Using CO_2 Concentrations to Predict Energy Consumption in Homes

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ABSTRACT

The energy consumption in residential buildings is determined by both technical features and the occupants' behavior. The quantification of the occupants' contribution to the energy use is generally based on models that can be difficult to collect or only loosely associated to the level of occupant activity. In this paper we report on an investigation of using monitored carbon dioxide (CO_2) concentrations as a generalized parameter to predict occupant contribution to the variation in the energy consumption.

The energy consumption of an occupied single-family building was monitored during a heating-season. Collected data included indoor and outdoor temperatures, relative humidity, indoor CO_2 ratio and energy consumption for space heating, domestic equipment and water heating. The data were aggregated into daily averages and carefully investigated by a correlation analysis and a principal component analysis. One cluster of parameters was determined to be occupancy-related. An important parameter in this cluster was the monitored CO_2. Additionally, the CO_2 was found to be useable as input in a prediction model, based on a neural network.

We have compared two similar approaches — one approach with and one without access to the generalized CO_2 measure — for predicting the variation of the energy consumption. This evaluation indicates that the incorporation of CO_2 as a measure occupant activity improves the accuracy of the predicted energy consumption.

Introduction

The energy consumption for an occupied residential building is determined by both building technical features and occupant behavior. The building technical features can be obtained from the design stage or from measurements. The occupant-related energy consumption is most often treated more generally, since it can be difficult to predict. Also in the literature much attention isn't usually devoted to inhabitant influences on the variation of the energy consumption.

A multiple regression analysis indicated that inhabitants caused more than 80% of the variation in the heating load, of 87 single-family buildings in Sweden (Gaunt 1985). An investigation of the uncertainties in the energy consumption for Norwegian conditions indicated that, without knowledge of influences from the inhabitants, the total energy consumption could not be predicted more accurately than ±15-20% (Pettersen 1994). The corresponding uncertainty for heating demand was ±20-25% for buildings in cold Norwegian climates and ±35-40% for buildings in mild Norwegian climates.

There have also been studies attempted to analyze the predictability of occupancies end-use patterns. Time-series and standard deviation methods were applied on weekly end-use energy consumption in a University of Washington project (Emery and Gartland 1996). That model was based on measured indoor temperatures and energy end-uses patterns of four occupied buildings, which were measured during 1987-94. Also other methods of modeling these patterns can be applied for example simplified functional descriptions. Additionally, backpropagation neural networks have been applied to model the heating use for residential buildings (Olofsson, Andersson & Östin 1998).

Including descriptive parameters related to the occupants' behavior is important for modeling the energy consumption. For residential buildings it would be reasonable to expect that the indoor carbon dioxide (CO_2) ratio would be a good measure of the occupant's activity, since CO_2 is usually used for assessing outdoor air ventilation rates and indoor air quality in buildings. In buildings occupants are the main source of CO_2, which forms the basis for the 1 000 ppm guideline in (ASHRAE 1989).

In this work the possibility to model the occupancy related energy consumption for inhabited residential buildings was investigated based on an investigated set of parameters, including the CO_2 ratio. The investigated approach was based on principal component analysis and backpropagation neural networks.

Methodology

Data measurements

A single-family building was monitored during the time period 1995 to 1996 (Olofsson 97). One aim was to make an extensive measurement in order to study a model of the energy consumption based on the monitored parameter. The monitored building was an inhabited single story row house, built in 1974 and located in Umeå (700 km north of Stockholm, Sweden). The building was ventilated by a mechanical exhaust fan and the space heater and domestic hot water heater were both electric. The framework was made of wood, and the walls were insulated with 0.120 m mineral wool and the roof with 0.180 m. All windows were double-glazed with a double window frame. The floor area was 137 m^2 and the total UA-value was 189 W/°C.

