An Energy And Carbon Dioxide Emission Scenario For The UK Housing Stock: Some Preliminary Results

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This paper describes the development of a model which can be used to explore the technical feasibility and policy implications of attempting to achieve 60 - 90% reductions in the CO_2 emissions from the UK housing stock by the middle of the next century. Reductions of this order are likely to be required across the industrialised countries in order to stabilise the atmospheric CO_2 concentration and global climate. In order to be able to investigate this problem, a highly disaggregated physically based energy and carbon dioxide model of the UK housing stock has been developed. This model covers both the demand and supply side, and is being used to develop three scenarios of energy use and CO_2 emissions; namely: a Business-as-Usual scenario; a Technologically Advanced scenario; and, a Radical scenario.

Preliminary results indicate that under a Business-as-Usual scenario savings of around 165 PJ of delivered energy (a 9% reduction) and 59 million tonnes of CO_2 (a 33% reduction) are possible in the domestic sector by the year 2050, based on 1991 figures. The model also suggests that, at least in the domestic sector, the UK may meet both the Kyoto target and the earlier self-imposed 20% reduction target by the year 2010, with measures that appear collectively consistent with a continuation of current trends and policies. However, the more demanding long term goals associated with climate stabilisation are unlikely to be achieved without significant changes to current UK policy, and the implementation of technical measures that go beyond what is currently seen as economically viable or practical.

Introduction

There is widespread agreement within the scientific community that changes to the global climate are taking place, primarily due to an increase in anthropogenic CO_2 emissions [1]. Recent estimates suggest that reductions in CO_2 emissions of between 60 to 90% will be required by the middle of the next century, if CO_2 concentrations are to be stabilised at current levels, and disruption to the global climate system is to be minimised [1,2,3]. An attempt to address this problem was made at the World Climate Conference at Kyoto, where agreement was reached to reduce emissions of the six main greenhouse gases by an average of 5.2% based on 1990 levels, between 2008 and 2012. The scale of the reductions agreed varies between countries, with Europe, the USA and Japan contributing 8%, 7% and 6% respectively

[4]. The UK's contribution to the European target is a reduction in emissions of 12.5 % [5]. It is likely that this will supersede the earlier self-imposed reduction of 20 %, below 1990 levels, by the year 2010 [6]. In the UK, the Kyoto target will be achieved within the built environment mainly by promoting the efficient use of energy, whilst within the energy supply sector there is an intention to deliver 10% of the UK's electricity demand from renewables by 2010 [5].

The domestic sector contributes substantially to national CO_2 emissions with emissions of 149 million tonnes of CO_2 in 1996, some 30% of the UK's total emissions [7]. While the UK housing stock is characterised by long physical lifetimes and slow stock turnover, energy use in this sector has been much more stable than in the transport and commercial sectors, while CO_2 emissions have actually been declining for some years. It would therefore seem unlikely that the UK will be able to achieve large overall reductions in national CO_2 emissions without savings in the domestic sector being at least as large as those in the economy as a whole.

A number of practical case studies suggest that large reductions in CO_2 emissions in new and existing housing are technically feasible [8,9,10,11]. However, achieving such large reductions across the whole UK housing stock will be technically demanding, and if they are to be achieved, significant changes will be required to current UK policy. It is within this context that the present model has been developed.

The Physically Based Energy Model

In order to investigate whether such large reductions in the CO_2 emissions from the UK housing stock are technically feasible, scenario based modelling techniques have been used to develop a highly disaggregated, physically based "bottom-up" energy and carbon dioxide model of the UK housing stock. The structure of the developed model is shown in Figure 1.

The model has been developed around a modified worksheet version of the Building Research Establishment's Domestic Energy Model (BREDEM), Version 9.53 [12]. This emphasis has been chosen because the fabric of the housing stock is characterised by very long physical lifetimes. The thermal envelope of the UK housing stock has a much slower turn-over than domestic space and water heating systems, the major components of the energy supply and distribution sector, and is significantly slower than the turn-over of domestic lights and appliances.

