Uncertainty Quantification in Life Cycle Assessments

Interindividual Variability and Sensitivity Analysis in LCA of Air-Conditioning Systems

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eco-design
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Summary

The life cycle environmental profile of energy-consuming products, such as air conditioning, is dominated by the products' use phase. Different user behavior patterns can therefore yield large differences in the results of a cradle-to-grave assessment. Although this variation and uncertainty is increasingly recognized, it remains often poorly characterized in life cycle assessment (LCA) studies. Today, pervasive sensing presents the opportunity to collect rich data sets and improve profiling of use-phase parameters, in turn facilitating quantification and reduction of this uncertainty in LCA. This study examined the case of energy use in building cooling systems, focusing on global warming potential (GWP) as the impact category. In Singapore, building cooling systems or air conditioning consumes up to 37% of national electricity demand. Lack of consideration of variation in use-phase interaction leads to the oversized designs, wasted energy, and therefore reducible GWP. Using a high-resolution data set derived from sensor observations, energy use and behavior patterns of single-office occupants were characterized by probabilistic distributions. The interindividual variability and use-phase variables were propagated in a stochastic model for the life cycle of air-conditioning systems and simulated by way of Monte Carlo analysis. Analysis of the generated uncertainties identified plausible reductions in global warming impact through modifying user interaction. Designers concerned about the environmental profile of their products or systems need better representation of the underlying variability in use-phase data to evaluate the impact. This study suggests that data can be reliably provided and incorporated into the life cycle by proliferation of pervasive sensing, which can only continue to benefit future LCA.

Introduction

The past decade has seen increasing attention paid to the contribution of industry to greenhouse gas (GHG) emissions and climate change. In September 2014, Singapore became the 14th nation to ratify the Doha Amendment to the United Nations (UN) Framework Convention on Climate Change (UN 2012), commonly known as the Kyoto Protocol, which commits its parties by setting internationally binding emission reduction targets. If nations are to meet the challenge of growing demand for energy-intensive products, such as building cooling systems and automobiles, ways to minimize GHG emissions per unit product will become increasingly important.

In the humid tropical climate of Singapore, air conditioning accounts for between 30% and 37% of household electricity consumption (Boranian 2013; NEA 2014). A recent survey

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highlighted the wide range in intensity of this cooling related energy consumption within a sample of the population (NEA 2006). Air-conditioning systems have long useful lifetimes, during which the dynamics of use greatly influence their environmental impact. Weber (2012) stated that both the use-phase emissions and their uncertainty were likely to dominate the life cycle for many long-life energy-using products. Existing research has shown that air-conditioning use changes with the occupancy and activities rather than with target levels of indoor temperature (Kempton et al. 1992; Lutzenhiser 1992). Therefore, automated features, such as thermostats, can potentially increase energy consumption (Peffer et al. 2011) and thus increase the system's environmental footprint. Neto and Fiorelli (2008) found that there was a 13% discrepancy between modeled and actual air-conditioning energy use attributed to the user behavior. Considering the behavior of product users at the design stage is therefore becoming of increasing relevance, yet remains to be better understood in the context of life cycle assessment (LCA), when translating inventory flows into environmental impact potentials (Lloyd and Ries 2007; Ross et al. 2002). In today's society, pervasive sensing presents opportunities to collect rich data sets and improve profiling of user variation.

LCA stands today as the leading method accounting for the environmental impacts of products and their processes within a specified boundary. Reap and colleagues (2008) stated that reliably incorporating uncertainty was one of the key unresolved challenges to wider adoption of the LCA method. Huijbregts (1998) proposed a framework for application of uncertainty in LCA, but, although variation in parameters is inherent, treatment of uncertainty is often still prescribed as "optional" or only subject to qualitative treatment in frameworks (BSI 2011; GHG Protocol 2013). Variation in product user behavior is categorized as interindividual variability and can be assessed analytically or by simulation. Common techniques that evaluate the effects of this variation are uncertainty analysis and sensitivity analysis (Reap et al. 2008). The former models uncertainties in the inputs and propagates them to the results of the LCA, whereas the latter quantifies the effects of arbitrary changes in inputs on results and identifies the most influential input parameters. The appropriate representation of a given uncertainty mathematically is not straightforward and there exists no universal mathematical formalism. Various approaches have been proposed and implemented, including: stochastic processes, interval analysis, fuzzy numbers, and Bayesian statistics (Ross et al. 2002). Lloyd and Ries (2007) noted that application of some techniques may lead to unreliable outcomes and overconfidence in results; however, stochastic modeling is effective for assessing the probability of outcomes in LCA. Application of Monte Carlo analysis for stochastic modeling, implementing probability distributions in place of static input parameters, has been successfully implemented in many studies (Mattinen et al. 2014; Niero et al. 2014; Noshadravan et al. 2015; Weber 2012). In highly complex system models, application of Monte Carlo analysis can lead to excessive computational burden, necessitating development of surrogate models (Allaire and Willcox 2010). Recent studies have also evaluated analytical uncertainty propagation and possibility analysis as alternatives to sampling-based methods such as Monte Carlo (Clavreul et al. 2013; Groen et al. 2014; Heijungs and Lenzen 2014). However, with sufficient data to generate robust probability distributions, stochastic modeling remains the foremost method for propagating and quantifying parameter uncertainty in LCA.

Many studies have been conducted to standardize LCA methodology, improve life cycle inventories, and quantify the manufacturing phase of products, but published studies on quantifying interindividual use-phase variability in LCA are scarce. Azar and Menassa (2012) stated that although extensive sensitivity analyses have been conducted on technical and physical parameters of buildings, parameters that reflect the behavioral characteristics of occupants have rarely been evaluated. Given the high variability and uncertain effects of air-conditioning user behavior, uncertainty quantification can guide system design for minimal electricity consumption and related environmental impact.

