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Wang, Endong and Shen, Zhigang, "LIFECYCLE ENERGY CONSUMPTION PREDICTION OF RESIDENTIAL BUILDINGS BY INCORPORATING LONGITUDINAL UNCERTAINTIES" (2012). *Architectural Engineering -- Faculty Publications*. 148.
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LIFECYCLE ENERGY CONSUMPTION PREDICTION OF RESIDENTIAL BUILDINGS BY INCORPORATING LONGITUDINAL UNCERTAINTIES

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Received 19 Sep 2012; accepted 24 Oct 2012

Abstract. Accurate prediction of buildings' lifecycle energy consumption is a critical part in lifecycle assessment of residential buildings. Longitudinal variations in building conditions, weather conditions and building's service life can cause significant deviation of the prediction from the real lifecycle energy consumption. The objective is to improve the accuracy of lifecycle energy consumption prediction by properly modelling the longitudinal variations in residential energy consumption model using Markov chain based stochastic approach. A stochastic Markov model considering longitudinal uncertainties in building condition, degree days, and service life is developed: 1) Building's service life is estimated through Markov deterioration curve derived from actual building condition data; 2) Neural Network is used to project periodic energy consumption distribution for each joint energy state of building condition and temperature state; 3) Lifecycle energy consumption is aggregated based on Markov process and the state probability. A case study on predicting lifecycle energy consumption of a residential building is presented using the proposed model and the result is compared to that of a traditional deterministic model and three years' measured annual energy consumptions. It shows that the former model generates much narrower distribution than the latter model when compared to the measured data, which indicates improved result.

Keywords: lifecycle energy consumption, prediction, Markov chain, neural network.

Reference to this paper should be made as follows: Wang, E.; Shen, Z. 2013. Lifecycle energy consumption prediction of residential buildings by incorporating longitudinal uncertainties, *Journal of Civil Engineering and Management* 19(Supplement 1): S161–S171. <http://dx.doi.org/10.3846/13923730.2013.802744>

Introduction

A major challenge in estimating building's lifecycle energy consumption is how to adequately address the longitudinal variations of the parameters in the lifecycle energy consumption model. The longitudinal variation can be caused by the physical condition deterioration of the buildings (inner factor) and/or by the different weather conditions over the building's service life time.

In deterministic lifecycle energy consumption model, for each type of building, its lifecycle energy consumption can be simply expressed as (Fay *et al.* 2000; Junnila, Horvath 2003):

$$LEC = AEC \times BSL, \quad (1)$$

where: LEC represents lifecycle energy consumption; AEC represents annual energy Consumption; and BSL represents buildings' service life.

Building's annual energy consumption is often derived from a simple average of historical data (for existing buildings) or from simulations (for new buildings) with predefined parameters and boundary conditions. Building's service life, on the other hand, is often predetermined using fixed values such as 50, 75 or 100 years (Fay *et al.* 2000; Khasreen *et al.* 2009).

In reality, different buildings' annual energy consumptions vary considerably due to temporal and spatial variability of buildings and due to the differences in residential envelope thermal property, orientation, climate condition, occupants' behaviour and others (de Wilde *et al.* 2011; Guerra-Santin, Itard 2010; Tsikaloudaki *et al.* 2012; Wang *et al.* 2011a; Cole, Kernan 1996; Kaynakli 2011; Biekša *et al.* 2011).

The same is true of building's service life. Buildings' service lives vary from building to building and the corresponding range could be very large, due to the diversity in their design level, material use, workmanship quality, external climate, operational environment and maintenance level (Mc Duling 2006). For instance, according to the survey of the year 2009, the U.S. residential service lifetime is averaged to be 61 years but presents a wide 90% confidence range of 21 to 105 years. And building's service life's probabilistic distribution changes over time (Fig. 1) (Aktas, Bilec 2012).

Considering the existence of these variations developing a stochastic model that incorporates the identified uncertainties in both annual energy consumptions and building's service life is necessary (Trombe *et al.* 2012; de Wilde, Tian 2011) to improve the prediction of buildings' lifecycle energy consumptions.

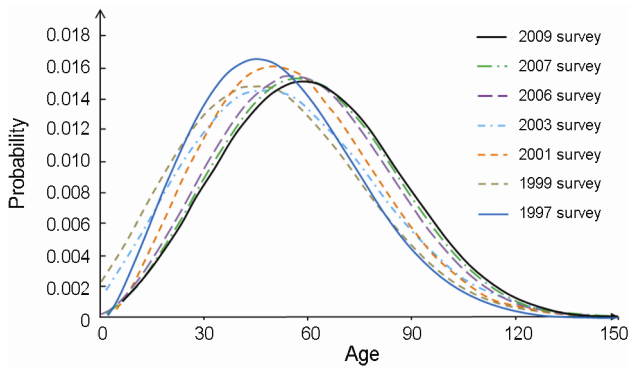


Fig. 1. The U.S. residential service life distributions (Modified on Aktas, Bilec 2012)

Models and approaches predicting periodical building energy use (e.g. hourly, daily, monthly or yearly) considering the differences of energy consumption influencers (e.g. building external envelope U-value, ambient climate, building area, and so forth) were proposed. They included regression analysis (Catalina *et al.* 2008), Fourier series models (Dhar *et al.* 1998), decision tree (Tso, Yau 2007), support vector machine and neural network (Zhao, Magoulès 2012).

Among of them, the neural network based artificial intelligence technique appears to be more accurate (Zhao, Magoulès 2012) due to its capability in adapting itself to the unforeseen pattern changes in the new available data (Catalina *et al.* 2008; Yalcintas, Akkurt 2005). Yalcintas and Akkurt (2005) applied neural network to predict the chiller energy consumption in a tropical climate using both climatic and chiller data. Two adaptive neural networks were proposed and tested by Yang *et al.* (2005) using simulated and measured data for building energy consumption prediction. Tso and Yau (2007) compared regression analysis, decision tree and neural network for the prediction of household electricity energy consumption in Hong Kong based on the electricity consumption survey data and obtained comparable results.