Transparency within the model has been preserved by adopting a parsimonious approach to detail. Thus, the model incorporates just two notional building types, which are deemed to be representative of pre- and post-1991 construction respectively. The physical properties of the main elements of these notional dwellings are averages which take into account the effects of demolition, new construction, refurbishment, heating system replacement and so on. This approach is justified on the grounds that variations in the energy performance and emissions associated with the various dwelling types are dwarfed by the reductions in energy use and CO_2 emissions that are required across the stock as a whole. It is the average performance of a "wall", "roof" and "window" across the UK housing stock, rather than the geometries and energy demands of particular house types, that dominate the picture in the long term. While this approach is likely to be more revealing in the long term, in the short term it leads to discrepancies when compared to the output of more detailed models. We do not consider these to detract from the main purpose of the exercise.

A more detailed description of the model and the techniques used to develop it can be found within Johnston [13] and Johnston et al. [14].

The Business-As-Usual Scenario

At present, only the Business-as-Usual (BAU) scenario has been comprehensively developed and evaluated. The remainder of this paper examines the results and insights obtained from this scenario. The BAU scenario assumes that current rates of uptake and improvements in the energy efficiency of the UK housing stock continue at levels which have been seen to occur in the past. This scenario has been developed using information from relatively uncontentious external data sources where possible. Such sources include: population projections from the Office for National Statistics [15]; numbers of households from the Government Statistical Service [16]; and projections of future energy demand for lights and appliances from the Domestic Equipment and Carbon Dioxide Emissions (DECADE) team at the University of Oxford [17,18]. Other information has been generated internally on the basis of the authors' own informed judgement, to provide a detailed technical projection of the UK housing stock to the year 2050.

It is impossible to present the whole of the BAU scenario here, but the nature of the scenario can be gauged from the following brief descriptions:

Thermal envelope improvements existing housing:
- 80% of existing cavity walls insulated by 2050.
- 10% of existing solid walls insulated by 2050.
- All existing single glazed windows replaced by 2020.
- 50% of first generation double glazed windows replaced with second generation glazing by 2050.

Thermal envelope improvements, new housing:
- Building Regulations wall U values fall to 0.3 W/m^2K by 2010, to 0.20 W/m^2K by 2020 and to 0.10 W/m^2K by 2030.
- Window U values fall to 2.0 W/m^2K by 2010 and 1.0 W/m^2K by 2020.
- Air leakage rates are introduced into the Building Regulations in 2005 at 10 ac/h @ 50Pa and fall to 5 ac/h @ 50Pa by 2025.
- 45% of new housing fitted with MVHR systems by 2050.

Space heating improvements in all housing:
- All dwellings will have a space heating system installed with an average efficiency of 90% by 2031.

Lights and appliances:

- Ownership of lights and appliances is assumed to saturate around 2020. Appliance efficiencies are assumed to continue to rise, with a resulting overall reduction in energy use for the period to 2050.

Table 1 summarises the impact of these measures on elemental U values averaged over all pre- and post- 1991 dwellings, whilst Figure 2 graphically represents the impact of these measures on the heat loss of pre- and post- 1991 dwellings. Where appropriate, historical data obtained from the latest version of the Building Research Establishment's Domestic Energy Fact Files [7] has been included.

The history of the last 50 years has shown that changes to the carbon intensity of energy supply are at least as important as those changes that have taken place in end-use systems such as dwellings. This observation applies both to combustible fuels, with natural gas progressively and now almost completely replacing more carbon intensive fuels such as oil and coal, and to electricity. A major simplification incorporated within the model is the assumption that the UK housing stock utilises just two forms of delivered energy over the period of the scenario – gas and electricity. In the case of natural gas, it has been assumed that there is no reduction in carbon intensity over the period to 2050. In principle, reductions could be achieved, for example, by introducing a significant component of biogas into UK gas supply, but we do not feel that such an assumption is appropriate for a BAU scenario.

Historical data on the carbon intensities of electricity generation have been obtained from Pout [19] (see Figure 3). These data form part of a much longer-term trend toward lower carbon intensities for electricity generation in the UK. It is possible that the carbon intensity will rise for a short period in the early years of the 21st century, as first Magnox and then AGR nuclear power stations are decommissioned [20]. There are however many technical options for reducing carbon intensity over the next 50 years, including more intensive development of renewables, further expansion of gas fired combined cycle generation, and the introduction of fuel cells. Given the existence - indeed the proliferation - of these technical options, and the ever increasing political awareness of the problem of climate change, we consider it inconceivable that historical trends will not continue in the medium to long term. We have therefore assumed a continued gentle decline in the carbon intensity of electricity (see Figure 3).