The data were measured every 30 seconds and stored as half-hourly mean values. A Data Taker (DT100, version 3.4) data logger, manufactured by Data Electronics (Aust) Pty Ltd. handled acquisition of data. The Data Taker was running in standalone mode and a telephone modem was used to transfer data to a personal computer. A combined temperature/humidity gauge was installed in the kitchen, dining room, bedroom and bathroom. Vaisala Oy manufactured the gauge of type HMW 30 YB. The temperature sensor was a Pt 100 (1/3 DIN 43760 B) and the relative humidity sensor was an HUMICAP® H0062. T-type thermocouples (copper-constantan) were used for measurements of air and surface temperatures in the living room, the kitchen and outdoors. Measurements concerning supplied space heating demand, domestic hot water preparation and supply of electricity for domestic equipment, were performed with Cewe gauges, model Wh 3063/640, class 2 IEC 1036. A CO_2-ratio gauge, which was equipped with an IR-detector and manufactured by Mitec Electronic AB as Valtronic model 2089, was installed in the dining room, which was in the center of the building.

Further, measured data of seven additional single-family buildings in Umeå have been used in this work. The data were monitored during 1989 and 1990 and compiled in an earlier project (Jonsson and Östin 92). All measured buildings were built in the late 1960s and early 1970s. For some buildings the frameworks were made of wood and for the others of concrete. The floor area varied between 112 to 196 m^2, the UA-values varied between 90 to 200 W/°C and the total annual energy demand were in the range of 120 to 270 kWh per m^2 floor area, while 70 to 160 kWh per m^2 were used for space heating. Measured data were outdoor and indoor temperatures, space heating demand, domestic hot water heating demand and energy demand for different apparatus.

Artificial Neural Networks

Neural networks have drawn attention for their capability to learn complex non-linear dependencies without any preconceptions of intrinsic relations in the processed data. Instead of demanding any explicit rules or knowledge the rules are included in the system (Pao 89; Wasserman 89; Wasserman 93). There are many different neural networks. In this work we investigated backpropagation networks updated with the generalized delta rule.

The backpropagation algorithm, which represents a training procedure, can be applied to neural network structures consisting of arranged connected neurones, or processing elements (PE). In figure 1 an example of a neural network structure is shown. It consists of three layers; input, hidden and output layer. Input data are fed into the input layer, through the network of connected PE's, to the output layer.

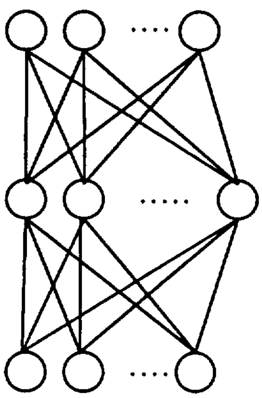

Figure 1. A schematic neural network structure with processing elements arranged in output, hidden and input layers.

Each PE in the network receives a signal (S), which is a weighted sum of (k) values of the transferred functions (I^k) from the PE's in the previous layer. The influence I^k from each PE is handled by the adjustable weighting factor (w^k) according to

$$S = \sum_k w^k I^k \tag{5}$$

Each obtained output ($\mathbf{I}$) in the output layer is compared with a desired output ($\mathbf{D}$). A correction of the values of the weights are calculated from the deviation between the desired and the actual output and the derivative (T') of the transfer function as

$$\mathbf{E} = T'(S)(\mathbf{D} - \mathbf{I}) \tag{6}$$

The correction **E** is used to adjust the weights backward through the network. After the correction process the input values can be transferred again and a new set of outputs is obtained. The process of adjusting the weights backwards is repeated until the correction value is less than a pre-defined limit. Then, the weights are fixed and a new set of data is fed through the network. This final step, called testing, represents the estimation process.

In the literature it can be found that backpropagation neural networks have been applied in a large number of fields, e.g. signal processing, pattern recognition and classification, but also for building energy demand predictions. In (Kreider & Wang 91) neural network techniques were used to model the energy demand for an office building. Neural network applications have also been used in HVAC-control systems in an office building (Curtiss, Kreider and Brandenmuehl 94) for optimizing the energy demand. In a building energy prediction evaluation organized by ASHRAE in 1993, called The Great Energy Predictor Shoot-out I, (Kreider & Haberl 94) five of the six most successful models used different neural network techniques. The winner of the competition (MacKay 94) used a model based on preprocessing the environmental input data set.

Principal Component Analysis

Principal component analysis (PCA) is a method that can be used when there is intercorrelations among independent multivariate parameters. The PCA obtains a coordinate transformation of a multivariate data set to a new set of orthogonal parameters. The transformed dataset describes most of the variation of the original dataset in a smaller number of parameters. The new set of parameters, or principal components (PC), are defined with a decreasing order of importance, from the first to the last.