However, the existing models using neural network approach have significant limitations when applied to building's lifecycle energy consumption due to the lack of models to address the longitudinal variations of the input parameters (e.g. future residential condition, future ambient climate status, etc.), which are stochastic in nature (Mc Duling 2006; Hussain, Ansari 2010; Wang *et al.* 2011b; de Wilde *et al.* 2011).

For a specific building candidate, the short term occupants' behaviour (e.g. hourly) varies but can be predicted based on historical data (Wang *et al.* 2011b), nevertheless, the long term behaviour (e.g. yearly or for even longer period) is relatively steady (i.e. repeats from year to year) for the fixed occupants. But it is difficult to predict (de Wilde *et al.* 2011). As a result, in most cases, the longitudinal variation in buildings' annual energy consumption could be explained by building envelope thermal property and climate variation (Day, Karayiannis 1999; de Wilde *et al.* 2011; Zhao, Magoulès 2011; Kim, Moon 2009).

Markov Chain, as a stochastic modelling tool, is capable of providing the statistical properties of future state at a given point based on the current state of a random process with Markov property using the historical data by a series of mathematical operations (Ross 1996). Markov Chain technique has been extensively used for modelling longitudinal variability, e.g. the wind power fluctuations (Trombe *et al.* 2012), as well as the deterioration of infrastructures (Kamaitis 2009), building components (like roof) and the whole building (Camahan *et al.* 1987; Madanat *et al.* 1995; Riveros, Arredondo 2010; Mc Duling 2006; Coffelt *et al.* 2010; Jiang *et al.* 1988), through which their practical service lifetimes can be predicted. Air temperature changes can also be modelled by Markov Chain technique (Yang *et al.* 2011; Hussain, Ansari 2010; Jordan, Talkner 2000; Nicolis 1990; Stamp 2012).

Based on the existing models predicting periodical building energy use, and research on Markov Chain models handling stochastic phenomenon, a Markov Chain based model for projecting lifecycle energy consumption is proposed in the paper to address the longitudinal uncertainties in annual energy consumption, building's service life and the corresponding linear-average algorithm.

Four subtasks are included: 1) A building Markov deterioration model is established based on building condition assessment through which the practical building service lifetime is estimated; 2) The ambient temperature variation is simulated using Markov Chain by examining the transition of the degree day level; 3) The annual energy consumption distribution for each possible combination of building condition and degree-day level is projected through neural network technique based on a measured dataset; 4) The transition between the possible energy consumption state (i.e. joint states of building condition and degree day level) is determined by the transition probability matrices (TPMs) in the established building Markov deterioration model and the temperature transition model. The lifecycle energy consumption is then aggregated with probabilistic approach, which is an improvement over the simple liner-average algorithm in the deterministic models. A residential building case is presented using the proposed stochastic approach and the traditional deterministic approach. The probabilistic lifecycle energy consumption is calculated and is compared to the value of the deterministic approach.

1. Methodology

1.1. Markov Chain model

1.1.1. Markov Chain basics

Markov Chain model can be used for simulating the random process with Markov properties (Ross 1996): 1) Future states are unknown; 2) The next state depends only on the current state and is independent of the sequence of past events; 3) The transition probability between the states is constant over time. For a typical discrete-time stochastic process $\{X_{(t)}, t = 0, 1, 2, \dots\}$ with the discrete state space of $\{j_0, j_1, j_2, \dots\}$, the Markov Chain model can be mathematically described by:

$$p(X_{t+1} = j_{t+1} | X_t = j_t, X_{t-1} = j_{t-1}, \dots, X_1 = j_1, X_0 = j_0) = p(X_{t+1} = j_{t+1} | X_t = j_t), \quad (2)$$

where: $j_1, j_2, \dots, j_b, j_{t+1}$ are a finite number of possible states for X_t ; p is the conditional probability function.

Given the initial state vector is r , and P is the transition probability matrix (TPM), after n time steps in the stipulated period of τ , the condition vector p_n will be:

$$p_n = rP^{(n)} = rP^n = rP^{\tau/T}, \quad (3)$$

where: p_n is state vector with m elements at time step n ; T is the time interval of the observations.

The corresponding expected state is:

$$E(I_n) = \sum_{i=1}^m i * p_n(i), \quad (4)$$

where: $E(I_n)$ is the expected state; i is the state value; $p_n(i)$ is the probability for the system to take the value i .

1.1.2. Methods for deriving Transition Probability Matrices (TPMs)

The development of TPM is one essential component in using Markov Chain based models. Namely, the difficulty in determining transition probabilities has been recognized to be one of major barriers for the wide application of Markov chain based models (Ortiz-Garcia *et al.* 2006).

1) The conceptual approach – counting method

The conceptual way for deriving TPM is the counting method (Jiang *et al.* 1988; Ortiz-Garcia *et al.* 2006). The prerequisite for using counting method is the collection of the sufficient standard data that are the time-series data from the history of the same (or similar) target stochastic process during a relatively long observing period. The typical element of a TPM P can be calculated by the follows:

$$p_{a,b} = n_{a,b} / n_a, \quad (5)$$

where: $n_{a,b}$ is the counts of transitions from the state a to the state b ; n_a is the total counts of transitions going out from the state a .

2) The expected-value method

In most cases, sufficient standard data are not readily available which makes it infeasible to apply the counting method in deriving TPM. Several further methods have been developed for dealing with this type of data scarcity situations, like fuzzy logic artificial intelligence (Mc Duling 2006), ordered probit technique based method (Madanat *et al.* 1995), expected-value (or so called “linear regression”) method (Carnahan *et al.* 1987), expert judgment (Zhang *et al.* 2005), hybrid approach combining random sampling and regression (Riveros, Arredondo 2010) and so forth. All these methods have their own virtues and shortcomings. Among them, the one

easiest and frequently used has been the expected-value method (Carnahan *et al.* 1987; Riveros, Arredondo 2010; Agrawal *et al.* 2009; Jiang *et al.* 1988; Madanat *et al.* 1995; Ortiz-Garcia *et al.* 2006).