Objectives of the present study were to: (1) utilize high-resolution data on user behavior to propagate interindividual variability in the life cycle of an air-conditioning system; (2) identify the state(s) within the use phase contributing the greatest uncertainty; and (3) consider how user behavior variability and the parametric uncertainty affect LCA modeling results and hence might influence eco-design decisions.

Methodology

Data Collection

High-resolution data on air-conditioning usage patterns and user behavior were collected from staff offices at a university in Singapore, spanning a period of 5 months from July to November 2014. Fifteen single-occupancy offices of comparable size were assessed, each incorporating one identical 2.5-kilowatt (kW) rated inverter-type air-conditioning system with outdoor compressor and indoor mounted wall unit (Mitsubishi 2005). Data were collected from the 15 offices using integrated sensor units, deployed as part of a smart meter pilot project (Tushar et al. 2016), each measuring internal environmental conditions of one individual office. Sensor measurements recorded at 5-minute intervals included: room temperature, humidity, lighting, motion, and noise. Usage of the cooling system and room occupancy were determined by analysis of trends in the high-resolution proxy measurements collected. Observed trends indicated rapid response in recorded variables to changes to environmental conditions, providing robust data on not only cooling system usage, but also the user occupancy. The course of a given day was subsequently divided into four states of user behavior based on the cooling system usage and occupancy of the room, comparable to the method of Virote and Neves-Silva (2012). These were defined as: system cooling and room occupied (on & in); system cooling and room unoccupied (on & out); system idle and room occupied (off & in); and system

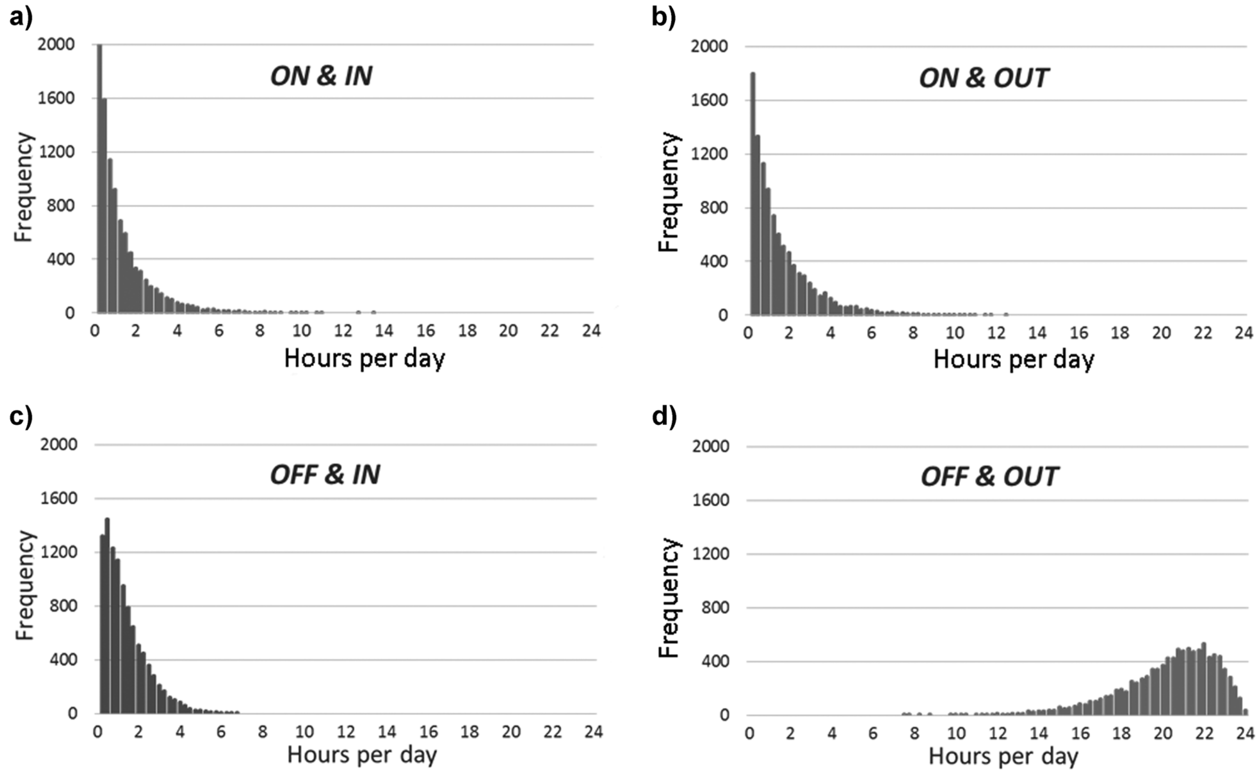

Figure 1 Histograms representing occupants' time spent in four states of user behavior in a period of 24 hours: (a) system cooling and room occupied (on & in); (b) system cooling and room unoccupied (on & out); (c) system idle and room occupied (off & in); and (d) system idle and room unoccupied (off & out).