Results And Discussion

Figures 4 and 5 show the delivered energy use and CO_2 emissions attributable to the UK housing stock under the BAU scenario. These results have been compared with historical data obtained from the BRE's Domestic Energy Fact File [7], and recent projections undertaken by Shorrock and Dunster [21]. The "Reference" scenario developed by Shorrock and Dunster represents what is likely to happen if current trends continue. These comparisons suggest that the scenario is indeed representative of business-as-usual, at least in the short to medium term.

The scenario shows delivered energy consumption in the UK housing stock remaining relatively constant from 1991 up until around 2010, whilst the corresponding CO_2 emissions drop substantially by almost 25% over the same period. Delivered energy use emerges from a number of opposing trends. Dwelling envelope, heating systems, and lights & electrical appliances all become more efficient over the period, which tends to reduce delivered energy use. Internal temperatures[1], appliance ownership and the total number of households all increase, driving sectoral delivered energy use up. Our scenario shows these opposing factors to be in balance until 2025, with a slow reduction in energy use thereafter. Small changes in our assumptions move the curve either way.

In the case of carbon emissions, the performance of energy supply systems – in our BAU scenario, the electricity supply industry – introduces a further layer of complexity. The steady decline in carbon intensity of electricity that we have assumed, together with the modest (9%) reduction in delivered energy use, results in a steady decline in sectoral carbon emissions over the whole of the modelling period. Carbon emissions in 2050 are 33% lower than in 1991. The CO_2 emission trajectory presented in Figure 5 has been compared against the UK's Kyoto target and the earlier self-imposed target of a 20% reduction by 2010. The results suggest that both of these targets can be achieved in the domestic sector, under our scenario assumptions. Conversely, the results also suggest that the much larger reductions in carbon emissions needed to stabilise the atmosphere and the global climate will require the pursuit of a more radical scenario. This perception will be most strongly held by those who consider our BAU scenario to be already technically optimistic.

Conclusion

The authors have developed a disaggregated physically based energy and CO_2 model of the UK housing stock, which is capable of exploring the implications and feasibility of attempting to achieve large reductions in the CO_2 emissions attributable to this sector. Our exercise is the first recent attempt to project the performance of this sector so far into the future – other studies have been truncated in the first or second decade of the next century. It is also the first to be predicated on the assumption of the need for reductions in emissions that go beyond those which can be achieved by the application of measures which are currently micro-economically viable.

We can perhaps be criticised for projecting so far into the future, although studies begun in the 1970s [22,23] set a precedent for 50 year scenarios. The long physical time constants associated with housing and energy supply, mean that the problem of climate change can only be considered over this sort of period. The alternative, of not doing the modelling at all, is not one that we are comfortable with. The purpose of this exercise is not to predict the future, but to structure the way in which we think about it, and to begin to make it possible to formulate rational and considered responses to the problems that it poses.

[1] Although BREDEM 9.53 incorporates a simple saturation mechanism, this depends only on dwelling heat loss parameter, and does not include the effects of income or energy price. Moreover, the saturation temperature (just below 19°C) appears too low in view of temperatures recorded in energy efficient dwellings. Our model includes all three effects, and at high incomes and in very well insulated dwellings, saturates at around 21°C.

This paper presents the first of three scenarios. Our discussion of this scenario shows how sectoral energy use and carbon emissions emerge from the interaction of a number of factors and trends, with the growth in the number of households, the rise in internal temperatures and the proliferation of domestic appliances being offset by better insulation, more efficient energy conversion and reduced carbon intensity of electricity. Over the period to 2010 it is likely that the reduction in the carbon intensity of electricity will be an important factor, but this is then expected to saturate, and thereafter a number of factors affecting delivered energy become increasingly important. Over the whole period, no single dominant factor emerges.

Preliminary results indicate that under a Business-as-Usual scenario, the domestic CO_2 emissions will be reduced by almost 25% by the year 2010. This suggests that both the Kyoto and the UK Government self-imposed CO_2 emissions targets will be achieved, by implementing the measures identified. By 2050, savings of around 165 PJ of delivered energy (a 9% reduction) and 59 million tonnes of CO_2 (a 33% reduction) are also possible. Although the Business-as-Usual scenario suggests that it is possible to achieve the targets set for 2010, significant progress beyond 2010 would appear to require implementation of measures that go substantially beyond what would be expected on the basis of current trends. Such measures are incorporated within our Technically Advanced and Radical scenarios [14], which will be the subject of future papers.