The detailed procedure of expected-value method for deriving TPM can be processed as follows (Carnahan *et al.* 1987; Ortiz-Garcia *et al.* 2006; Madanat *et al.* 1995):

Step 1: Choosing the residential buildings similar to the targeted one from data pool. This takes into account the fact that residential deterioration rate is a function of several previously stated explanatory variables (factors). These selected samples of distinct vintage present a series of residential condition ratings and age data.

Step 2: Using the (residential condition ratings) RCR as the dependent variable and the age as the independent variables to develop the following linear regression model:

$$RCR = \alpha + \beta * Age + \varepsilon, \quad (6)$$

where: α and β are the parameters to be determined; ε is random term for residuals.

Step 3: Using nonlinear optimization algorithm to estimate TPM by minimizing the distance measure between the estimated condition ratings from Eqn (6) and the expected condition ratings derived from the desired Markov chain model according to Eqn (4). The mathematical expression of the optimization process is shown in:

$$Z = \min \sum_{Age} (R\hat{C}R_{Age} - E(I_n)_{Age})^2$$

Subject to

$$0 \leq p_{ab} \leq 1; \quad a, b = 1, 2, \dots, m \quad (7)$$

$$\sum_{b=1}^m p_{ab} = 1; \quad a = 1, 2, \dots, m$$

where: $R\hat{C}R_{Age}$ and $E(I_n)_{Age}$ are the estimated RCR and the expected RCR at some age point derived from Eqns (6) and (4), respectively; m is the size of TPM.

1.2. Neural network model

Neural network models have been extensively utilized for nonlinear prediction in many cases through mimicking the neurophysiology properties of the biological neurons of the human brain (Yu *et al.* 2011). Specifically, it generally predicts the new events via the critical learning and training process on other existing events, especially useful in the situation of unknown relationship between the inputs and outputs (Tso, Yau 2007). A typical information processing unit in neural network is shown in Figure 2.

The feed-forward network in which the information flow only moves forward (from the input layer, through the hidden layer, finally to the output layer) is the most commonly used network type (Tso, Yau 2007). Its output error gradient is often calculated by back-propagation algorithm for learning and training process in which the weights of the inputs (Fig. 2) are updated and determined.

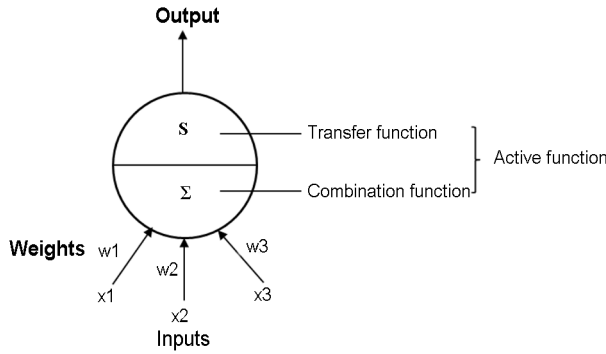


Fig. 2. Typical processing unit in neural network (Tso, Yau 2007)

The improved resilient back-propagation (iRPROP) training algorithm is one of the best and fastest neural network training methods and it often performs well in most cases based on its good ability of adaption (Igel, Husken 2000). The multilayer perception with iRPROP training is used for predicting the Energy Use Intensity (EUI) of the residential. The activation function for both hidden and output layers is sigmoid:

$$\text{Sigmoid}(x) = 1 / (1 + \exp(-x)). \quad (8)$$

The total number of the layers is often set to three (one input layer, one hidden layer and one output layer) (Yu *et al.* 2011).

1.3. Fuzzy C-Means Clustering

The state space for a typical Markov Chain is discrete and finite. Annual degree-day information (including heating degree-day and cooling degree-day) is usually continuous. To use Markov Chain for modelling degree-day level transition process, the clustering technique which is a mathematical algorithm for identifying the “nature” classes (clusters) of objects from data sets, is used for leveling the heating degree-day and cooling-degree-day information. Particularly, Fuzzy C-Means is adopted to avoid the rigid clustering problem (Dunn 1973) by minimizing the following objective function with the iterative algorithm until the desired criterion is satisfied:

$$\sum_{i=1}^C \sum_{j=1}^K \mu_{ji}^v \|A_j - C_i\|^2;$$

$$\mu_{ji} = 1 / \sum_{m=1}^C (\|A_j - C_i\| / \|A_j - C_m\|)^{2/(v-1)}; \quad (9)$$

$$C_i = (\sum_{j=1}^K \mu_{ji}^v A_j) / (\sum_{j=1}^K \mu_{ji}^v),$$

where: C is the number of cluster centres; K is the number of measured data points; v is weighting index (>1); A_j is the j^{th} measured data; C_i is the centre of the cluster I ; μ_{ji} is the degree of membership of A_j in the cluster I ; and $\|*\|$ is expressing the similarity between measured data and the centroid.

1.4. Stochastic lifecycle energy consumption model development

The proposed stochastic model consists of three sub-models (Fig. 3). The first sub-model is the building Markov deterioration model, through which, the building service life and the expected building condition at the specific time point can be computed. The second sub-model is the degree-day Markov transition model, via which the expected DD level around the building’s location at the specific time point can be forecasted. The third sub-model is the annual energy consumption Markov transition model used to calculate the expected energy consumption level and the lifecycle energy consumption within the predicted service lifetime.