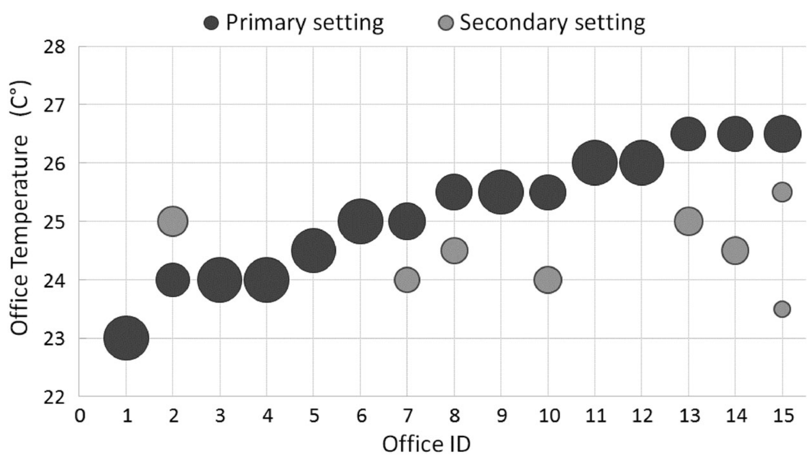

Figure 2 Range of observed user preferences for air-conditioning temperature settings.
Note: Relative area of plotted data points reflect the proportion of time individual users applied each temperature setting during cooling.

idle and room unoccupied (off & out). Histograms derived from data for the entire population, describing frequency of air-conditioning use and room occupancy, are presented in figure 1. These four states were then used to categorize periods of time in the use phase of the LCA. It is noted that both the average periods of individual daily office occupancy (2.4 hours; standard deviation [s.d.] = 1.6) and daily cooling time (2.6 hours; s.d. = 2.2) were quite low compared to the period of what would be considered a typical working day. However, these periods displayed a range in users' behavior from zero daily hours to 13.5 and 15.5 hours occupancy and cooling, respectively. Data also revealed distinct preferences in terms of variation in users' office temperature settings, presented in figure 2. Preferred office temperature settings ranged from 22°C to 27°C, with some users demonstrating a tendency to have more than one preferred setting. Singapore has a typical tropical climate, displaying consistently high and uniform diurnal temperatures and humidity with little month-to-month variation. Data were therefore considered reflective of a calendar year and could be extrapolated to provide an estimate of the rooms' cooling and occupant behavior on an annual basis.

Life Cycle Assessment

The life cycle system boundary was defined as "cradle to grave," covering the stages from extraction or acquisition of raw materials up to the end-of-life (EoL) treatment. The impact category was global warming potential (GWP), expressed in kilograms of carbon dioxide equivalents (kg CO_2-eq), and the functional unit for this study was the lifetime of a 2.5-kW rated inverter air-conditioning system used to cool a single office. Overall life cycle GWP impact was estimated by summation of emissions from the appliance manufacture and transport phases; the product use phase and the end of product life phase. In LCA, emissions arising from consumption of energy by a product are considered direct use-phase emissions (GHG Protocol 2013). In the present study, the use-phase therefore included all emissions arising from operation of the air conditioner, from installation to uninstallation of the system. This incorporated emissions associated with upstream power generation for electricity consumption, as well as those associated with refrigerant leakage.

Disaggregated electricity consumption data were not available for individual offices or appliances. Estimated energy consumption of the cooling system therefore depended on several factors, including: period of time cooling or idle; external temperature; users' preference for internal office temperature; the power rating; and coefficient of performance (CoP) of the appliance. The rated CoP of an air conditioner is defined by equation (1) (Schroeder 1999):

$$\mathrm{CoP} = \frac{P_{output}}{P_{input}} \tag{1}$$

The CoP is therefore a measure of the ratio of rated cooling capacity P_{output} (kW) to the actual power input P_{input} (kW), typically a factor of 3 to 4 in cooling systems of this size and era. Carnot's rule specifies limits on the maximum efficiency any heat engine can obtain, which solely depends on the difference between the hot and cold temperature reservoirs. The maximum theoretical CoP (CoP_{max}) therefore measures the efficiency of a system moving heat from one space (the office being cooled) to another (outside). For an air-conditioning system, Carnot's rule can be reduced to equation (2) (Schroeder 1999):

$$\mathrm{CoP}_{max} = \frac{T_{inside}}{(T_{outside} - T_{inside})} \tag{2}$$

where $T_{outside}$ is the temperature outside and T_{inside} the preferred temperature inside the cooled office space. For this equation, temperatures are converted to absolute values in units of degrees Kelvin. The CoP and CoP_{max} typically differ by a factor of 10; thus, the required electrical power for air cooling at a given set of temperatures was estimated using equation (3):

$$P_{input} = \frac{P_{output}}{0.1 \times \left(\frac{T_{inside}}{(T_{outside} - T_{inside})} \right)} \tag{3}$$

Equations describing the life cycle model used and calculation of the use-phase GWP impact are described in table 1. The use phase was defined to include background electrical demand for maintaining refrigerant temperature when the system was idle and was assumed to be a constant 0.03 kW. During cooling, systems were assumed to operate with a partial loading of 50% (Mitsubishi 2005). The average emissions factor used for electricity consumption in Singapore was 442 grams of CO_2-eq per kilowatt-hour $(\mathrm{kWh})^{-1}$ (EMA 2014; Finenko and Cheah 2016). Noting the consistency of prevailing weather conditions in Singapore throughout the year, mean daily maximum outside temperature was 31°C (MSS 2015). The refrigerant used was R410a, which has a GWP 1,725 greater than that of CO_2 (IPCC 2005). Refrigerant was delivered by 6-meter piping and leakage estimated to be 2% annually (De Kleine 2009; IPCC 2005). The life span of users' air-conditioning systems could not be determined because no units were replaced during the period of the study; therefore, the average useful life span of a system was modeled from literature values, assumed to be 10 years (Attia 2012) with a minimum life span of 5 years in line with manufacturer's warranty (Mitsubishi 2014). An exact breakdown of the system components was not available; therefore, emissions embedded in the materials and manufacture processes were derived from a study involving a comparable air-conditioning unit (De Kleine 2009). Emissions associated with transport and delivery of the product system to Singapore assumed a transport distance by container ship of 4,000 kilometers from manufacture in China, in agreement with a previous study based in Thailand (Harabut et al. 2004). In the absence of available Singapore-specific data, EoL emissions were estimated from literature (De Kleine 2009), assuming materials were 90% recyclable and 85% of refrigerant gas was recoverable (De Kleine 2009; GHG Protocol 2013).

