advocated by Chu et al. (2015).
The approach is to extend the unit-operations cooling model of Chu et al. (2015) to incorporate realistic values for large-scale commercial parameters, and adapt the probabilistic method of Davey and co-workers in which a new dimensionless risk factor for the energy strategy (p) is defined. This risk factor is convenient as all $p > 0$ can be used to characterize the *on-only* energy strategy as a 'fail'.
The probabilistic simulations are based on a refined Monte Carlo (with Latin Hypercube) sampling (r-MC) of parameters (Vose, 2008). An advantage is that all practical scenarios that could exist operationally, including energy strategy failures, are evaluated and quantified.
Practical benefits and new insights gained through this probabilistic approach are discussed. It is envisaged that findings can be generalized.
The research will be of interest to operators and managers responsible for cooling of large public and commercial buildings.

2. MATERIALS AND METHODS
The model developed by Chu et al. (2015) is well-suited both in terms of its formative nature and underlying unit-operations mathematical synthesis. A single room is considered to have of width W, vertical length L, and interior depth D, Figure 1.
All symbols used are defined carefully in the Nomenclature.

2.1. Cooling model
A single glass pane (10 mm thick), comprised each of two external walls of the room was exposed to ambient. Because of the massive nature of materials of construction, the room ceiling and floor were assumed to be thermally insulated. The two opposing internal walls were assumed to be made from commercial clay bricks (110 mm thick), laid in a standard double-brick on-flat with an air gap. The air gap provided was, reasonably, assumed to provide a thermal barrier to ambient (or adjoining room in a multiple-room building).
It was assumed all heat transfer to and from the structure was by natural convection i.e. radiation and forced convection were ignored.

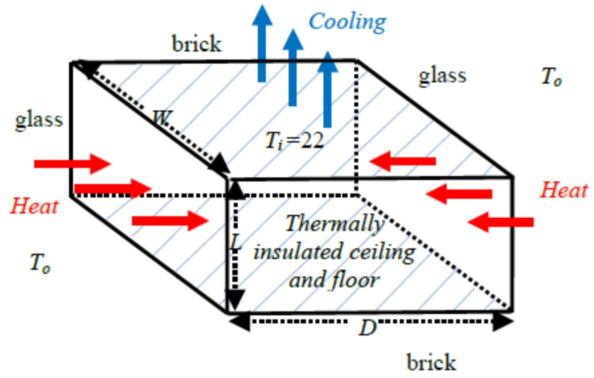

Figure 1: Simplified schematic of cooling unit-operations for a room during summer

Radiative heat transfer is ignored because it is widespread industry practice that curtains will be drawn closed, to mitigate radiative heat transfer.
The rate of heat energy transferred from ambient through both the glass and brick wall to the room interior, q, was given by (Holman, 2010; Perry and Green, 1997; Anon., 2013)

$$q = U_o A \Delta T \qquad (1)$$

such that for the glass

$$q_{glass} = U_{o,glass} A_{glass} \Delta T \qquad (2)$$

and for the brick

$$q_{brick} = U_{o,brick} A_{brick} \Delta T \qquad (3)$$

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

$$U_o = \frac{1}{\frac{1}{h_o} + \frac{d}{k} + \frac{1}{h_i}} \qquad (4)$$

such that for the glass

$$U_{o,glass} = \frac{1}{\frac{1}{h_{o,glass}} + \frac{d_{glass}}{k_{glass}} + \frac{1}{h_{i,glass}}} \qquad (5)$$

and for the brick

$$U_{o,brick} = \frac{1}{\frac{d_{brick}}{k_{brick}} + \frac{1}{h_{i,brick}}} \qquad (6)$$

Because it was assumed that the wall had an air gap (cavity), there is no outside convective heat transfer coefficient shown in Eq. (6).
The total area for heat transfer for the glass panes was

$$A_{glass} = 2 \times L \times W \tag{7}$$

and, that for the brick walls was

$$A_{brick} = 2 \times L \times D \tag{8}$$

For cooling, T_o must be greater than T_i, and gave a temperature gradient such that

$$\Delta T = T_o - T_i \tag{9}$$

The temperature of the glass and air film on the glass was given by

$$T_{air,glass} = \frac{1}{2}(T_o + T_i) \tag{10}$$

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

$$T_{air,brick} = \frac{1}{2}(T_{brick} + T_i) \tag{11}$$

in which T_{brick} = T_o i.e. it was assumed the temperature of the brick walls reached equilibrium with ambient in a short time once air cooling was switched off. Chu et al. (2015) argued this assumption was justified for example in hotels, where common practice is that this would occur mid-morning when the housekeeping staff finish cleaning and leave the room.
The correlation for Nusselt number was used to determine the convective heat transfer coefficient (Holman, 2010; Anon., 2013) for natural convection of air along the vertical glass wall (on either outside or inside) and the brick wall (inside only)