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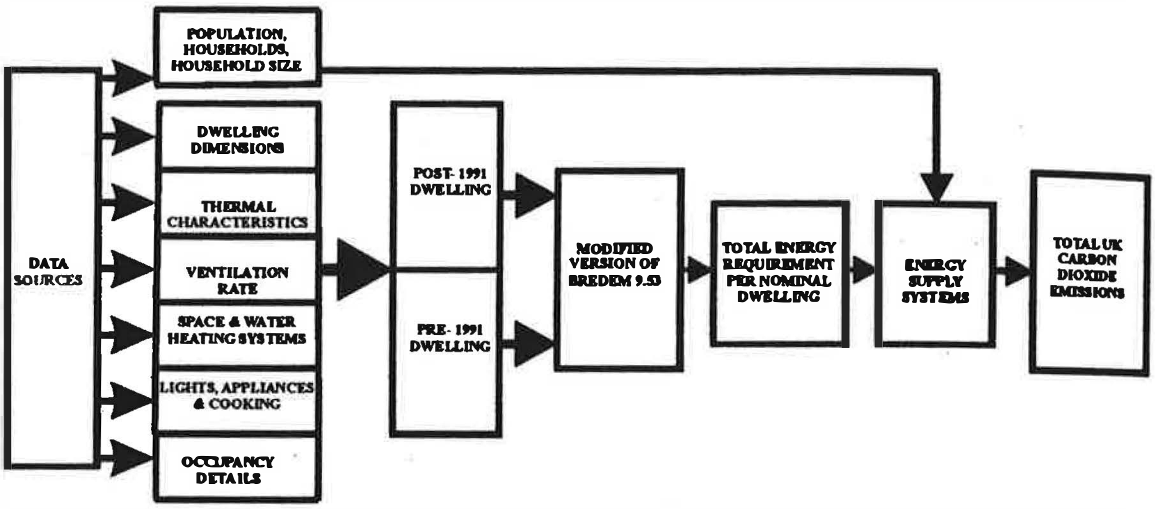

Figure 1. Structure of the physically based energy and carbon dioxide model of the UK housing stock