Suppose a p-dimensional variable $X^T=(X_1,X_2,\ldots,X_p)$ with mean μ and covariance matrix Σ. The transformation of X^T can be described as an orthogonal rotation (Chatfield & Collins 92). The new set of variables $Y^T=(Y_1, Y_2,\ldots, Y_p)$ is linear combinations of the X:s according to

$$Y_j = a_{1j}X_1 + a_{2j}X_2 + \ldots + a_{pj}X_p = \mathbf{a}_j^T\mathbf{X} \quad (1)$$

where the vector of constants $\mathbf{a}_j^T=(a_{1j},a_{2j},\ldots,a_{pj})$ is orthonormal, i.e. $\mathbf{a}_j^T\mathbf{a}_j=1$. The principal components, Y_j, are uncorrelated with decreasing variance. Thus, the first principal component Y_1, or PC1, can be found by choosing an $\mathbf{a}_1$ that maximizes the variance of Y_j. Using equation (1) and by introducing Σ the variance can be given by

$$Var(Y_1) = Var(\mathbf{a}_1^T X) = \mathbf{a}_1^T \Sigma \mathbf{a}_1 \quad (2)$$

By applying the method of Lagranges multipliers it can be found that $(\Sigma-\lambda_j)\mathbf{a}_j=0$. Further, it can be assumed that Σ has p eigenvalues, or latent roots, which are defined according to $\lambda_1>\lambda_2>\ldots>\lambda_p\geq 0$. Thus, equation (2) can be written as

$$Var(Y_1) = a_1^T(\lambda_1 a_1) = \lambda_1 \quad (3)$$

The second principal component, PC2, with an eigenvalue equal to λ_2, is an orthogonal vector to PC1. PC2 is found with the same method and the procedure can be repeated until the last orthogonal PC is defined. A scaled vector of the properties of the investigated parameter with respect to the principal components is given by the component loadings defined as $\mathbf{a}_j$*. It is possible to obtained $\mathbf{a}_j$* by scaling $\mathbf{a}_j$ according to

$$\mathbf{a}_j^* = \sqrt{\lambda_j}\,\mathbf{a}_j \tag{4}$$

If the component loadings are added in a matrix $\mathbf{C}=(\mathbf{a}_1^*,\mathbf{a}_2^*,..,\mathbf{a}_p^*)$ the definition of Σ is given by $\Sigma=\mathbf{C}\mathbf{C}^T$.

PCA has been applied in different fields, see for example (Reddy 95; Ruch 93; Madsen 93) for guidance of how to reduce the number of modeled physical variables and also to describe the most significant explanation in a fewer number of transformed PC's. Measured building performance data are often noisy and PCA has additionally been used in order to reduce the noise.

Model

The energy consumption for a residential family building can be modeled from factors related to the technical features and the influences of the occupant's behavior. A certain interest in this work concerns a description of the occupants' influences on the energy consumption. Based on the monitored building, the supplied electricity for domestic equipment $P_{el}(t)$ and the demand for hot water preparation $P_{DHW}(t)$, can be described as occupant related energy consumption. The sum of these two parameters is defined as the domestic heat load $P_{dom}(t)$.

The following investigation for describing the occupants' influences on the energy consumption is based on daily average values of the parameters of the monitored single-family building, which were measured during the heating season 1995 and 1996. Based on a preliminary analysis the following nine parameters were selected for further investigation:

x1: The difference between average T_{IA} and T_{EA}, (θ).
x2: Measured indoor air CO_2-ratio, CO_2.
x3: The indoor average relative humidity, (RH).
x4: An annual sinusoidal distribution of solar irradiation, (I_S).
x5: A typical weekly distribution of inhabitant activity, (I_W).
x6: Supplied load for electrical equipment, $P_{el}(t)$.
x7: Supplied load for domestic hot water preparation, $P_{DHW}(t)$.
x8: Supplied domestic load, $P_{dom}(t)$.
x9: Supplied space-heating load, ($P_{heat}(t)$).