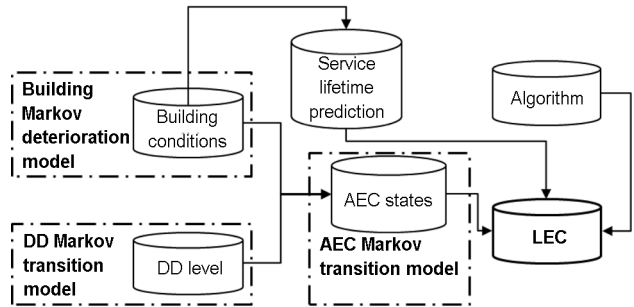


Fig. 3. The stochastic lifecycle energy consumption model (AEC represents Annual Energy Consumption; DD represents Degree-day; LEC represents Lifecycle Energy Consumption)

1.4.1. The building Markov deterioration model

Six-point scale building condition assessment system (Table 1) (Barry 2011) will be used for evaluating the building envelope condition and indicating the level of the thermal property. Although it is not accurate enough, it is still the mainstream approach due to its convenience (Straub 2009). Then the state space, which contains a set of possible building condition states, is defined as $S = \{6, 5, 4, 3, 2, 1\}$. For a specific building, the state value at some time point can be observed based on the predefined rating criteria. It is assumed that the building degradation process is continuous from the long trend perspective

Table 1. Building condition assessment table (Modified based on Straub 2009; Mc Duling 2006; Barry 2011)

Rating	Condition	Brief criteria
6	Excellent	“Like new” and only planned preventative maintenance is needed
5	Good	Degradation starts and planned and/or unplanned condition-based maintenance actions are needed
4	Fair	Object is still functional normally but medium repairs are needed to return its satisfactory condition
3	Poor	Object is still functional but major repairs are needed to return its satisfactory condition
2	Bad	Object is still functional but in need of rehabilitation to return its satisfactory condition
1	Very bad	Object is dysfunctional and needs to be replaced

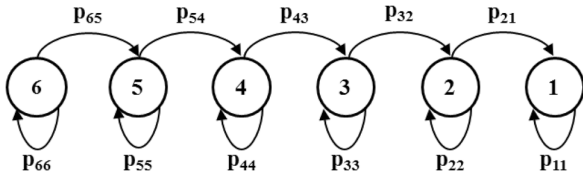


Fig. 4. Markov process for building deterioration

(Fig. 4), i.e. the building can only transit from a better state to its adjacent worse state in one time step (Coffelt *et al.* 2010; Mc Duling 2006). Building condition data is often supplied in the form of the same time point assessment on different building objects, which is similar to other structures, like pavement (Carnahan *et al.* 1987). Therefore, the transition probability matrix P can be obtained by the foregoing expected-value method. In this study, Matlab code on the basis of FMINCON function is made to implement the above nonlinear optimizing process. The expected building condition at specific time point can be calculated through following Eqns (3) and (4) and the service life can be predicted by defining targeted condition to be “3” (Fig. 5).

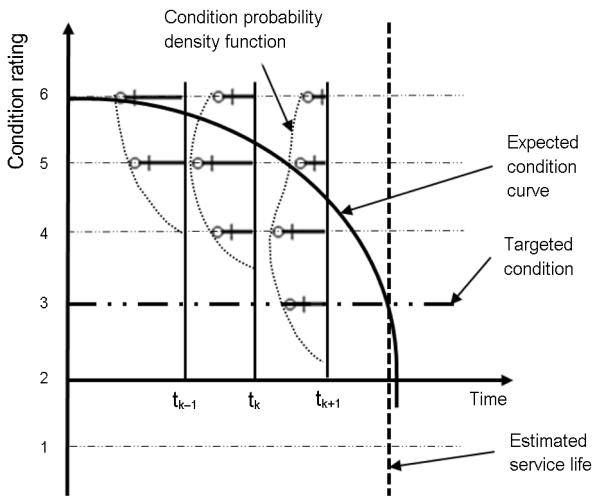


Fig. 5. Service life prediction (based on Hovde, Moser 2004)

1.4.2. The degree-day Markov transition model

Degree-days can be used to represent the ambient temperature level (Day, Karayiannis 1999). According to previous study, the longitudinal variation of degree-day can also be simulated by Markov Chain, an example can be seen in Figure 6 (Yang *et al.* 2011; Hussain, Ansari 2010; Jordan, Talkner 2000; Nicolis 1990; Stamp 2012). Before the model development, the annual degree-day needs to be classified into different classes (e.g. C_1, C_2, C_3, \dots) by clustering technique using heating degree-day and cooling degree-day to describe two-dimensional degree-day level. The transition probability between classes

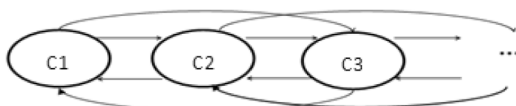


Fig. 6. Degree day transition process

can be obtained by the stated counting method. The expected degree-day level at specific time can also be calculated by Eqns (3) and (4).

1.4.3. The annual energy consumption Markov transition model

Building conditions and degree-day states are jointed to describe the possible annual energy consumption states (Fig. 7). The transition probability between the joint states can be computed by Eqn (10) assuming the annual building condition is independent of the degree-day state:

$$p(i, C_j | k, C_l) = p(i | k) * p(C_j | C_l), \quad (10)$$

where: i and k are building conditions; C_j and C_l are degree-day states.

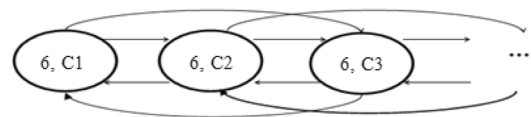


Fig. 7. Annual energy consumption transition process

Since many other factors, such as residential style, floor area and so forth, can also affect the energy consumption, for each fixed joint state, the probabilistic distribution of EUI will be generated through neural network by changing other influencing parameters. Then the lifecycle energy consumption can be calculated based on:

$$p_{E,y} = qP_E^{(y)}; E_y = \sum_{i,j} E_{i,C_j} * p_{E,y,i,C_j}; E_{total} = \sum_y E_y, \quad (11)$$

where: $p_{E,y}$ is state vector at time step y ; p_{E,y,i,C_j} is the probability for the system to take the state (i, C_j) ; P_E is the transition probability matrix; q is the initial state vector; E_y is the annual energy consumption at time step y ; E_{i,C_j} is the annual energy consumption for (i, C_j) ; E_{total} is lifecycle energy consumption.