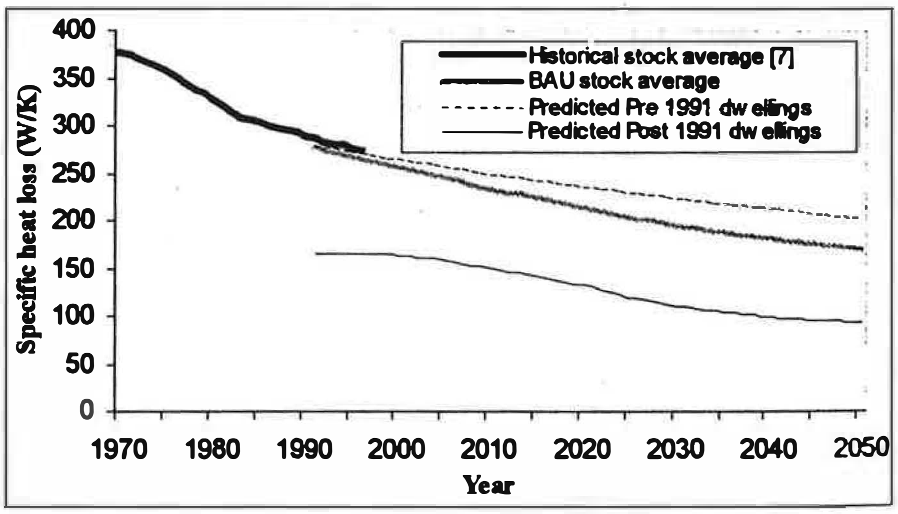

Figure 2. Specific heat loss of the UK housing stock

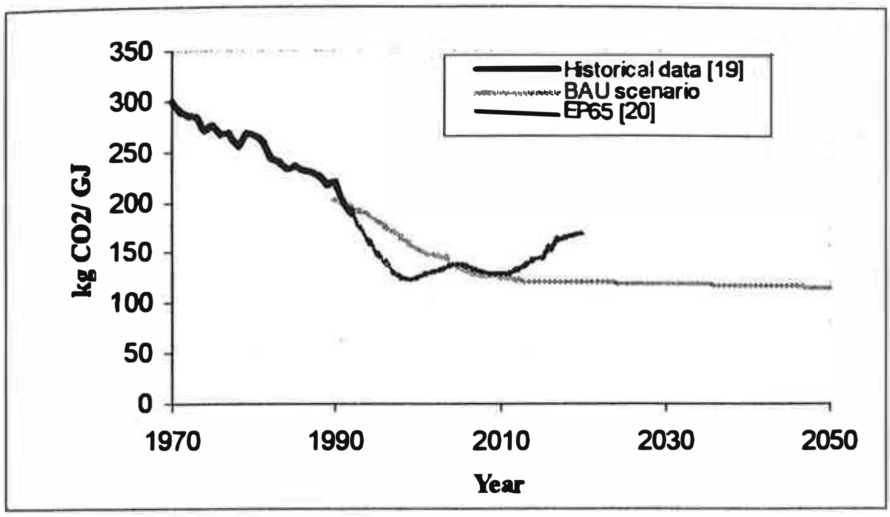

Figure 3. Carbon dioxide emission factors for electricity for the BAU scenario.

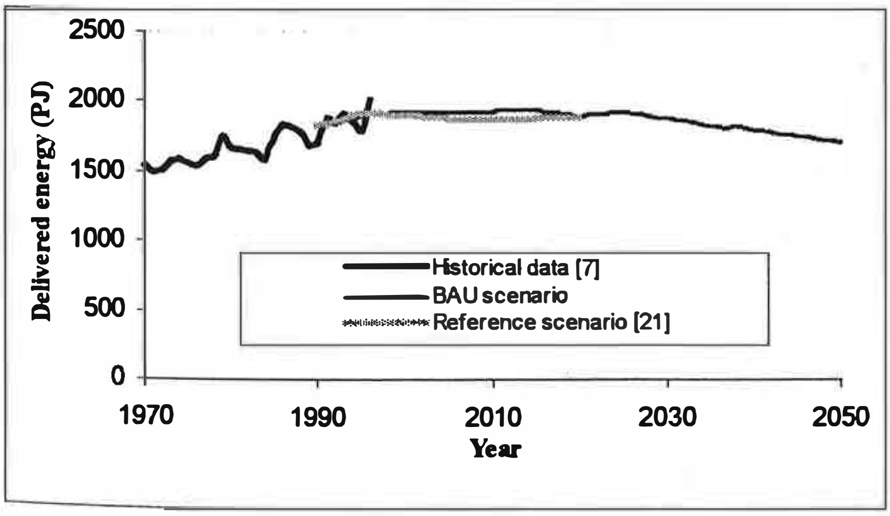

Figure 4. Total delivered energy use of the UK housing stock

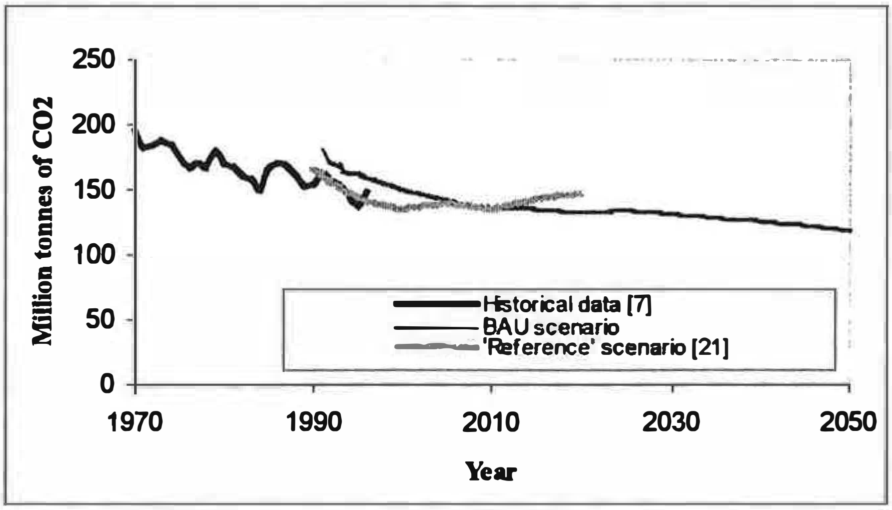

Figure 5. Total CO_2 emissions attributable to the UK housing stock

Element	Pre- 1991 dwellings		Post- 1991 dwellings	
	1991 (W/m²K)	2050 (W/m²K)	1991(W/m²K)	2050 (W/m²K)
External wall	1.10	0.80	0.45	0.29
Ground floor	0.55	0.51	0.45	0.30
Roof	0.43	0.30	0.25	0.16
Glazing	3.93	2.04	3.30	1.30
External door	3.70	2.10	3.30	1.00

