Analysis of Heating Expenses in a Large Social Housing Stock Using Artificial Neural Networks

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Abstract: This paper presents an analysis of heating expenses in a large social housing stock in the North of France. An artificial neural network (ANN) approach is taken for the analysis of heating consumption data collected over four years in 84 social housing residences containing 13,179 dwellings that use collective heating. Analysis provides an understanding of the influence of both physical and socio-economic parameters on heating expenses and proposes a predictive model for these expenses. The model shows that the heating expenses are influenced by both the buildings' physical parameters and social indicators. Concerning the physical parameters, the most important indicators are the area of the dwellings, followed by the building age and the DPE (energy performance diagnostic). The family size as well as tenant age and income have an important influence on heating expense. The model is then used for establishing a data-based strategy for social housing stock renovation.

Keywords: social housing; heating expenses; artificial neural network; income; energy performance diagnostic; savings; renovation

1. Introduction

The social housing sector in France has an important social and economic role. It includes 4.6 million units and accounts for 17% of all housing. The current expenses in this sector constitutes around 35% of the tenant's budget. However, 35% of the social housing tenants currently live below the poverty line. In the period between 1991 and 2011, the running costs in the social housing in France increased by around 60% [1].

Furthermore, the authorities in France consider the reduction of CO_2 emissions as a top priority. In France, the 2007 political debate, known as Grenelle de l'environnement, led to legislation in the form of the Grenelle I Act and the Grenelle II Act, which set specific targets to reduce CO_2 emissions [1].

The reduction of heating expenses in social housing constitutes a major socio-economic and environmental challenge. It requires an important effort for the renovation of the aging stock to meet today's sustainability requirement. Involvement of tenants in this effort is necessary because their behavior largely influences the energy consumption [2–5].

The authors of [6,7] conclude that energy efficiency cannot be achieved without addressing the human factor, especially in social housing [8].

Other studies focus more on the relation between energy or heating consumption and technical issues such as special insolation, the building direction, and the type of heating [9,10].

Social housing managers need cost–benefit analysis or predictive models to establish strategies for the reduction of energy consumption [11].

Statistical assessments of energy consumption provide tools for consumers to efficiently manage their energy loads [12].

Prediction of the social housing energy consumption should take into consideration both the physical and socio-economic indicators. The consideration of these parameters in an inclusive model requires the use of an advanced method such as an artificial neural network (ANN). This approach has been successfully used in analyzing energy modeling consumptions.

Tso and Yau used the ANN approach for electricity consumption analysis [13]. Hamsacebi used the ANN approach to forecast Turkey's electricity consumption [14]. Koksal and Ugursal developed an ANN-based model for energy consumption in a residential sector [15]. Aydinalp et al. used the ANN method to analyze the energy consumption in a residential sector [16].

In this paper, the ANN approach is used to analyze the influence of building characteristics and socio-economic indicators on the energy consumption in a large stock of social housing composed of 84 residences containing 13,179 dwellings that use collective heating. The analysis aims at exploring the influence of both physical and socio-economic indicators on the energy consumption and at developing a predictive model that takes building characteristics and socio-economic factors into consideration. This model is then used to establish a renovation strategy to reduce energy consumption in the social housing stock.