In order to examine the effect of users' office temperature preferences upon the life cycle, the model was then run with office air-conditioning thermostat setting, T_{inside}, fixed at successive integer values over the range of user preferences observed in the data (22°C to 27°C). Significant differences between different use-phase categories in terms of estimated GWP impact, and the effect of varying user office temperature, were assessed by way of analysis of variance (ANOVA). Because the obtained distributions of results were skewed, data were log-transformed in order to better facilitate ANOVA, meeting the assumption of normality (McDonald 2008). Significant differences between mean GWP of different scenarios were determined by pair-wise comparison using the Tukey method.

Table 1 Equations describing model used for calculation of global warming potential impact from the life cycle of the case study air-conditioning system

Variable	*Units*	*Equation*
GWP_{total}	kg CO_2-eq	$= GWP_{manufacture} + GWP_{transport} + GWP_{use} + GWP_{end\ of\ life}$
GWP_{use}	kg CO_2-eq	$= GWP_{on\&in} + GWP_{on\&out} + GWP_{off\&in} + GWP_{off\&out} + GWP_{leakage}$
$GWP_{on\&in}$	kg CO_2-eq	$= t_{on\&in} * P_{cooling} * EF_{electricity} * t_{lifetime}$
$GWP_{on\&out}$	kg CO_2-eq	$= t_{on\&out} * P_{cooling} * EF_{electricity} * t_{lifetime}$
$GWP_{off\&in}$	kg CO_2-eq	$= t_{off\&in} * P_{idle} * EF_{electricity} * t_{lifetime}$
$GWP_{off\&out}$	kg CO_2-eq	$= t_{off\&out} * P_{idle} * EF_{electricity} * t_{lifetime}$
$GWP_{leakage}$	kg CO_2-eq	$= m_{R410a} * loss_{R410a} * EF_{R410a} * t_{lifetime}$
$P_{cooling}$	kW	$= P_{input} * 0.5$
P_{input}	kW	$= P_{output} / [0.1*(T_{inside} /(T_{outside} - T_{inside}))]$

Note: GWP = global warming potential; t = time; P = power; EF = emissions factor; m = mass; T = temperature; kg CO_2-eq = kilograms of carbon dioxide equivalents; kW = kilowatt.

Table 2 Model inputs for life cycle use phase with fitted probabilistic distributions and distribution parameter information for stochastic variables

Input	*Description*	*Units*	*Distribution*	*Mean/ likely*	*s.d.*	*Min*	*Max*	*Shape parameters*	
								a	*b*
$t_{lifetime}$	Useful lifetime	Years	Lognormal	10.0	2.50				
$t_{on\&in}$	State (on & in)	h day^{-1}	Beta-general	1.15		0.0	13.47	0.74	7.77
$t_{on\&out}$	State (on & out)	h day^{-1}	Beta-general	1.42		0.0	12.60	0.83	6.35
$t_{off\&in}$	State (off & in)	h day^{-1}	Beta-general	1.23		0.0	10.33	1.18	8.75
$t_{off\&out}$	State (off & out)	h day^{-1}	Beta-general	20.20		0.0	24.00	11.61	2.16
$T_{outside}$	Outside temperature	°C	Lognormal	31.0	1.96				
T_{inside}	Office temperature	°C	Lognormal	25.7	1.77				
$P_{cooling}$	Power draw when cooling	kW	Beta-pert	0.389		0.030	0.888		
$EF_{electricity}$	Average electricity EF	kg CO_2-eq kWh^{-1}	Normal	0.442	0.010				
$loss_{R410a}$	Annual refrigerant leak	%	Lognormal	2.0	1.0				
EF_{R410a}	Refrigerant R410a GWP	Dimensionless	Normal	1,725	302				
P_{idle}	Power draw when idle	kW	n/a	0.03					
P_{output}	Appliance rated capacity	kW	n/a	2.5					
m_{R410a}	Mass of refrigerant R410a	kg	n/a	0.31					

Note: EF = emissions factor, GWP = global warming potential; kg CO_2-eq = kilograms of carbon dioxide equivalents; kWh = kilowatt-hour; kW = kilowatt; s.d. = standard deviation; Min = minimum; Max = maximum; n/a = not applicable.

Uncertainty and Sensitivity Analysis

Stochastic simulation analysis was conducted to assess the effect of statistical variation in use-phase parameters upon the output from impact assessment. Uncertainty in this analysis refers to an estimate of the variability of results attributed to the variation inherent in inputs. Sensitivity in this analysis refers to an estimate of the scale of influence of arbitrary changes in inputs upon the LCA output. Input parameters were replaced in the model by probability distributions, and Monte Carlo simulations were performed using the @RISK package (Palisade Corporation 2015). This software and approach to life cycle uncertainty quantification has previously been effectively used in environmental LCA studies, including waste management (Couth et al. 2011), carbon sequestration (Wriedt et al. 2014), and agricultural systems (Basset-Mens et al. 2009; Ross et al. 2014). The periods of time spent in the four states of user behavior defined in the model were assigned probabilistic distributions fitted in @RISK from a range of 26 possible distributions. An open-ended distribution extending to infinity, such as the commonly implemented Gaussian (normal) or lognormal distributions, was not acceptable because parameters were necessarily constrained between zero and 24 hours in a day. Possible bound distributions available included the triangular, beta-general, and pert distributions. Goodness of fit of was assessed in @RISK using multiple tests applicable to continuous data: Kolmogorov-Smirnoff, Anderson-Darling, and the Bayesian information criterion. All three tests determined that a beta-general distribution satisfied the best fit from the available distributions to the data for each of the four states. Using the beta distribution enabled specification of maximum and minimum values, whereas its definition by two-shape parameters also preserved asymmetry in the respective distributions (Gibbons et al. 2006). Lognormal distributions were used to