The first step in the investigation determined if some groupings were identifiable in the chosen set of parameters. This identification was based on an analysis of the correlation matrix. If this analysis indicated on clusters, the next step for eliminating original parameters contributing relatively little information would be a PCA. The PCA was used to minimize the dimensionallity, i.e. the number of variables, since PC1 includes as much as possible of the variation in the original data set, PC2 as much as possible of the residual variation and so on. It is important to notice that the elimination of the latter PC's assumes small variances. This variance can be indicated by an examination of λ_j, which also can give an indication of the effective dimensionallity of the original data. Based on the PC's, that have relatively high variances, the explanation in the original variables can be investigated from the component loadings. Thus, the examined PC's can confirm and indicate if certain parameters may be clustered and if the clusters are related to either influences of technical features or influences of occupants behavior.

The last step in this analysis concerned the cluster describing the occupant-related energy consumption. Parameters from this cluster were used for predictions, which were based on neural networks. The investigated models were used to predict $P_{dom}(t)$. All predictions concerned the annual variation and were based on access to daily averages of a short time period, typically 3-5 weeks. This test concerns two approaches of models. In the first approach no access were presumed to the measured CO_2 for the reference building. In the second approach the measured CO_2 parameter was included. For a more detailed description of the implementation of parameters and the training and testing of the neural networks, see (Olofsson, Andersson & Östin 98).

Results

Based on the introduced procedure the correlation matrix was calculated for the suggested nine parameters, in order to get a first indication of eventual groupings of variables. A rather high correlation is found between *x1*, *x4* and *x9*, i.e., θ , I_s and $P_{heat}(t)$, see table 1. The relatively high correlation between *x2* and *x6*, i.e., CO_2 and $P_{el}(t)$, is also noticeable.

***Table 1.** The correlation matrix calculated for the investigated nine parameters.*

	x1	*x2*	*x3*	*x4*	*x5*	*x6*	*x7*	*x8*	*x9*
x1	1.000								
x2	0.241	1.000							
x3	-0.671	0.184	1.000						
x4	0.828	0.400	-0.424	1.000					
x5	-0.032	0.415	0.123	0.036	1.000				
x6	0.468	0.703	-0.220	0.494	0.377	1.000			
x7	-0.185	-0.013	0.199	-0.168	-0.069	-0.024	1.000		
x8	0.290	0.242	-0.201	0.287	0.076	0.365	-0.002	1.000	
x9	0.860	0.189	-0.704	0.770	-0.024	0.451	-0.154	0.319	1.000

Since the correlation matrix indicates some obvious groupings a PCA was carried out both in order to confirm and to get further indications of eventual patterns in the data set. The result of the investigation of the principal components is presented in figure 2 as two plots. In the first plot values of λ_j are shown in percentage of the total variance minus a noise limit, which is defined at 12.5%. In the investigated data set two latent roots were found above the limit of noise, defined at 0% in figure 2. This indicates that the first two PC's can be considered for further investigations and the latter PC's can be excluded, since they contain too little description and too much noise.