2. Presentation of the Social Housing Stock

The social housing stock is managed by Lille Metropole Habitat (LMH). It is composed of 353 collective residences that contain 29,778 dwellings. Figure 1 shows the history of the construction of this stock. The major part of this stick was built before 1978, particularly in years 1950, 1968, 1970, 1973, 1975, 1976, 1977, and 1978. About 52% of this stock uses collective heating, while 40% uses individual heating, and only 8% uses a mixed heating system. The analysis presented in this paper concerned 84 residences (13,179 dwellings) that use collective heating.
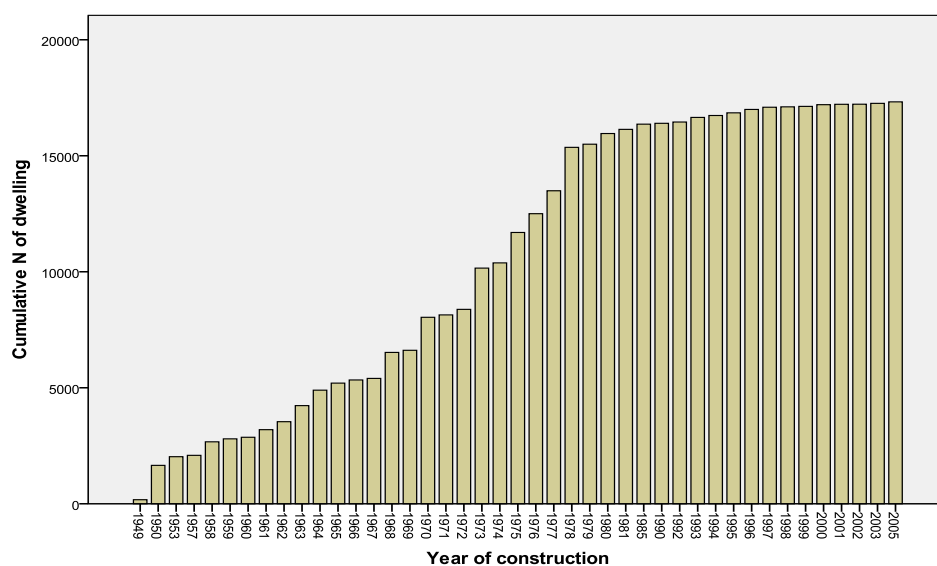

Figure 1. History of construction of the Lille Metropole Habitat (LMH) social housing stock (cumulative).

Table 1 summarizes the indicators, provided by LMH, that are used in the analysis of the heating expenses. Concerning the buildings physical characteristics, LMH provided the following indicators: energy performance diagnostic (DPE), building age, dwelling area, and number of floors. It is well-known that the first two indicators have a direct influence on heating expenses. The last two parameters are usually not used in analyses of energy performance. Our analysis of heating expenses provides more information about the pertinence of these parameters.

Table 1. Indicators used in the analysis of heating expenses in social housing.

Physical Indicators	Socio-Economic Indicators
Energy Performance Diagnostic (DPE)	Tenant age
Dwelling area	Family size
Building age	Tenant income
Number of floors	

The socio-economic indicators are tenant age, family size, and tenant income. These parameters influence a tenant's behavior, which influences their energy consumption [17].

3. The Use of the ANN Approach for Energy Expenses Modeling

3.1. The Presentation of the ANN Approach

The ANN approach is inspired by the ability of the human brain to predict patterns based on learning and recalling processes [18]. This approach is largely used for modeling complex physical or social phenomena. It allows the construction of relationships between input variables (parameters affecting the phenomena) and output variables (parameters describing the phenomena) and includes artificial neurons known as "processing elements," "nodes," or "neurons." Processing elements in ANN models are usually arranged in layers: an input layer, an output layer, and one or more intermediate layers called hidden layers.

A three-layer back-propagation neural network is used in this paper. This model is based on the following equation:

$$Y_k = S\left(\sum_{j=1}^{m} W_{jk} \times S\left(\sum_{i=1}^{n} W_{ij} X_i\right)\right)$$

where Y_k stands for the output values and X_i denotes the input values; W_{ij} designates the weights of connection between the input layer and the hidden layer; W_{jk} stands for the weights of connection between the hidden layer and the output layer. The sigmoid transfer function used is as follows:

$$S(X) = \frac{1}{1 + e^{-X}}$$

The determination of the network architecture constitutes a major task in the use of the ANN. The overall performance of an ANN model depends on the numbers of hidden layers and nodes. The optimal ANN structure is generally achieved by exploring different ANN configurations [19]. It has been shown that one hidden layer is sufficient for approximating any continuous function [20]. The authors of [21] argue that a single hidden layer of neurons, operating a sigmoidal activation function, is adequate for modeling any solution surface of practical interest. In some applications, one hidden layer is commonly used [22]. Analyses presented in the paper were conducted using one or two hidden layers. The optimal configuration was identified by exploring different ANN scenarios. The performance of the ANN modeling is assessed using an R^2 criterion:

$$R^2 = 1 - \frac{\frac{1}{N}\sum_{i=1}^{n}(T_i - Y_i)^2}{\frac{1}{N-1}\sum_{i=1}^{n}(T_i - \bar{T}_i)}.$$

Ti and *Yi* stands for the target, T_i, and the predicted values, respectively.