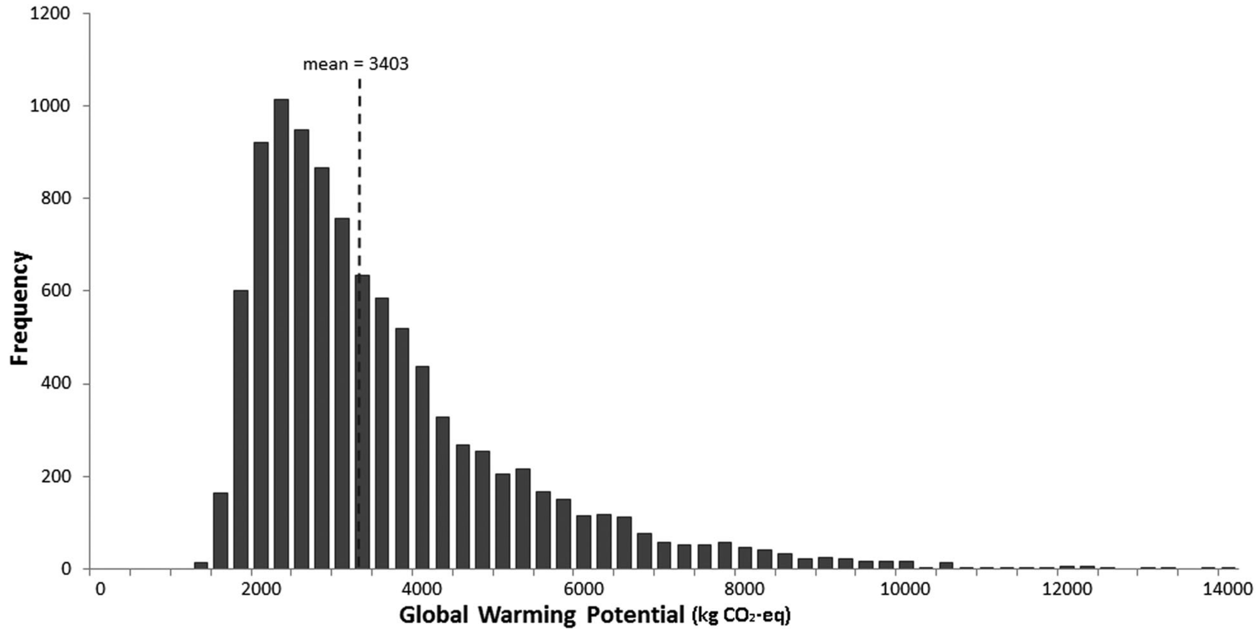

Figure 3 Histogram depicting distribution of output total global warming impact arising from variation in use phase of the air-conditioning system. kg CO_2-eq = kilograms of carbon dioxide equivalents.

represent the majority of parameters in the model, in line with commercial LCA packages (Heijungs and Frischknecht 2005; PRé 2013). A fixed-bound beta-pert distribution was considered appropriate for the appliance cooling energy, however, given that the electrical power drawn when cooling could not exceed the maximum rating of the appliance and was bound by a minimum power when on standby. Uncertainty parameters and distributions representing inputs were those presented in table 2.

Monte Carlo simulation ran 1,000 iterations of the model, generating a distribution of the resulting output (kg CO_2-eq). A sample size of 1,000 was considered to be sufficient, but not excessive (Henriksson et al. 2015, Klöpffer and Grahl 2014). It has been argued that increasing the number of simulations in Monte Carlo analysis inherently increases the risk of false-positive results and concluding significant differences from any hypothesis test (Henriksson et al. 2015). This number of simulations was also considered sufficient for estimation of parameters' contribution to variance (CTV), noted by Mutel and colleagues (2013) to be approximately 100 simulations per stochastic variable. CTV was calculated using Spearman's rank-order correlation, squaring the rank-order correlation coefficients and normalizing them to 100%. Quantifying CTV estimates what percentage of the variance or uncertainty in the output forecast is caused by assumption of variation in each input parameter and has been forecast as a global sensitivity test for LCA (Mutel et al. 2013).

Results

As expected for an electrical appliance, the combined four states of user behavior contributed a majority (79%) of the total life cycle GWP of 3,404 kg CO_2-eq per unit. The total use phase accounted for 82% of the total lifetime GWP, inducing a range of 6,449 kg CO_2-eq between the 5th and 95th percentile in the distribution of results, as presented in figure 3. The use-phase state off & out had the highest GWP of the four states, marginally higher than on & out. Off & in was the lowest contributing state by a considerable margin, accounting for only 2% of the overall GWP. Results from impact assessment showing the estimated contribution from each life cycle phase to overall GWP are presented in table 3.

Across the range of variation in users' preferred office temperature settings, the mean life cycle GWP varied from 3,021 to 4,624 kg CO_2-eq. The mean GWP for different temperature settings were all significantly different to one another ($p < .005$). Maintaining an office temperature of 27°C lowered overall GWP by 35% compared to 22°C. Each successive 1°C increase in users' office temperature setting decreased the estimated life cycle GWP by 8%. The coefficient of variation of the estimated output GWP distribution was narrower with increasing office temperature setting. A breakdown showing the estimated GWP of an air conditioner consistently set at different temperatures is presented in table 4.

The results of sensitivity analysis, displaying Spearman's rank-order coefficient and CTV for use-phase variables, are presented in table 5. The variable representing time spent in the state "on & out" made the highest contribution to output uncertainty. Sensitivity in LCA output was negligible for the two states where the cooling cycle was not active. For variation in the modeled behavioral state "on & in," the cooling electricity drawn and the system useful lifetime held comparable influence upon uncertainty in results.