$$Nu = \frac{hL}{k} = \left(0.825 + \frac{0.387\,Ra^{\frac{1}{6}}}{\left(1 + \left(\frac{0.492}{Pr}\right)^{\frac{9}{16}}\right)^{\frac{8}{27}}} \right)^2$$

for $10^{-1} < Ra < 10^{12}$ (12)

in which the Raleigh (Ra) number was (Holman, 2010)

$$Ra = Gr\,Pr \tag{13}$$

with

$$Gr = \frac{L^3 \rho^2 g \beta \delta T}{\mu^2} \tag{14}$$

and

$$Pr = \frac{c\mu}{k} \tag{15}$$

For the glass panes

$$\delta T_{o,glass} = (T_o - T_{air,glass}) \tag{16}$$

$$\delta T_{i,glass} = (T_{air,glass} - T_i) \tag{17}$$

For the brick

$$\delta T_{i,brick} = (T_{brick} - T_i) \tag{18}$$

Eqs. (1) through (18) were used to define the underlying unit-operations model for cooling of the room interior air to an *auto-set* temperature in summer.

2.2. *On-off* and *on-only* energy strategies

The model was applied to investigate two possible (and mutually exclusive) energy strategies.
In the *on-off* strategy, because the room cooling was turned off when unoccupied and turned on when occupied, the two brick walls that were assumed by Chu et al. (2015) to have reached equilibrium with ambient temperature would need to be cooled i.e.

$$q_{on-off} = (q_{glass} + q_{brick}) \tag{19}$$

This strategy they titled *on-off*.
However, the room was unlikely to be occupied every day. They defined traffic flow with an overall occupancy, η %. This meant that for the *on-off* strategy, energy use was a linear function of η, and Eq. (19) could be written as

$$q_{on-off} = \frac{\eta}{100}(q_{glass} + q_{brick}) \tag{20}$$

Chu et al. (2015) reported that the most likely occupancy, based on industry-wide (anecdotal) historical data for South Eastern Australia (Clarion Gateway, Choice Hotels International, Melbourne, *unpublished data*), was η = 75 %.
Their alternative strategy was to simply leave the room with cooling on continuously. This they titled *on-only*.
Because the room was continuously cooled, the interior walls of the room were assumed to be permanently at the room interior *auto-set* temperature T_i (= 22 ^{O}C). Therefore only the energy transferred from ambient through the two glass panes would need to be removed in cooling. The overall energy demand for the *on-only* strategy was therefore

$$q_{on-only} = q_{glass} \tag{21}$$

2.3. Traditional deterministic single value assessment (SVA)

A traditional, deterministic and single value assessment (SVA) (Sinnott, 2005) of the unit-operations model of Chu et al. (2015) for cooling of the air is carried out as follows:

For the (commercial building silica type) glass pane wall, each of L = 2.5 m, W = 4.5 m and d = 0.01 m, $k_{glass,}$ = 0.78 W m^{-1} K^{-1} and k_{brick} = 0.69 W m^{-1} K^{-1} is specified; the mean thermal properties of air, ρ = 1.1774 kg m^{-3}, g = 9.81 m s^{-2}, μ = 1.862 x 10^{-5} kg m^{-1} s^{-1}, c = 1005.7 J kg^{-1} K^{-1}, k = 0.0262 W m^{-1} K^{-1} and β = 3.3333 x 10^{-3} K^{-1} are given at 300 K (Holman, 2010).

From Eq. (7) the area for heat transfer through the glass pane is A_{glass} = 22.5 m^2. For an assumed mean ambient work-day summer temperature (December through February, South East Australia) T_o = 35 ^{O}C, the value ΔT = (35 – 22) = 13 K, is obtained from Eq. (9). $T_{air,glass}$ = ½(35 + 22) = 28.5 ^{o}C (301.65 K) is computed from Eq. (10). From Eqs. (16) and (17) respectively, δT = 6.5 K for both the outside, $\delta T_{o,glass}$ and inside, $\delta T_{i,glass}$ of the glass wall.