The ANN analyses presented in this paper were conducted using SPSS, version 20.

3.2. Determination of the ANN Architecture

The use of the ANN approach is based on splitting data into three sets:

- the training set, which is used to train the ANN model and to adjust the connection weights;

- the testing set, which measures the ability of the model to be generalized; and
- the holdout set, which is used to determine the performances of the ANN model on patterns, which were not used in the previous two phases.

For the determination of the optimal data repartition, the ANN method was used with five repartition models. Table 2 summarizes the results obtained with these models. It shows that Model 5 provides the best results. It uses the following repartition: 74% for training, 18% for testing, and 8% for validation.

Table 2. Determination of the optimal data repartition in artificial neural network (ANN) modeling.

Model	% of Training	% of Testing	% of Holdout	R^2
1	50	25	25	0.71
2	70	30	0	0.58
3	100	0	0	0.72
4	66	26	8	0.67
5	74	18	8	0.74

Table 3 and Figure 2 summarize results obtained with five configurations of the ANN model. They show an important influence of the ANN architecture on modeling performances. Best results are obtained with the configuration B2, which includes one hidden layer and five nodes.

Table 3. Configurations used for the determination of the optimal ANN architecture.

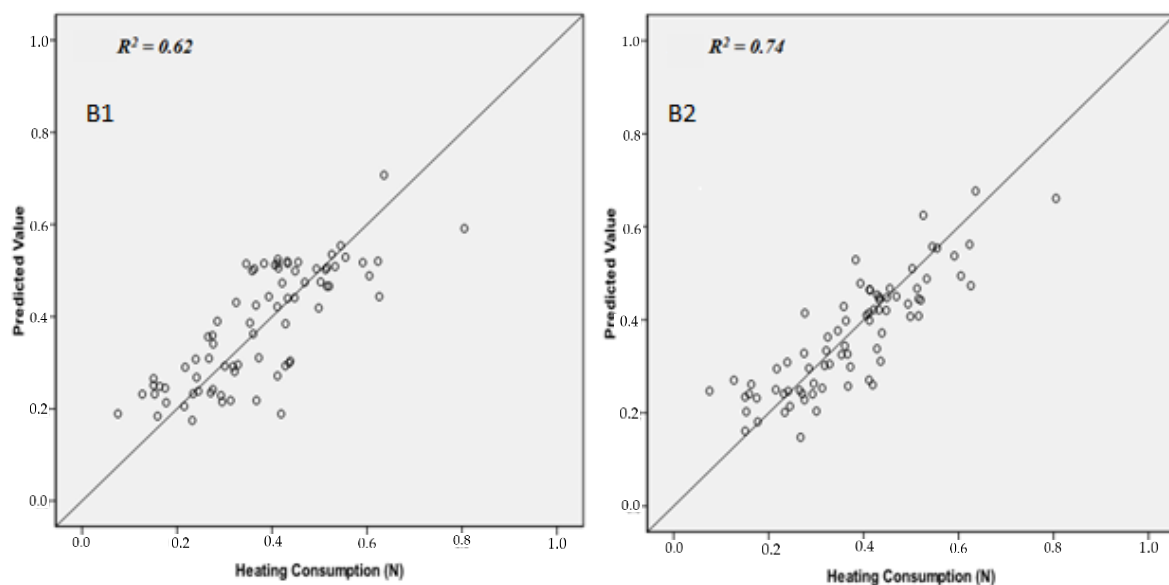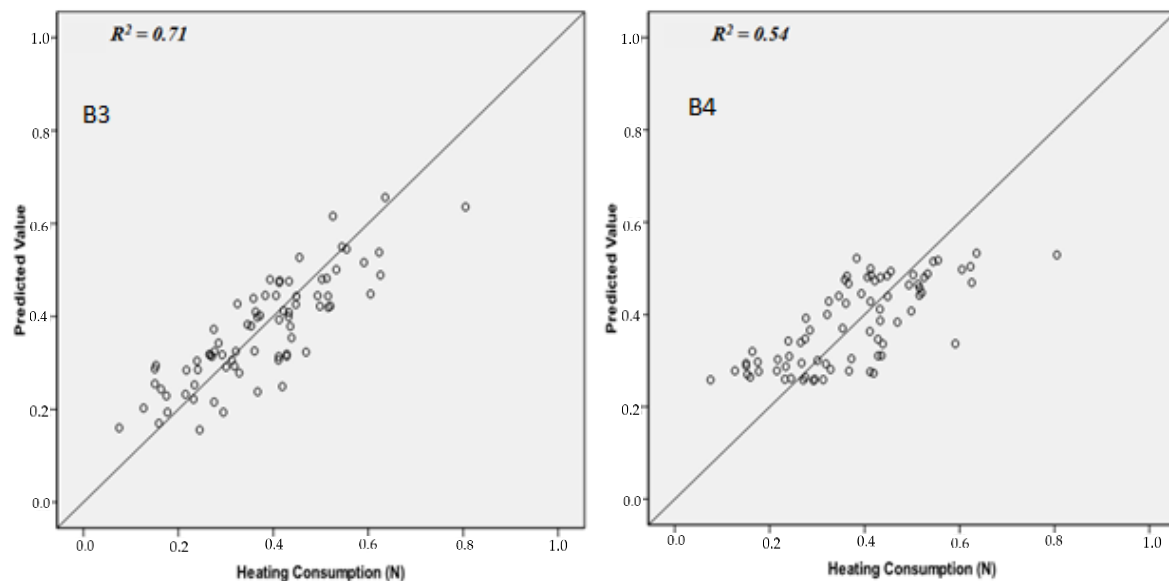| Model	No. of Hidden Layers	No. of Nodes	Sum of Squares Error for Training	Sum of Squares Error for Testing	Relative Error for Training	Relative Error for Testing	R^2