Table 3 Breakdown of estimated global warming impact of different phases of life cycle contributing to overall GWP, with standard deviation (s.d.) and coefficient of variation (CV)

Variable	*Level*	*Global warming impact (kg CO_2-eq)*			
		Mean	*s.d.*	*CV*	*Proportion of total*
Embodied emissions	Manufacture	317			0.09
	Transport	6			0.00
Use-phase energy	On & in	728	979	1.34	0.21
	On & out	913	1,142	1.25	0.27
	Off & in	59	52	0.88	0.02
	Off & out	978	269	0.27	0.29
	(subtotal of four states)	(2,678)	(1,765)	(0.66)	(0.79)
Use-phase leakage	Refrigerant leakage	107	64	0.60	0.03
End of life		294			0.09
Total		3,404	1,758	0.52	1.00

Note: Subtotal is the combined effect of the four defined states of user behavior.
kg CO_2-eq = kilograms of carbon dioxide equivalents.

Table 4 Breakdown of estimated overall global warming potential associated with scenarios running air conditioning at different preferred temperatures; mean, standard deviation (s.d.), standard error (s.e.), and coefficient of variation (CV)

Temperature setting (°C)	*Global warming potential (kg CO_2-eq)*			
	Mean	*s.d.*	*s.e.*	*CV*
22	4,624[a]	2,457	24.6	0.53
23	4,303[b]	2,236	22.4	0.52
24	3,968[c]	1,992	19.9	0.50
25	3,656[d]	1,785	17.8	0.49
26	3,323[e]	1,523	15.2	0.46
27	3,021[f]	1,356	13.6	0.45

Note: different superscript letters denote significant differences between mean global warming potentials ($p < .005$).
kg CO_2-eq = kilograms of carbon dioxide equivalents.

Table 5 Spearman's rank-order correlation coefficient (ROCC) and contribution to variance (CTV) of use-phase variables to uncertainty in life cycle model output

Rank	*Contributing variable in model*		*ROCC*	*CTV*
#1	$t_{on\&out}$	State (on & out)	0.51	0.24
#2	$t_{on\&in}$	State (on & in)	0.45	0.18
#3	$P_{cooling}$	Power draw when cooling	0.45	0.18
#4	$t_{lifetime}$	Useful lifetime	0.44	0.17
#5	$T_{outside}$	Outside temperature	0.36	0.12
#6	T_{inside}	Inside temperature	−0.34	0.10
#7	$t_{off\&out}$	State (off & out)	0.09	0.007
#8	$EF_{electricity}$	Average electricity EF	0.04	0.001
#9	$t_{off\&in}$	State (off & in)	0.04	0.001
#10	$loss_{R410a}$	Annual refrigerant leak	0.03	0.001
#11	EF_{R410a}	Refrigerant R410a GWP	0.02	<0.001

Note: AC = air-conditioning system; EF = emissions factor; GWP = global warming potential.

Discussion

Use-Phase Contribution to Greenhouse Gas Emissions

The LCA of a cooling system examined in this study incorporated real-world data to propagate interindividual variability and use-phase uncertainty in the model. The mean output GWP was 3,404 kg CO_2-eq per unit, and the distribution of uncertainty surrounding the results displayed a full range extending two thirds lower and 7 times higher, emphasizing the considerable influence that use-phase variation has upon overall uncertainty. Although the average period of daily office cooling was relatively low at 2.6 hours per day, the two behavioral states involving cooling still contributed 48% of the total life cycle GWP and held the highest sensitivity for results. Further, despite the low frequency of observed cooling periods, the use phase still accounted for over 80% of the estimated total life cycle GWP. This dominance of the life cycle by the use phase is not necessarily intuitive for a product whose operation, unlike that of a diesel automobile, for example, does not physically produce emissions in situ beyond low-level refrigerant leakage. The emissions arising from a product that directly consumes energy (fuels or electricity) during use, however, are considered direct use-phase emissions for that product's life cycle (GHG Protocol 2013). Tan and Nutter (2011) stated that the opportunity to reduce GHG emissions in buildings should focus first on operational energy efficiency gains, identifying regional electrical emission factors, building type, and climate as primary factors that influenced the emission rate. However, the results of the present study highlight the importance of quantifying and understanding the influence of user-behavior parameters as well.

It is perhaps not surprising that the use-phase states where the air conditioning was switched on in cooling cycle (on & in, on & out) contributed a high proportion of the total GWP. This is further likely when considering that the average power drawn during cooling (0.39 kW) was 13 times greater than during the off state. The coefficient of variation for the GWP associated with these two states was also considerably higher than other states of the use-phase inputs. However, it is important to note that 29% of the total life cycle emissions arose from electricity consumption when the system was idle and the only energy use was directed toward maintaining the refrigerant temperature. In Singapore, this maintenance is necessitated by daily mean temperatures in excess of 30°C and overnight temperatures around 26°C all year round, in contrast to temperate regions where the system may be switched off away from summer season. Although estimated refrigerant leakage contributed just 3% of total life cycle GWP, the magnitude of this owes to the considerably higher emissions factor for the refrigerant R410a, 1,725 times more impactful than CO_2 (IPCC 2007).

A point of great importance in this study was the scale of the emissions arising from the use-phase state on & out. Overall 27% of the life cycle emissions generated, and 33% of the use phase, occurred from active air cooling when there were no occupants in the room. This suggests that users simply switched on cooling upon arrival in the office, using automated thermostat control to manage the cooling throughout working hours, irrespective of time actually spent outside their respective office, that is, in meetings, teaching classes, etc. This is also supported by the fact that the use-phase state off & in, where the office was occupied but without active cooling cycle, accounted for just 2% of the GWP. Theoretically, if time residing in the on & out state could be minimized and transferred to the off & out state, the potential exists in this case of single-office cooling systems for up to 24% reduction in overall life cycle GWP. Further, users increasing their preferred office temperature setting by 1°C could result in further life cycle emissions reduction of 8%. These insights demonstrate the value of being able to acquire high-resolution use-phase data and incorporate into the life cycle calculation.