Substituting values for each of L, ρ, g, μ, k, c, β and δT into Eqs. (14) and (15), the Grashof and Prandtl number are respectively Gr = Gr_{glass} = 1.33 x 10^{10} and Pr = 0.71. From Eq. (13) the Raleigh number, Ra = Ra_{glass} = 9.48 x 10^9. Since 10^{-1} < Ra < 10^{12} Eq. (12) applies for the air outside and inside, yielding the 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. (5), yields the overall heat transfer coefficient, $U_{o,glass}$ = 1.28 W m^{-2} K^{-1}. Substituting $U_{o,glass}$, A_{glass} and ΔT into Eq. (2), the rate of heat energy transferred from the outside ambient to the interior of the room, q_{glass} = 374.75 W.

That is for the *on-only* strategy, following an initial start-up of cooling, given a uniform outside ambient summer temperature of 35 ^{O}C, 374.75 W will need to be removed to keep the room interior at 22 ^{O}C.

For the *on-off* strategy, the energy use is calculated as follows: From Eq. (18) $\delta T_{i,brick}$ = 13 K. Substituting $\delta T_{i,brick}$ together with values for each of L, ρ, g, μ, k, c, and β into Eqs. (14) and (15), the Grashof and Prandtl number are respectively Gr = Gr_{brick} = 2.66 x 10^{10} and Pr = 0. 71. From Eq. (13) the Raleigh number, Ra = Ra_{brick} = 1.90 x 10^{10}. Since 10^{-1} < Ra < 10^{12} Eq. (12) applies for the room interior air, yielding the heat transfer coefficient $h_{i,brick}$ = 3.24 W m^{-2} K^{-1}.

Substituting $h_{i,brick}$, d_{brick} and k_{brick} into Eq. (6), yields the overall heat transfer coefficient, $U_{o,brick}$ = 2.14 W m^{-2} K^{-1}. From Eq. (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), the rate of heat energy transferred from the brick wall to the interior of the room, q_{brick} = 695.05 W.

That is, given a uniform outside ambient summer temperature of 35 ^{O}C, the energy transfer from Eq (19) is therefore $q_{on\text{-}off}$ = 374.75 + 695.05 = 1069.80 W.

The difference in energy use between the two energy strategies can be written as

$$q_{difference} = q_{on-only} - q_{on-off}$$
$$= q_{glass} - \frac{\eta}{100}(q_{glass} + q_{brick}) \qquad (22)$$

It is seen that a practical and convenient advantage of Eq. (22) is that for all $q_{difference}$ > 0, the *on-off* strategy should be applied and when $q_{difference}$ < 0, the *on-only* strategy is better. At $q_{difference}$ = 0 either strategy will be equally effective.

3. *Fr 13* RISK MODEL

In contrast to the SVA, in the probabilistic *Fr 13* risk method of Davey and co-workers, the value of key input parameters is defined by a distribution, together with the probability (i.e. likelihood) of the value actually occurring in practical operation, and not by a single value.

The output is therefore a distribution of values of the probability of the particular outcome (Davey, 2015; Davey et al., 2015; Abdul-Halim and Davey, 2015) including unwanted outcomes i.e. failed strategies.

Additionally, a fundamental requirement of a rigorous application of this risk method is a practical and unambiguous definition of failure (Davey, 2011; Davey, 2015; Zou and Davey, 2015).

3.1. Defining failure

The amount of energy used in the two strategies can be used to define an energy strategy risk factor such that P = $[q_{glass}\,(1 - \eta/100)]' - [q_{brick}\,(\eta/100)]'$ in which $[q_{glass}\,(1 - \eta/100)]'$ and $[q_{brick}\,(\eta/100)]'$ are particular (instantaneous) values (or more strictly, mathematically, one probabilistic simulation). However a computationally more convenient form of the energy strategy risk factor (Davey, 2015; Davey et al., 2015; Abdul-Halim and Davey, 2015) is

$$p = \left(\frac{[q_{glass}(1-\frac{\eta}{100})]'}{[q_{brick}\,\frac{\eta}{100}]'} - 1 \right) \qquad (23)$$

Eq. (23) is computationally convenient because all p > 0 underscores a ‘failed’ adoption of the *on-only* strategy advocated by Chu et al. (2015).

3.2. *Fr 13* simulations

Eqs. (1) through (23) define the probabilistic *Fr 13* simulation for a failure in the *on-only* strategy for cooling of the room air.

The model is seen to be identical in form to the SVA because all mathematical operations that connect the parameters are the same. However, unlike the SVA where a single input and output value are computed, the inputs and outputs from the simulation are a distribution.