B1	1	3	14.23	1.14	0.467	0.134	0.62
B2	1	5	9.16	1.58	0.30	0.186	0.74
B3	1	6	9.94	1.76	0.326	0.206	0.71
B4	2	4	16.39	2.42	0.537	0.284	0.54

Figure 2. *Cont.*

Figure 2. Influence of the ANN configurations on modeling performances.

3.3. Analysis of the Influence of the Input Indicators on the Heating Expenses

Table 4 summarizes the weight of each input indicator in the estimation of heating expenses. Concerning the building physical parameters, ANN analysis shows that the dwelling area has the largest influence. An increase in dwelling area induces a decrease in heating expenses. This influence is surprising, and we need more data to enhance our understanding of this result. The building age and DPE have a similar influence on heating expenses. Their increase is generally correlated with a decrease in building energy performance and, consequently, with an increase in heating expenses.

Table 4. Weight of the indicators in the heating expenses.

Parameter	Weight
Building age	0.23
DPE	0.26
Number of floors	−0.24
Area	−0.58
Tenant age	−0.22
Family size	0.32
Tenant income	0.07

Concerning the influence of the socio-economic indicators on heating expenses, family size has the largest influence. The increase in family size leads to an increase in heating expenses. Tenant age also has an important influence: the increase in this indicator reduces heating expenses. This result could be related to the fact that older people may pay more attention to heating expenses. Tenant income has the lowest influence: an increase in income leads to a moderate increase in heating expenses.