1.5. Comparison and validation

Two indicators including the “shape” parameter which is the coefficient of variance (COV) and the “position” parameter which is $distance$ are used for measuring the difference between the resulting distributions. COV is a normalized indicator for measuring the dispersion of probability distribution. The larger COV value indicates the higher variability. $Distance$ is an indicator for measuring the position difference between intervals and the larger value means farther distance. COV can be calculated as:

$$COV = \text{Standard Deviation} / \text{Mean} \quad (12)$$

In particular, the distances between 10 and 90% certainty intervals of the resulting distributions are calculated. $Distance$ can be calculated as (Xu, Sun 2002; Wang *et al.* 2012):

$$D(I_p, I_q) = \sqrt{(V_q^L - V_p^L)^2 + (V_q^U - V_p^U)^2}, \quad (13)$$

where: I_p and I_q are intervals with the lower bounds V_p^L , V_q^L and the upper bounds V_p^U and V_q^U , respectively. In other words, $I_p = [V_p^L, V_p^U]$, $I_q = [V_q^L, V_q^U]$.

2. Case study

The case is to predict the probabilistic lifecycle energy consumption of a single-family detached house, with one floor of 107.95 m², one bathroom and three bedrooms, and full basement, using central air conditioning system, constructed in 1995. Currently, it is in excellent condition, located at Woodbine, Iowa. 1) The practical service lifetime of the building and the expected building condition at specific time are predicted by the developed building Markov deterioration model based on the historical condition record of similar buildings (from the local 480 residential samples data set); 2) The future temperature condition is estimated by Markov Chain model based on the local historical weather record; 3) The annual energy consumption variation is simulated as a joint process of the building deterioration and temperature change (i.e. the above two models); 4) To calculate annual energy consumption, the corresponding energy consumption probabilistic distribution for each joint state is estimated by neural network with the above available data set.

2.1. Service lifetime estimation

The observed building condition data for the buildings with different age are shown in Figure 8 and the statistical details are listed in Table 2. With these data, as is seen in Figure 9. The relationship between the condition rating and the building age is described by the following equation:

$$RCR = -0.0199 * Age + 5.2308. \quad (14)$$

The building deterioration matrix is then derived based on Eqns (7) and (14) as the follows:

Condition Rating	6	5	4	3	2	1
6	0.40	0.60	0.00	0.00	0.00	0.00
5	0.00	0.99	0.01	0.00	0.00	0.00
4	0.00	0.00	0.94	0.06	0.00	0.00
3	0.00	0.00	0.00	0.83	0.17	0.00
2	0.00	0.00	0.00	0.00	0.61	0.39
1	0.00	0.00	0.00	0.00	0.00	1.00

With Eqns (3) and (4), the expected condition at different time is calculated (Fig. 10). The case building is currently in the state of “6”. Accordingly, the service lifetime is estimated to be 89 years with the corresponding targeted condition of “3”, i.e. after 89 years, the residential will reach the condition below the rating “poor” and considered to be unfit for human habitation. This result is closer to the assumption of 100 years than 50 years and 75 years assumptions in the traditional approach, with the percentage error of 12%. The consideration of building renovation is beyond the scope of this

research due to the data availability issue and the extra difficulty in deriving the residential deterioration TPM.

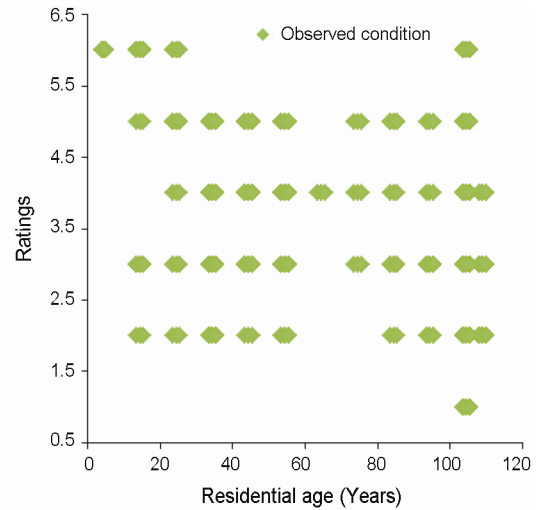


Fig. 8. Building condition rating versus building ages

Table 2. Frequency table with the variables of age and building condition

Age (Years)	Frequency	Residential Condition Rating (RCR)						Weighted Mean
		6	5	4	3	2	1	
4	2	2	0	0	0	0	0	6.00
14	16	11	1	0	3	1	0	5.12
24	11	2	5	1	2	1	0	4.45
34	41	0	14	4	17	6	0	3.63
44	30	0	13	8	8	1	0	4.10
54	19	0	5	7	6	1	0	3.84
64	1	0	0	1	0	0	0	4.00
74	3	0	1	1	1	0	0	4.00
84	8	0	5	1	1	1	0	4.25
94	9	0	1	1	5	2	0	3.11
104	161	8	31	28	35	56	3	3.32
108	8	0	0	3	2	3	0	3.00
Total	309	23	76	55	80	72	3	