To emulate the naturally occurring fluctuations in value of the model input parameters with time the probability distributions need to be realistically defined. There are some 40 distribution types (Vose, 2008).

A refined Monte Carlo (with a Latin Hypercube) sampling (r-MC) is used to ensure values are sampled that cover the entire practical range of the probability distributions used to define the key parameters.

As pointed out by Abdul-Halim and Davey (2015) and others (e.g. Davey et al., 2015; Vose, 2008) sampling with 'pure' MC cannot be relied on to replicate the parameter distribution because it can both over- and under-sample from various parts of the distribution.

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

Cooling parameter	**SVA***	***Fr 13* simulation†**	
η (%)	75.0	21.66	**RiskTriang**(5,75,100)
T_o (^{O}C)	35.0	33.46	**RiskNormal**(35,5,**RiskTruncate**(25,45))
T_i (^{O}C)	22.0	22.0	Constant
L (m)	2.5	2.5	Constant
W (m)	4.5	4.5	Constant
d_{glass} (m)	0.01	0.01	Constant
k_{glass} (W m^{-1} K^{-1})	0.78	0.78	Constant
ρ (kg m^{-3})	1.1774	1.1774	Constant
g (m s^{-2})	9.81	9.81	Constant
μ (kg m^{-1} s^{-1})	0.00001862	0.00001862	Constant
c (J kg^{-1} K^{-1})	1005.7	1005.7	Constant
k (W m^{-1} K^{-1})	0.02624	0.02624	Constant
β (K^{-1})	0.0033333	0.0033333	Constant
L (m)	2.5	2.5	Constant
D (m)	5.0	5.0	Constant
d_{brick} *(m)*	0.11	0.11	Constant
k_{brick} (W m^{-1} K^{-1})	0.69	0.69	Constant
A_{glass} (m^2)	22.5	22.5	Eq. (7)
ΔT (K)	13.0	11.46	Eq. (9)
$T_{air,glass}$ (K)	28.5	27.73	Eq. (10)
$\delta T_{o,glass}$ (K)	6.5	5.73	Eq. (16)
$\delta T_{i,glass}$ (K)	6.5	5.73	Eq. (17)
Gr_{glass} (dimensionless)	13279136800	11706069825	Eq. (14)
Pr_{glass} (dimensionless)	0.713648	0.713648	Eq. (15)
Ra_{glass} (dimensionless)	9476634723	8354017994	Eq. (13)
$h_{o,glass}$ (W m^{-2} K^{-1})	2.61	2.503538258	Eq. (12)
$h_{i,glass}$ (W m^{-2} K^{-1})	2.61	2.503538258	Eq. (12)
$U_{o,glass}$ (W m^{-2} K^{-1})	1.28	1.231997634	Eq. (5)
q_{glass} (W)	374.75	317.6705899	Eq. (2)
A_{brick} (m^2)	25	25	Eq. (8)
ΔT (K)	13.0	11.5	Eq. (9)
$T_{air,brick}$ (K)	28.5	27.73	Eq. (11)
$\delta T_{i,brick}$ (K)	13.0	11.5	Eq. (18)
Gr_{brick} (dimensionless)	26558273600	23412139651	Eq. (14)
Pr_{brick} (dimensionless)	0.713648	0.713648	Eq. (15)
Ra_{brick} (dimensionless)	18953269446	16708035988	Eq. (13)
$h_{i,brick}$ (W m^{-2} K^{-1})	3.24	3.12	Eq. (12)
$U_{o,brick}$ (W m^{-2} K^{-1})	2.14	2.08	Eq. (6)
q_{brick} (W)	695.05	596.65	Eq. (3)
$q_{on\text{-}off}$ (W)	802.35	198.04	Eq. (20)
$q_{on\text{-}only}$ (W)	374.75	317.67	Eq. (21)
p (dimensionless)		**92.55**	Eq. (23)

* Traditional, Single Value Assessment.
† One only of 5,000 scenarios.

When the number of samples is sufficiently large, the output mean will be normally distributed (Vose, 2008; Davey 2015). Davey and co-workers (e.g. Zou and Davey 2015; Abdul-Halim and Davey, 2015; Davey et al., 2015, 2013; Davey, 2011) have reported that this usually requires some 1,000 to 50,000 samples for a typical unit-operation simulation. 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. A random number generator is used (Vose, 2008). Importantly, with *Fr 13* simulations with a sufficiently large number of r-MC samples, all possible combinations of input parameter values and resulting output process scenarios that could occur in the energy strategy for room interior cooling will have been simulated, including failure.