4. The Use of the ANN Model for Establishing Renovation Strategy

The ANN model presented in the previous section is used to establish priorities in the renovation of low energy performing buildings (Categories E, D, and C). For each building, the ANN model is used to analyze the impact of its renovation from the actual category (E, D, or C) to the new category (B) on heating expenses.

Figure 3 displays the results obtained for the renovation of Category E buildings (very low energy performances). It shows that the impact of the transformation of these buildings from Category E to

Category B depends on other indicators. For some buildings, this transformation reduces heating expenses by about 45%; while for others it reduces heating expenses by only 5%. The average impact of this renovation on the reduction in heating expenses is equal to 20%.
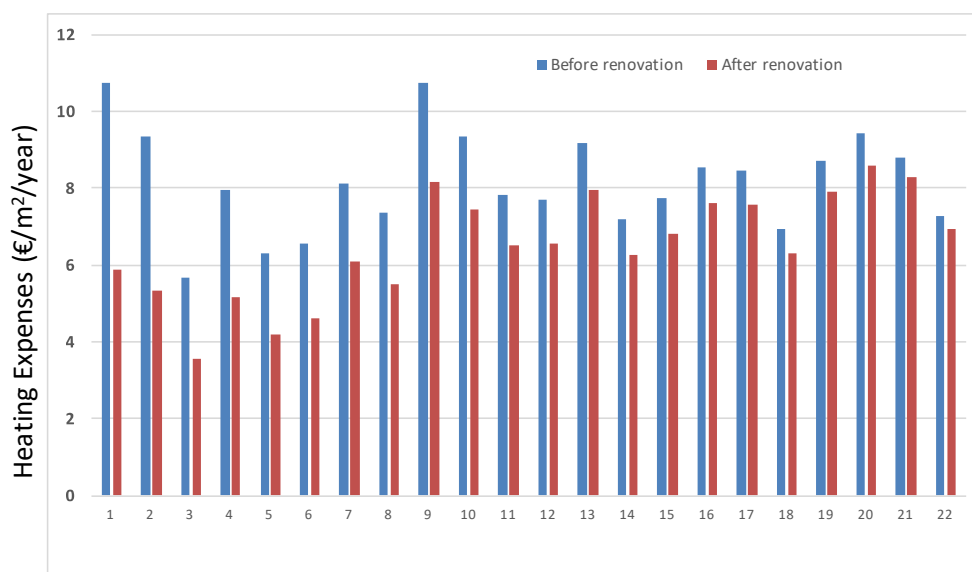

Figure 3. Impact of renovation of Category E buildings on the heating expenses.

Figure 4 displays the results obtained for the renovation of Category D buildings (low energy performances). It shows that, for some buildings, the renovation reduces heating expenses by about 40%; while for others it reduces heating expenses by only 3%. The average reduction in heating expenses is equal to 17%, which is lower than that obtained for buildings in Category E (20%).
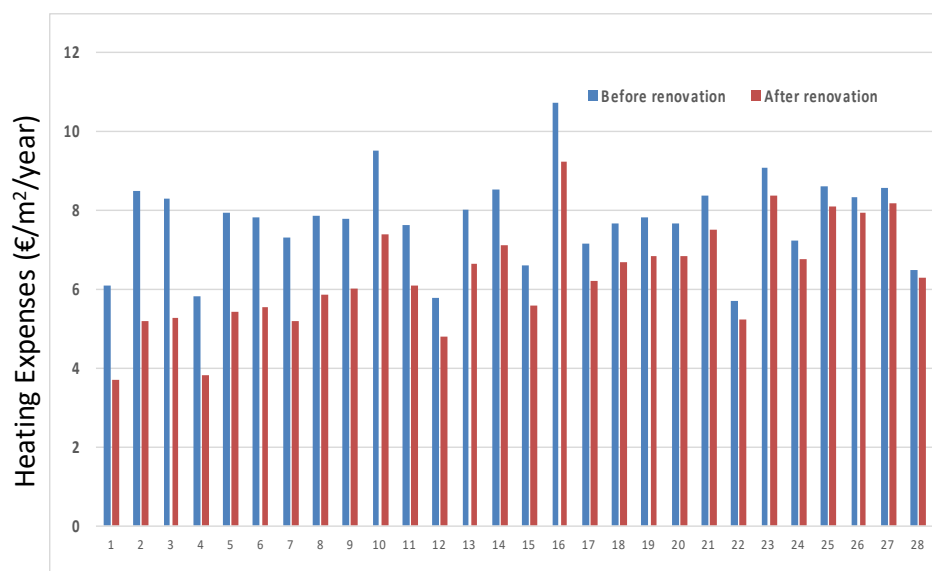