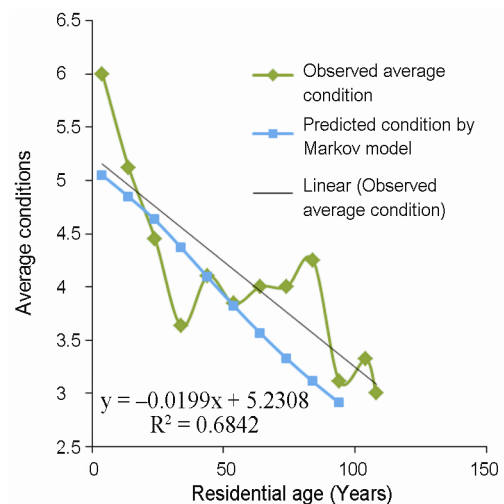


Fig. 9. Relationship between building's condition rating and age

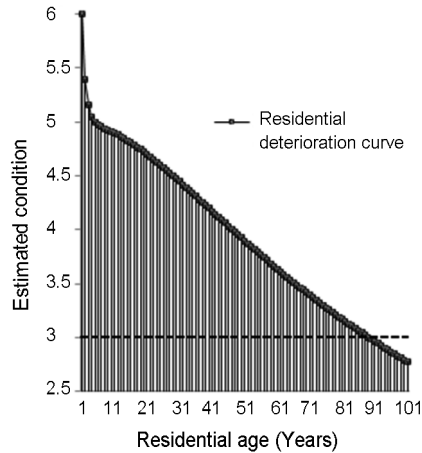


Fig. 10. Residential deterioration curve

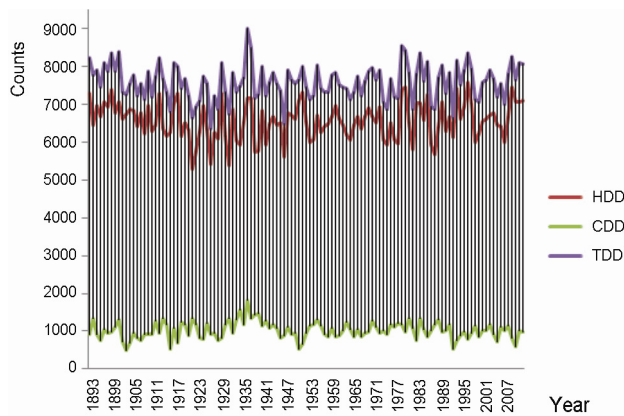


Fig. 11. Annual degree days profile in Woodbine, IA (HDD represents Heating Degree-Day; CDD represents Cooling Degree-Day; TDD represents Total Degree-Day)

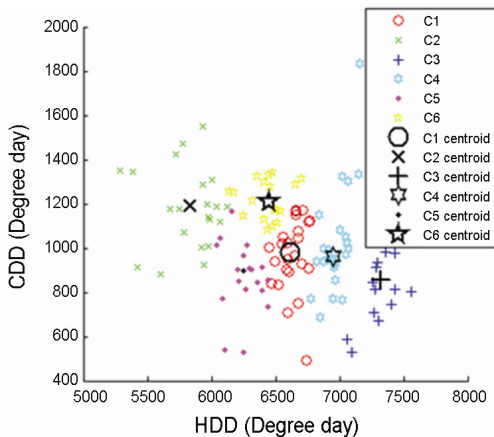


Fig. 12. Degree days clustering (6 classes)

2.2. Degree-day level variation

Longitudinal records for weather condition are relatively rich and thus counting method is useful for deriving degree-day level TPM. To make the referred period as complete as possible, the degree-day information of 119 years (1893–2011) is gathered from U.S. Cooperative Observer Program (COOP) Logan site which is around eight miles away from Woodbine, Iowa (UNL 2012). For the missing data, the most pertinent average value is used.

The degree-day profile is shown in Figure 11. It can be seen there is large variation in heating degree-day (43% error between the maximum and the minimum), cooling degree-day (274% error between the maximum and the minimum) and total degree-day (42% error between the maximum and the minimum). After degree-day information is grouped into six classes by Fuzzy C-Means clustering (Fig. 12), the degree-day level TPM is calculated with the counting method (Eqn (5)):

DD Level	C1	C2	C3	C4	C5	C6
C1	0.33	0.08	0.13	0.25	0.13	0.08
C2	0.10	0.33	0.05	0.14	0.14	0.24
C3	0.21	0.14	0.21	0.14	0.00	0.29
C4	0.17	0.17	0.13	0.22	0.22	0.09
C5	0.28	0.11	0.11	0.22	0.17	0.11
C6	0.11	0.22	0.06	0.22	0.22	0.17

2.3. Annual energy consumption TPM

As stated above, annual energy consumption transition process is the joint process of building deterioration and degree-day level transition. The 36 possible joint states are created (e.g. (6, C1), (6, C2), (6, C3)...). The transition probability between the joint states is derived based on the obtained building deteriorate rate and degree-day level transition probability via Eqn (10).

2.4. Energy distribution for the different joint states

For each building sample, the parameters including the construction year (e.g. 1900), the building style (e.g. 1.5 story), the square footage, the basement type (e.g. partial), the number of bedrooms and bathrooms, the building condition rating (e.g. excellent), the monthly electricity, gas consumption (from the year 2008 to the year 2010), and the corresponding monthly cooling degree-days, heating degree-days are collected. For convenient aggregation and comparison, the delivered energy is converted into the form of primary energy (with the conversion coefficients for electricity and gas being 3.412 and 1.027, respectively). The parameter EUI in terms of the annual primary energy is used as targeted output and the other parameters are adopted as inputs for neural network learning and predicting. From Figure 13, it can be seen there is large variation in EUI for the sampled buildings.

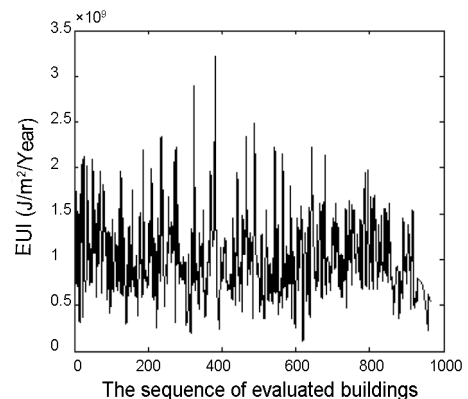


Fig. 13. Variation in Energy Use Intensity for the evaluated building samples (3 years data)

The simple traditional deterministic lifecycle energy consumption model will definitely produce the results with large errors. For each possible joint state, the probabilistic distribution of EUI is generated by changing the above input parameters, with the building style of one story.