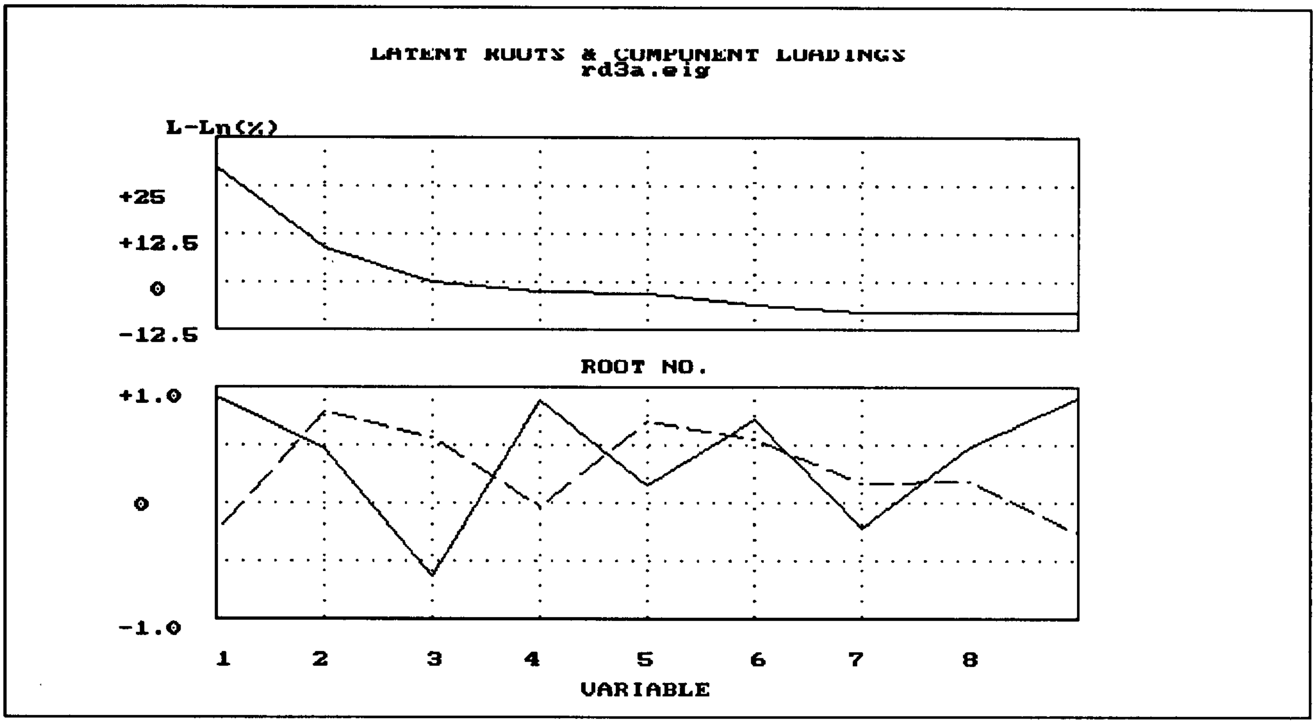

***Figure 2.** Results of a PCA for the parameters of the investigated building. Values of λ_j minus a defined limit of noise are presented for each PC in the upper plot, where PC1 is the first root to the left and PC9 is the last root to the right. In the lower plot the component loading is shown for variable x1 to x9, from the left to the right on the x-axis.*

The second plot in figure 2 presents the component loading, i.e., the properties of each parameter with respect to the principal components, where PC1 is plotted as a solid line and PC2 as a dashed line. The first PC, PC1, seems to be rather dependent on *x1*, *x4* and *x9*, i.e., θ , I_s and $P_{heat}(t)$. This is in agreement with the correlation matrix, see table 1. The second PC, PC2, is dependent on the parameters *x2*, *x5* and *x6*, i.e., CO_2, I_w and $P_{el}(t)$. Also this is in agreement with the correlation analysis, although I_w then was less correlated. This analysis shows that PC1 mainly depends on variables that can be grouped as specific for the climate impact on the supplied heat load. Additionally, it is shown that PC2 depends on variables that reflect influences of the activities of the inhabitants living in the building.

Based on the indications achieved from both the correlation analysis and the PCA, two parameters describing occupancy have been distinguished: CO_2 and $P_{el}(t)$. A next question would then be if CO_2 can be used in order to predict the variation of $P_{el}(t)$, which in this work was investigated based on a neural network model. The used neural network, which consisted of two hidden layers of 2x10 PE:s, was trained using CO_2 and I_w as inputs in order to predict the variation of $P_{el}(t)$. The model was trained on daily average data from one month and tested on a data set including the first six months of 1996. The predicted $P_{el}(t)$ was well adapted to most of the short time fluctuations, as seen in figure 3. The RMS for measured and predicted $P_{el}(t)$ was for the investigated periods better than 5%. Thus, one indication from this analysis is that knowledge of the variation of CO_2 can be useful for predicting $P_{el}(t)$.