Sensitivity Analysis

In another study based in a tropical climate, Santos-Silva and Ghisi (2014) estimated that 38% of uncertainty in the energy consumption for cooling a building could be explained by user-behavior factors, as opposed to physical factors such as temperature and building materials. Results of the present study are broadly comparable, with the CTV of the combined four states of user behavior explaining 43% of uncertainty from the use phase. The calculated CTV allows us to rank the input parameters based on their level of contribution to the variance in GHG emissions. The use-phase factors in the present study can effectively be divided into tiers of sensitivity impact. It is not surprising that the variables inducing highest sensitivity in results and highest CTV were those describing the two use-phase states where cooling was on. These two states contributed a combined 48% of overall GWP and explaining 42% of the observed variance. The intensity of energy demand during cooling and the product useful lifetime made contributions comparable to the state on & in. In a second tier of factors displaying moderately high sensitivity, we find both the outside and office temperature. The lifetime emissions from the air-conditioning system were found to be more sensitive to the observed daily variation in some aspects of user behavior than to variation in the useful life span of the system itself. Perhaps more interestingly, however, results also indicate that sensitivity to variation in both the users' preferred office temperature and the prevailing outside temperature was lower than the states of user behavior when cooling was on. Together, the outdoor and office temperature variables had a combined CTV of just 22%. Outside temperature contributed just 12% of variance, but this can be explained, to some extent, by the consistency of daily temperatures in Singapore. Despite contributing the greatest proportion of the total life cycle GWP, the use-phase state off & out was found in the third tier, with a negligible contribution. This can be explained as attributable to the comparatively low and constant energy consumption of this use-phase state, where power was drawn at a consistent 30 watts. Thus, although the state off & out accounted for the largest period of time in the life cycle, and the largest proportion of GWP, the low energy draw resulted in a very low contribution to uncertainty in results. Despite the high level of variation surrounding the emissions factor for refrigerant gas R410a, given to be ±35% (IPCC 2005), its CTV in the output was negligible. The coefficient of variation associated with GWP from refrigerant leakage, however, was comparable with that for the combined four states of behavior. Therefore, the low sensitivity of the overall GWP to uncertainty in the refrigerant emissions factor (EF) is attributed to the low mass of refrigerant required by the air-conditioning systems in this study.

Informing Eco-Design

Reducing energy demand and environmental burden of air conditioning has been met, in part, through technical innovation in these systems. Harabut and colleagues (2004) stated that life cycle energy costs could be as much as 30% lower using an inverter system, as considered in the present study, compared to a rotary compressor system. More-recent design innovation includes development of variable rate flow (VRF), an extension of the split-type system whereby an outdoor condensing unit may be linked up to several dozens of indoor fan units, ideal for the office scenario in this study. The VRF system is able to regulate the flow of refrigerant to individual terminals according to the cooling demand of the zones served, in theory resulting in still more-favorable energy running costs (Whitman et al. 2012). Modern air-conditioning systems also do already incorporate features that can account for some elements of user behavior or preference, such as thermostat control; however, the design carries no guarantee of how they may be utilized by users. Withanage and colleagues (2016) identified a lack of user awareness of energy and power interactions among appliances and household settings as the key underlying cause of wasteful user behavior. Peffer and colleagues (2011) noted that automated thermostats could actually increase energy consumption of a cooling system. The results of the present study support those findings, given that it is clear that the faculty offices continued to be cooled for substantial periods when unoccupied. With advances in technology and sensing new features are available, such as dual ceiling and floor-level temperature sensing to prevent overchilling (Mitsubishi 2014) and passive infrared occupancy detection sensors (EPV 2015). Hard-wired motion sensors, which operate in conjunction with door and window sensors, can monitor the room and shut down cooling when nobody is present (Ecosense 2014). Such sensors can be controlled remotely by an app on the users' phone or tablet, with the stated aim to reduce spiraling energy costs, GHG, and unnecessary strain on equipment. There is even a system in the market that incorporates a placebo effect, informing users that the temperature is lower than actuality (Ecosense 2014). Although such innovation provides a step toward more-sustainable cooling, it does not necessarily address the uncertainty issue of the use phase. Parys and colleagues (2006) stated that to minimize the effect of different types of user behavior, the current method is to apply extensive oversized cooling systems. In a similar way, sensor control acts effectively as a band aid over variability, treating the symptom without evaluating the underlying source of the issue. The option to operate the air-conditioning remotely adds another variable to the use phase and further adds to the uncertainty of the life cycle as a whole. Indeed, the possibility remains that users' remote operation to precool a room in advance of arrival may also, much like thermostat control, ultimately lead to an increase in energy consumption for the use phase overall.

In an initiative to improve energy efficiency, Singapore introduced updated regulations in 2014 mandating improvements in the CoP rating for all new energy-intensive appliances, including air-conditioning systems. Similar, albeit less-stringent, regulations, have also been introduced to the United States in recent years (Hendron and Engebrecht 2010). These regulations necessitated energy efficiency improvements through engineering and represent a case where design for environment has already advanced to reduce running cost and emissions. The user-behavioral caveat here is that such reductions are dependent on users adopting smaller models, or at least not purchasing larger units to achieve greater cooling power for the same energy expenditure. Nations have also striven to reduce GWP from the use of electrical products through adjusting the energy mix for electricity generation and implementing renewable energy sources. In the past few years, the energy mix for grid electricity generation in Singapore has shifted from approximately 80% up to 95% natural-gas–dependent (EMA 2014), lowering the marginal emissions factor by 11% from 511 kg CO_2-eq kWh^{-1} in 2007 to 457 kg CO_2-eq kWh^{-1} in 2014. Thus, two of the key opportunities to reduce GHG emissions from buildings identified by Tan and Nutter (2011) have, in some capacity, already been addressed. With these advances in operational energy already in place, there is even greater need to understand the influence of interindividual variability and minimize uncertainty in use-phase variables in order to identify and continue environmental improvements.