2.5. Lifecycle energy consumption results of the proposed stochastic approach

Based on the estimated service life, using the annual energy consumption Markov transition model, the joint condition vector is obtained with the initial condition of (6, C4). Combining the probabilistic EUI distribution, the probabilistic EUI for each year is calculated and accumulated to the probabilistic lifecycle energy consumption (Figs 14 and 15). Normal distribution is fitted with mean value of 1.93×10^{11} J and the standard variation of 9.16×10^9 J. The COV value for the resulting lifecycle energy consumption is 0.05. The (10%, 90%) certainty interval is $(1.81 \times 10^{11}, 2.05 \times 10^{11})$ J, which means the resulting values lying in this interval takes up 80% of the all possible values.

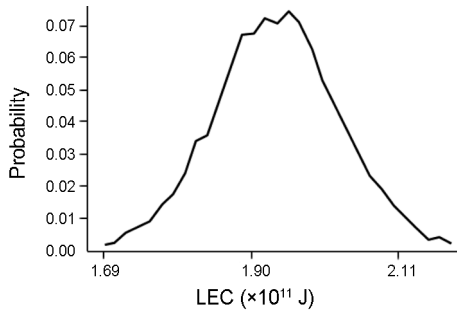


Fig. 14. Lifecycle energy consumption (Probability density function)

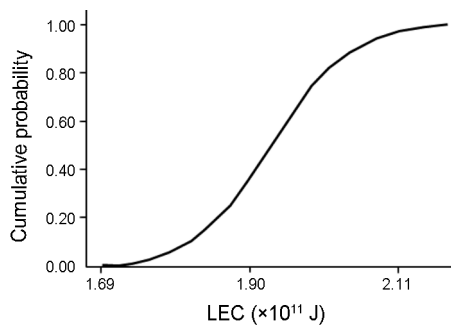


Fig. 15. Lifecycle energy consumption (Cumulative distribution function)

2.6. Comparing with the traditional approach

With the traditional approach, the uncertainty associated with the three scenarios (50 years, 75 years, and 100 years) results which are obtained according to the rule of taking deterministic EUI from similar buildings, is quantified (Figs 16 and 17). It is assumed that the chance of each EUI value in the data set for one story building is equal. From Figure 16, it can be seen that the resulting distributions are quite different from the one of the proposed stochastic model, with the COV of 0.37, which

means there is large uncertainty in the traditional approach result even with the fixed assumption of service lifetime. Therefore, the result of the deterministic result is very problematic. The proposed stochastic approach can produce the relative percentage decrements (RPD) of 86.5%, which is calculated using Eqn (15). It indicates that the proposed approach can significantly reduce the uncertainty in the lifecycle energy consumption result by simulating the longitudinal uncertainty in building condition and degree-day level through Markov Chain.

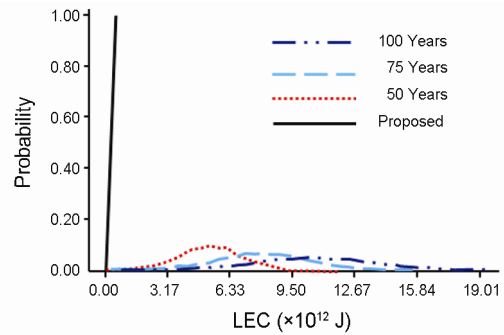


Fig. 16. Comparison of the results from different methods (Probability density function)

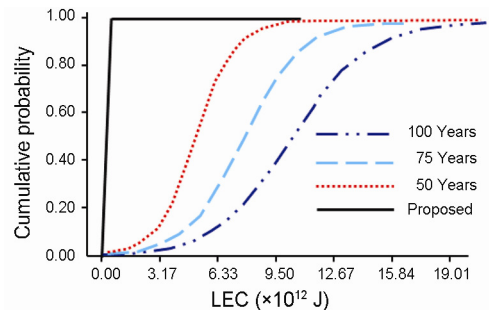


Fig. 17. Comparison of the results from different methods (Cumulative distribution function)

$$RPD = [(COV \text{ of the traditional approach result} - COV \text{ of the proposed stochastic approach result}) / COV \text{ of the traditional approach result}] \times 100\% \quad (15)$$

The 10–90% certainty interval distances between distributions are shown in Table 3, from which it can be seen that the result of the traditional approach with 50-year service life assumption is closer to that of the proposed stochastic approach (i.e. indicated by closer distance) although the predicted service lifetime is closer to the 100 years assumption.

Table 3. The 10–90% lifecycle energy consumption certainty interval distances

Distance ($D(I_p, I_q)$)	T_{50}	T_{75}	T_{100}
Distance to S ($\times 10^{12}$ J)	7.88	11.92	16.04

Notes: “S” denotes the proposed stochastic approach; “ T_{50} ” denotes the traditional approach with service lifetime of 50 years; “ T_{75} ” denotes the traditional approach with service lifetime of 75 years; “ T_{100} ” denotes the traditional approach with service lifetime of 100 years.

Theoretically, the proposed stochastic approach needs to be validated by checking the closeness between its resulting distribution and the practical measured lifecycle energy consumption data of the case building in terms of predefined criteria, such as *COV* and *distance*. This requires large amount of data within a long period (may be around 100 years), which is not practical and even impossible due to the data scarcity and long period constraint (de Wilde *et al.* 2011). A practical approach is to compare the available measured data for several years of annual energy consumption with the corresponding results of the traditional approach and the proposed stochastic approach. The random three years EUI data are used to perform validation. The annual EUI results for the years of 2008, 2009 and 2010 are mutually compared (Fig. 18). The average *COV* and *distance* results are shown in Table 4.