Figure 4. Impact of renovation of Category D buildings on the heating expenses.

Figure 5 displays the results obtained for the renovation of Category C buildings. It shows that the impact of the transformation of these buildings from Category C to Category B is moderate: it induces a reduction in heating expenses. The average reduction in heating expenses is equal to 10%,

which is lower than that obtained for buildings in Category E (20%). The importance of the DPE in the renovation strategy agrees well with other studies [10,21].
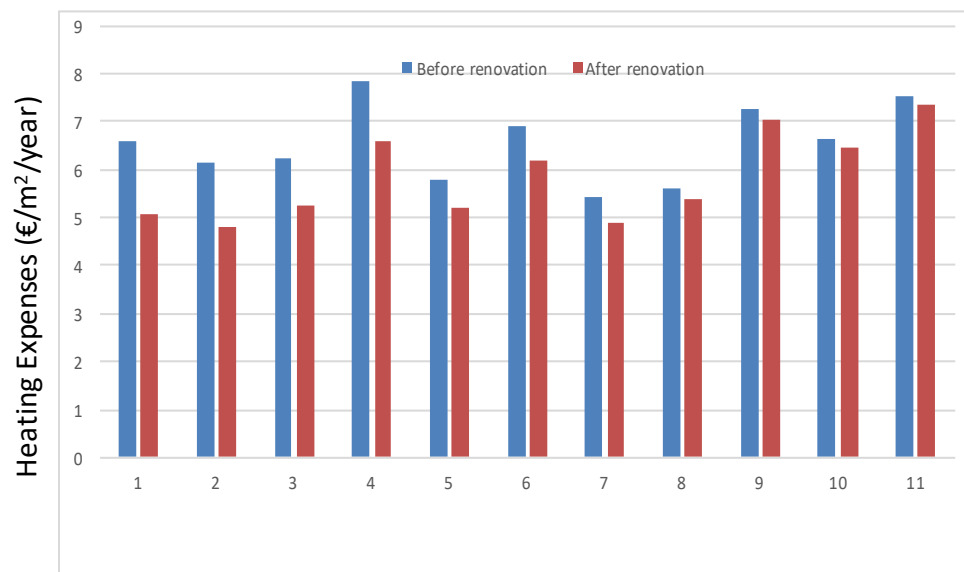

Figure 5. Impact of renovation of Category E buildings on the heating expenses.

5. Conclusions

This paper presents an ANN analysis of heating expenses in a large social housing stock in Northern France. The ANN model was constructed using data provided by the social housing manager, which included four physical building parameters (age, DPE, number of floors, and dwelling area) and three socio-economic parameters (family size, tenant age, and income). Preliminary analyses gave an optimal ANN architecture, with one hidden layer containing five neurons.

Analysis of the influence of building physical indicators on heating expenses showed that dwelling area has the largest influence, followed by DPE and building age. Concerning the socio-economic indicators, family size has the greatest influence, followed by tenant age and income.

The ANN model was also used to analyze the influence of the renovation of buildings on heating expenses. Results showed an important variation in the impact of the renovation on heating expenses, particularly for Categories E and D. For the former, the reduction in heating expenses varies between 45% and 5%; for the latter, it varies between 40% and 3%. This result shows that the renovation strategy should not be based only on the DPE category, that it should take the influence of other parameters into consideration as well.

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