Implications for Life Cycle Assessment

The Intergovernmental Panel on Climate Change (IPCC) guidelines for GHG accounting state that accuracy and precision of estimates should strive toward the tier 3 level (IPCC 2006), representing the most detailed parameter information available. The present study has demonstrated how pervasive sensing data can satisfy this detail and how incorporation into the product life cycle enables multiple benefits. Application of high-resolution use-phase parameters provided not only the ability to more accurately quantify the life cycle GWP of an air-conditioning system, but also provided insight into user-behavior patterns that were otherwise unavailable. From an LCA perspective, it is paramount to be able to quantify uncertainty in the phase that dominates the overall life cycle and identify which parameters invoke the greatest sensitivity in the output. Further, confidence in the LCA is improved by understanding how overall uncertainty may increase or decrease with variation in a certain parameter, demonstrated in this study by the office temperature setting. More than this, however, such data provide the capability to determine patterns of the users' behavior and how these patterns affect the way in which a product or system is used. This information opens the road toward scenario analysis for emissions reduction using real feasible outcomes. In turn, design for environment, through incorporation of pervasive sensing on future appliances, could collate use-phase information with which to inform both users and designers of system usage, highlighting areas in which to reduce environmental footprint. Weber (2012) noted that the use phase of a long-lived high-energy product was not only uncertain because of a lack of scenario information of how and for how long a product will be used, but was also highly geographically variable. Countries at higher latitudes will display greater annual and diurnal variation in outside temperature, influencing both the period and intensity of air-conditioning use, as well as efficiency of cooling performance. The elasticity of the marginal emissions factor means that it too should be included as a variable contributing use-phase uncertainty in any future studies, given that this may be subject to fluctuations owing to external factor,s such as economics, or an environmental policy shift toward renewable energies. Countries such as the United States, with a more-diverse energy mix, demonstrate significant spatial and temporal variation in their marginal emissions factors across different regions of the country (Siler-Evans et al. 2011).

It was previously noted that Reap and colleagues (2008) stated that one of the key unresolved challenges to wider adoption of the LCA method was the reliable incorporation of uncertainty. Heijungs and Frischknecht (2005) discussed the problems that arose when trying to translate uncertainty information between its original mathematical form, an LCA database and an analytical tool. Thus, in spite of the potential for high-resolution data to account for the life cycle use-phase uncertainty, its basis for sound decision making in the future will rest in how adequately it can be represented in LCA modeling. The manner of this representation, or characterization of the data, is inexorably linked to the issue of computation burden and decisions made in studies' approach to uncertainty analysis. Groen and colleagues (2014) noted that using a stratified sampling approach in a variant of Monte Carlo analysis could outperform Monte Carlo in terms of accuracy of estimates and speed of convergence, although with a corresponding increase in calculations burden. Recent studies have examined methods of analytical uncertainty propagation incorporating Taylor series expansion as an alternative to Monte Carlo analysis (Heijungs and Lenzen 2014; Imbeault-Tétrault et al. 2013). The analytical method has been shown to reduce computing cost when a large number of inputs are needed. Although providing only the output mean and variance as metrics, as opposed to the wide range of output statistics available from Monte Carlo, this method also permits estimate of the CTV by inputs. Without determining a distribution of results, the analytical approach is unable to test significant differences between the environmental performance of products or scenarios (Heijungs and Lenzen 2014), as is commonly the aim of LCA practice. Recent studies have proposed an assumption of lognormal distributions (Hong et al. 2010; Imbeault-Tétrault et al. 2013); however, this would undermine the effort and rationale of collecting high-resolution data to profile key parameters such as the use-phase behavior in the present study. Clavreul and colleagues (2013) stated that the selection of input probability distributions in LCA often appears arbitrary and proposed that the investigator select the propagation method that seems best suited to convey information. With the present case study, we demonstrate that in a world of pervasive sensing and opportunity to collect rich information, then a statistical representation is justifiable to characterize the range and variability among use-phase variables. In the present study, the appropriate fit to user behavior data was determined by goodness-of-fit tests, using a feature within the @RISK package offering 28 different types of statistical distribution. The range of distributions available to fit may prove more limited in some LCA tools, however, necessitating use of less-robust fits to the data. Future studies could consider the effect of using different statistical distributions to represent the dominant phase or parameters in an LCA.

Conclusions

The present study has demonstrated the range and influence of uncertainty in the life cycle use phase of a building cooling system from a case study of single-occupancy offices and the importance of better understanding interindividual variability in the use phase in LCA. Through a simplified LCA model, the uncertainty was quantified from different user states and parameters, as well as the sensitivity of the overall life cycle global warming impact to these defined states. Occupants relied on automated thermostat control to manage cooling throughout working hours, regardless of occupancy time and at detriment to the environment. The use phase dominated the product life cycle, and analysis of the uncertainty identified plausible reductions in global warming impact through modifying user behavior. Defining different categories of air-conditioning users will enable cooling systems design to be tailored to specific user behavior in the future. Designers concerned about the environmental profile of their products or systems need better representation of the underlying variation and uncertainty in use-phase data to evaluate the impact. This study suggests that data can be reliably provided by the proliferation of pervasive sensing, which can only continue to benefit LCA in the future.

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