4. RESULTS

Table 1 presents a comparative summary of results from the traditional SVA with those of the new *Fr 13* method.

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 cooling of the room interior air are given in column 1 of Table 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).

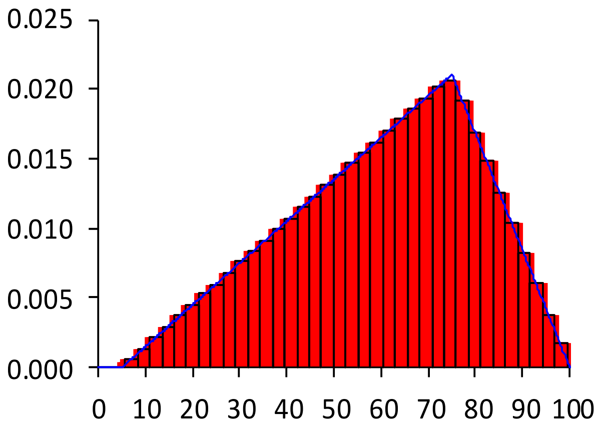

Figure 2. Distribution **RiskTriang** (5, 75, 100) for room traffic flow showing a minimum, most likely and maximum 5, 75, 100, % occupancy, η

The distributions used for the *Fr 13* simulations for each of traffic flow (as occupancy) (η %) and ambient temperature (T_o) are defined in column 4 of Table 1. For example, occupancy, (row 2 of Table 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 Figure 2.

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.

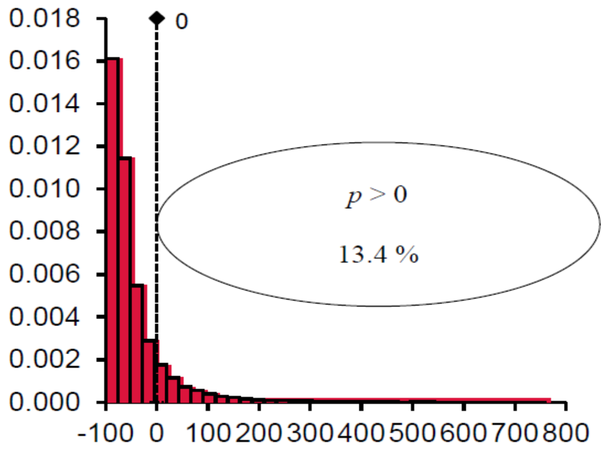

Figure 3. *Fr 13* simulation of *on-only* energy cooling strategy with 5,000 scenarios. The 670 failure scenarios (13.4 %) are shown to the right of the figure ($p > 0$)

A total of 670 (13.4 %) scenarios were identified with $p > 0$ in the 5,000 simulations, Figure 3. In this figure the x-axis is the value of the energy strategy risk factor, p, from Eq. (23) 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.

Ten (10) of these 670 failures which could occur as a result of adopting the *on-only* energy strategy are presented in Table 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 2 (row 6, for failure scenario 4) is the particular scenario reported in Table 1.

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

Row	η (%)	T_o (^{O}C)	p (dimensionless)
1	5.67	30.16	757.77
2	15.02	40.08	215.84
3	18.80	34.38	131.67
4[&]	**21.66**	**33.46**	**92.55**
5	24.94	39.70	67.56
6	26.45	34.01	48.76
7	29.35	40.49	34.69
8	31.24	38.46	21.63
9	33.00	38.86	12.47
10	32.95	27.22	0.94

[&] Particular scenario of Table 1.

5. DISCUSSION

5.1. Model confirmation

An extensive test of model simulations showed them to be stable. Because predicted trends agreed closely with those of Chu et al. (2015) over a wide range of inputs 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.

5.2. 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.

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

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

5.3. Establishing appropriate probability distributions

It appears reasonable that the ambient temperature would be normally distributed as has been assumed. The distribution is seen (Table 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 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.

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 cooling 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 cooling model on the distribution chosen for traffic flow, Table 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 cooling in this cooling model.

Table 3: Spearman rank correlation coefficient (Snedecor and Cochran, 1989) for the two input parameters to the *Fr 13* cooling model for traffic flow (as occupancy, η) and ambient temperature (T_o) on the energy strategy risk factor, *p*.

Input parameter	Coefficient
η	- 1.0
T_o	0.05

5.4. Results overview

A key insight is that the *on-only* energy strategy advocated by Chu et al. (2015) is predicted to fail in only about 10 % of all cases, averaged over the long term. This information is not currently available from alternate risk and hazard analyses.