Table 4. Results (averaged) comparison for the annual Energy Use Intensity distributions

Measures	S	T	M
<i>COV</i>	0.08	0.36	0.16
<i>Distance</i> to S ($\times 10^8 \text{J/m}^2$)	0	4.81	1.18
<i>Distance</i> to M ($\times 10^8 \text{J/m}^2$)	1.18	3.79	0

Notes: “S” denotes the proposed stochastic approach; “T” denotes the traditional approach; “M” denotes the measured data.

As stated before, the validation remains a challenging task for most of the LCA (Life Cycle Assessment) related research. In this case, it is difficult to find the desired validation residential samples (with same floor area, same age, same structure and so on). Therefore, the measured data is only an approximate value. From Table 4, the distribution resulting from the proposed stochastic approach shows the smallest *COV* value which implies that the application of Markov Chain to model the longitudinal uncertainty in building condition and temperature change has reduced much uncertainty. It also appears that the proposed stochastic approach result is closer to the measured data in terms of *distance* value.

Conclusion

Accurate prediction of lifecycle energy consumption is critical for improving residential building LCA. Due to

the complex nature of building energy system, it is quite difficult to achieve such an accurate prediction regardless of the used approach (Zhao, Magoulès 2012). Traditionally, lifecycle energy consumption is often projected with deterministic linear-average approach which ignores the longitudinal variability of ambient temperature and the residential thermal condition. The presented study attempts to depict the updating building properties by a comprehensive term “Building Condition” with which the service lifetime is estimated and the overall thermal condition is indicated. The degree-day information is used to represent the temperature conditions. After the residential deterioration process and the temperature variation are separately modelled by Markov Chain, the annual energy consumption variation is modelled by jointing the above two Markov Chains with the joint state of building condition and degree-day level. The energy consumption for each joint state is estimated by neural network using the historical data record and fitted with probabilistic distribution, considering other factors, like basement type, number of bedrooms and so forth. Based on the joint Markov Chain and the energy distribution for each joint state, the lifecycle energy consumption is aggregated by probabilistic approach.

The case study shows the service lifetime assumption in the traditional approach is relatively arbitrary. This case residential shows the assumption of 100 years is more reasonable in the case area but it is not always the truth because many factors can affect the residential longevity. The traditional approach shows large uncertainty and unreliability which means the decision made based on the traditional approach is quite risky. The proposed stochastic approach can produce much narrower distribution and seems closer to the measured data, which indicates the longitudinal uncertainty in both building thermal condition and temperature can explain much uncertainty in residential energy performance variation. The final lifecycle energy consumption result distribution is closer to that of the traditional approach with 50 years assumption (not the 100 years consumption) because the deterministic EUIs adopted in the traditional approach are from the context of the extreme climate (with greater heating degree-day and cooling degree-day).

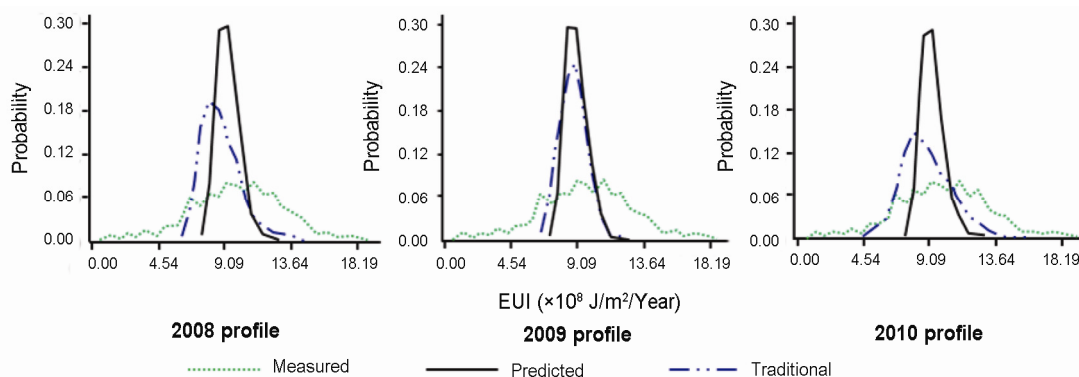


Fig. 18. Comparison of results of different approaches

The case study confirms the conclusion from de Wilde *et al.* (2011) that the stochastic approach is feasible but needs much reliable data and mathematical computations. As the number of Markov states increases, the computation burden becomes heavier. It also presents an example of the impact of product service lifetime on its LCA result. However, the prediction of the individual building service lifetime is still a challenging task and needs many assumptions (Aktas, Bilec 2012). Although Markov process based deterioration model appears better than other methods, there are still subjectivities in the process (Carnahan *et al.* 1987; Ortiz-Garcia *et al.* 2006; Madanat *et al.* 1995; Mc Duling 2006; de Wilde *et al.* 2011).

Limitations of the proposed model

Although the proposed approach improved the lifecycle operation energy prediction results, it only addresses variability of longitudinal building deterioration and degree days, which are primarily associated with the energy consumption of cooling and heating. Energy consumption variations due to different occupants' behaviours associated with home appliances electronic and electrical devices and equipment are not addressed in the proposed model. Totally different models are needed to deal with human factors in order to model such variations. It is our understanding that significant part of the differences between the measured results and the predicted results in Figure 18 can be explained by the omitted occupants' behaviour factors. Future study can be extended to combining both physical factors and occupants' behaviour factors in lifecycle energy consumption predictions.

Acknowledgement

The authors would like to thank US Environmental Protection Agency for the support through Grant CR-83419301-1.

Disclaimer

The U.S. Environmental Protection Agency, through its Office of Research and Development, funded and managed, or partially funded and collaborated in, the research described herein. Any opinions expressed in this paper are those of the author (s) and do not necessarily reflect the views of the Agency, therefore, no official endorsement should be inferred. Any mention of trade names or commercial products does not constitute endorsement or recommendation for use.

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