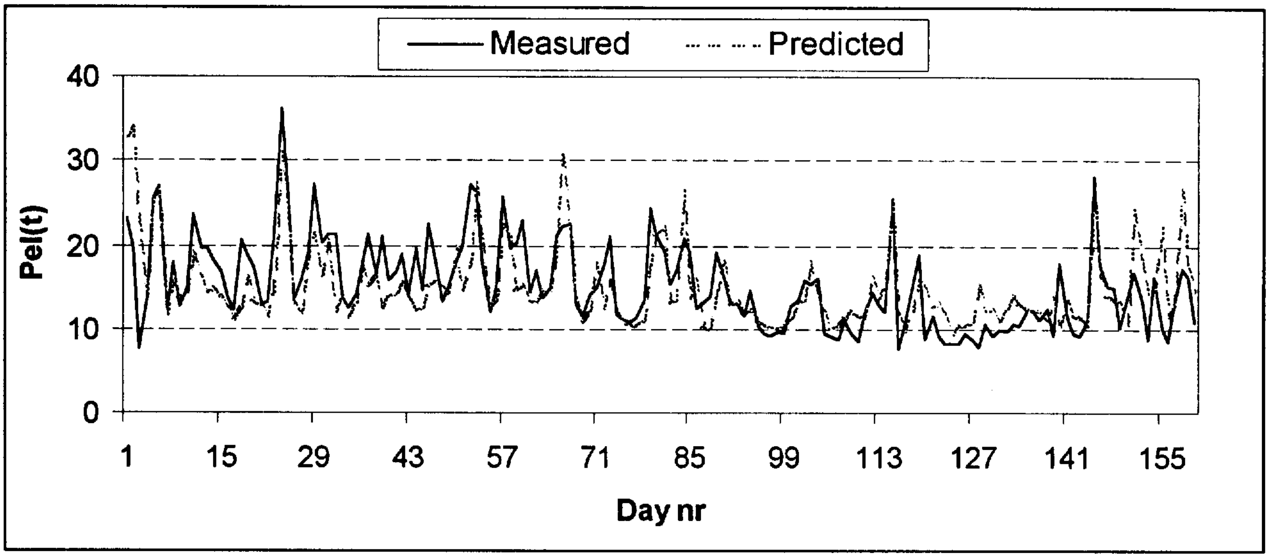

Figure 3. Measured and predicted $P_{el}(t)$ based on data from May, i.e. day number 100 to 115.

As mentioned earlier $P_{dom}(t)$ is the sum of $P_{DHW}(t)$ and $P_{el}(t)$. From the correlation analysis and PCA presented above, we noticed that $P_{dom}(t)$ is not as strongly correlated to CO_2 as $P_{el}(t)$. However, in order to investigate if the use of a generalized model of CO_2 would also improve the annual prediction of $P_{dom}(t)$ two somewhat similar approaches to model the domestic load in buildings are included in this work. One approach with and one without access to monitored CO_2. For both approaches a neural network model was used, in order to predict the domestic load based for the set of buildings measured during the heating season 1989/1990.

No access to CO_2 was included in the first approach. Measured temperatures and I_S, were used as inputs in a neural network model in order to predict $P_{dom}(t)$ (Andersson, Olofsson & Östin 1996). The model was based on implanted PC:s of T_{EA}, T_{IA}, I_S and $P_{dom}(t)$ of a similar reference building measured during the same heating time period. Thus, an indirect generalization of the dependency between the parameters was achieved. From this investigation the deviation between the predicted supplied heating load $P_{dom}(t)_{NN}$ and the measured supplied heating load $P_{dom}(t)$, $[P_{dom}(t)_{NN}/P_{dom}(t)-1]$, is shown in the left histogram in figure 4.

The detailed measurements of the new reference building with access to CO_2 were used as reference performance data for the second approach. As inputs T_{EA}, T_{IA}, I_S, $P_{dom}(t)$, CO_2 and I_W were used, transformed to PC's and implemented in the neural network model (Olofsson, Andersson & Östin 1998). This model was tested on buildings without access to the measured CO_2-ratio. The results of applying this approach are presented in the right histogram in figure 4.