A crucial reason is that these alternate 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 advantages because it permits the effect of each parameter to be studied separately.

6. CONCLUSIONS

A new probabilistic *Fr 13* assessment of the proposed cooling strategy of *on-only* of Chu et al. (2015) for major structures such as public building and hotels, has predicted that it will fail in some 13.4 % of cases i.e. 12 unexpected, or *Fr 13*, failures each summer, averaged over a prolonged period.

Simulations highlight this cooling strategy is highly dependent on unplanned traffic flow (as occupancy).

Because all scenarios that could practically exist have been simulated, the *Fr 13* assessment is an advance over more traditional assessments.

Nomenclature

Numbers in parentheses after description refer to the equation in which the symbol is first used or defined.

A	area (m^2) (1)
A_{glass}	area of glass panes (m^2) (2)
A_{brick}	area of brick walls (m^2) (3)
c	specific heat at constant pressure = 1005.70 (J kg^{-1} K^{-1}) (15)
d	Thickness of medium surface (m) (4)
d_{glass}	thickness of glass pane = 0.01(m) (5)
d_{brick}	thickness of brick wall = 0.11 (m) (6)
D	depth of room = 5 (m) (8)
g	acceleration constant = 9.81 (m s^{-2}) (14)
Gr	Grashof number (dimensionless) (14)
h	heat transfer coefficient for air (W m^{-2} K^{-1}) (12)
h_o	heat transfer coefficient of outside air (W m^{-2} K^{-1}) (4)
$h_{o,glass}$	heat transfer coefficient of outside air adjacent glass pane (W m^{-2} K^{-1}) (5)
h_i	heat transfer coefficient of inside air (W m^{-2} K^{-1}) (4)
$h_{i,glass}$	heat transfer coefficient of inside air adjacent glass pane (W m^{-2} K^{-1}) (5)
$h_{i,brick}$	heat transfer coefficient of inside air adjacent brick wall (W m^{-2} K^{-1}) (6)
k	thermal conductivity of air = 0.026 (W m^{-1} K^{-1}) (4)
k_{glass}	thermal conductivity of glass (W m^{-1} K^{-1}) (5)
k_{brick}	thermal conductivity of glass (W m^{-1} K^{-1}) (6)
L	vertical length of room = 2.5 (m) (7)
Nu	Nusselt number (dimensionless) (12)
Pr	Prandtl number (dimensionless) (12)
p	energy strategy risk factor (dimensionless) (%) (23)
q	heat transfer (W) (1)
$q_{difference}$	heat difference between *on-only* and *on-off* (W) (22)
q_{glass}	heat transfer from glass (W) (2)
q_{brick}	heat transfer from brick (W) (3)
q_{on-off}	heat transfer for Strategy 1 (W) (19)
$q_{on-only}$	heat transfer for Strategy 2 (W) (21)
Ra	Raleigh number (dimensionless) (12)
ΔT	temperature (bulk) difference of air between outside and inside of room (K) (1)
$\delta T_{o,glass}$	temperature difference between glass wall and air film outside of room (K) (16)
$\delta T_{i,glass}$	temperature difference between glass wall and air film inside of room (K) (17)
$\delta T_{i,brick}$	temperature difference between brick wall and interior of room (K) (18)
$T_{air,glass}$	average film temperature air on glass (K) (10)
$T_{air,brick}$	average film temperature of air on brick (K) (11)
T_{brick}	equilibrium temperature of brick (^{O}C) (11)
T_i	*auto-set* (desired) bulk temperature of room interior air (K) (9)
T_o	mean daily bulk ambient temperature (outside air) (K) (9)
U_o	overall heat transfer coefficient (W m^{-2} K^{-1}) (1)
$U_{o,glass}$	overall heat transfer coefficient from glass (W m^{-2} K^{-1}) (2)
$U_{o,brick}$	overall heat transfer coefficient from brick (W m^{-2} K^{-1}) (3)
W	width of room = 4.5 (m) (7)
Greek Symbols	
β	volumetric coefficient of expansion of air = 3.3333 x10^{-3} (K^{-1}) (14)
ρ	density of air = 1.1774 (kg m^{-3}) (14)
μ	dynamic viscosity of air = 1.862 x 10^{-5} (N s m^{-2}) (14)
η	traffic flow (as occupancy) over the long term (%) (20)
Subscripts	
i	inside
o	outside
$'$	a particular r-MC scenario (23)

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