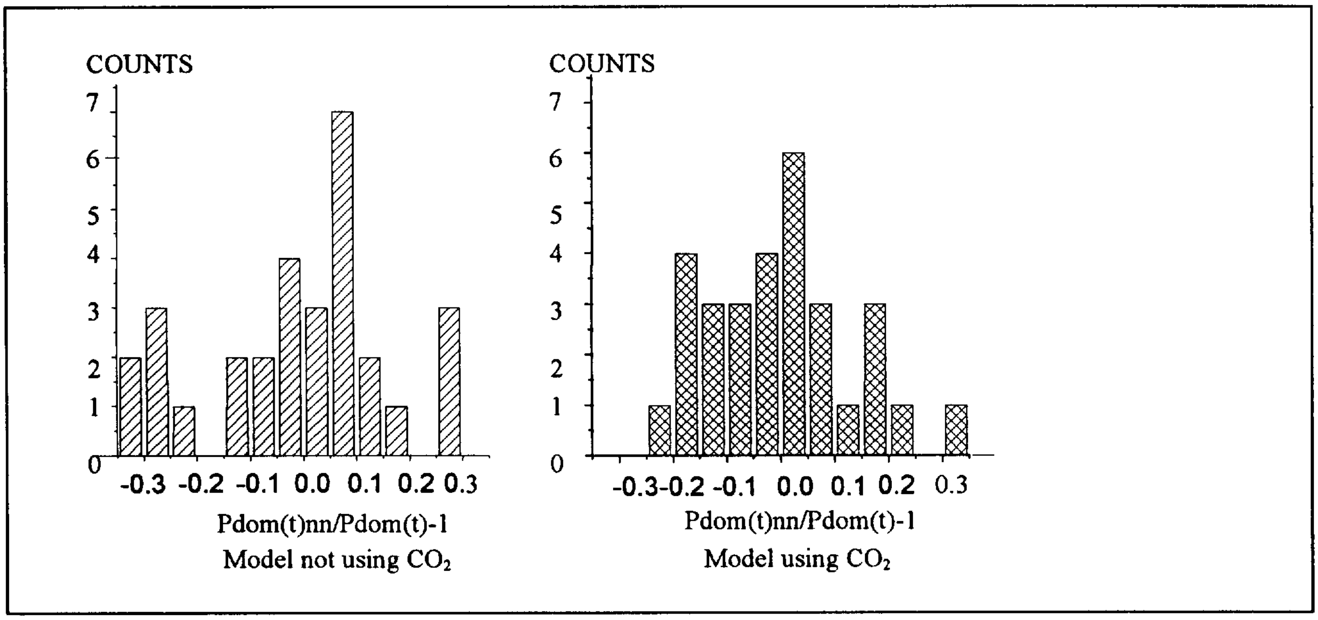

***Figure 4.** The deviation between predicted supplied heating load $P_{dom}(t)_{NN}$ and measured supplied heating load $P_{dom}(t)$, $[P_{dom}(t)_{NN}/P_{dom}(t)-1]$ is shown on the x-axis and number of periods on the y-axis.*

The distribution of the average accuracy was improved from a maximum deviation of about ±0.3 in the left histogram, figure 4, to ±0.2 in the right histogram. The more accurate and stable estimations of the domestic load were obtained from the model based on data including the generalized model of CO_2. Although the two approaches are not fully compatible, it is reasonable to believe that an important part of the improvement is due to the incorporation of a social activity parameter, in terms of CO_2.

Conclusions

An investigation has been made of measured data based on a daily average of a monitored residential building. This investigation included a correlation analysis and a PCA. From this investigation two clusters were identified. One cluster was more related to building technical features and the other to the occupants' behavior. From the second cluster it was indicated that CO_2 could be a good descriptor of the occupied related energy consumption. This was also confirmed from a test of prediction with a neural network.

Additionally, two different approaches were investigated in order to predict the annual variation of $P_{dom}(t)$ (i.e. the sum of $P_{DHW}(t)$ and $P_{el}(t)$), one approach with and one without access to a general description of CO_2. Both approaches were based on neural networks and the aim was to investigate if using CO2 could indicate eventual improvements. The approaches were based on measurements in different reference buildings and are not fully compatible. However, the estimations were made on the same measured data sets. In this investigation the range of the average accuracy was improved from ±0.3 to ±0.2 by using the approach including a generalization of CO_2. This we take as an indication that CO_2 could be used as a measure of the inhabitant activity.

In the future it will be of interest to investigate the model based on a more diverse set of residential buildings, concerning both building type and climate, which all have access to monitored CO_2. In this study the investigated models assumed access to daily averages of CO_2. Thus it is reasonable to expect that the predicted accuracy will be improved based on shorter time periods than daily averages. An additional matter to consider is that the modeled buildings had a rather constant ventilation rate. A more random variation of the ventilation rate would adversely effect the CO_2 rate as a measure of occupant activity.

Finally, it is of importance to notice that this study was performed on buildings located in northern Sweden, where the climate is relatively cold. Energy consumption in these buildings is dominated by the heating demand and the domestic load will represent a minor contribution to the heating. Conditions are different in warmer climates, where the relative contribution of the domestic load of buildings to the heating load is larger. Thus, the relevance of studying the domestic load may be even more important and the use of a generalized model including CO_2 would be a topic for later studies.

Acknowledgments

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