Table 1. Predicted average elemental U-values for the UK housing stock.

Soft-computing models for naturally ventilated buildings

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In this study, a mixed mode building, namely the Portland Building at the University of Portsmouth is considered. It combines both Natural Ventilation and conventional Heating Ventilating and Air Conditioning systems to maintain the internal comfort. The paper presents the development of Soft Computing models to predict the internal temperature in one of the offices using information from neighbouring rooms, corridor and the outside. To derive this model, the so called Adaptive Neuro Fuzzy Inference System method is used. This is a well established Soft Computing method using Fuzzy Logic for the modelling framework and Neural Networks to adapt the model parameters. The fuzzy model is of the Takagi-Sugeno type with linguistic if-then rules in the antecedent part and linear algebraic equations in the consequent part. Regression Delay and Proportional Difference model structures are investigated which are taken from classical control theory and extended in the paper for the purpose of fuzzy modelling on the basis of sensor readings.

Introduction

Interest in naturally ventilated buildings is growing because they consume less energy to maintain acceptable indoor conditions for occupants in comparison to their equivalent air conditioned counterparts. In addition, their usage results in a lower level of environmental pollution. The authors have been developing empirical operational strategies for buildings using a model-based philosophy. The essence of this philosophy is to make the decisions for the Building Management Systems controls on model predictions rather than on current sensor readings. However, for the methods to work well, the models need to be good which is not a trivial task because their performance is significantly affected by climatic and occupancy effects which are strongly stochastic in nature and extremely difficult to quantify.

Although conventional parametric models yield good prediction accuracy, the fact that they require specialist knowledge at the identification stage makes their utilisation on a wide scale difficult. Normally, the models have to be adaptable for different operating regions throughout the year through self-tuning or by using multiple models. Soft Computing methods offer an alternative approach and the present paper introduces the concepts and describes the implementation on a full-scale facility.

Soft Computing is a heuristic methodology which has received considerable interest in recent years and has shown to be successful in many areas such as modelling, control, fault diagnosis and detection, and pattern recognition. It is based on the implementation of different approaches such as Fuzzy Logic, Neural Networks, Genetic Algorithms and others [4]. Each of these techniques is suited for solving specific types of problems. In this respect, Fuzzy Logic is powerful for knowledge-based modelling and reasoning using expert knowledge, Neural Networks are well suited for learning-based adaptation, while Genetic Algorithms are efficient for evolutionary-based optimisation. In fact, the underlying idea of Soft Computing is to use these heuristic approaches in combination with each other as well as with other classical techniques, rather than using each of them separately. In this sense, the main aim of the work presented here is to investigate the applicability of Soft Computing methods to the built sector.

It must be pointed out that Fuzzy Logic, Neural Networks and Genetic Algorithms appeared and have developed separately for a long period of time. As such, they were known under the name of Intelligent Techniques. The reason for using the term 'intelligent' was the analogy with some similar heuristic capabilities of human beings, e.g. approximate reasoning, self learning, etc. In this way, Intelligent Techniques were also contrasted to the so-called Conventional Techniques which were based on precise mathematical computations within fundamental systematic theories. In this respect, the term 'soft' (approximate) was chosen as an antonym to the 'hard' (precise) computing, typical for most Conventional Techniques. It was not until a decade ago, when the co-operative idea of Soft Computing was promoted so that flexible and powerful solutions could be produced. These solutions became feasible as a result of the utilisation of the advantages of Intelligent and Conventional Techniques in combination. More specifically, Intelligent Techniques turned out to be more adequate to the inherent uncertainty in many real plants while Conventional Techniques gave the tools for enriching the heuristic nature of Intelligent Techniques in a more systematic direction, thus gradually transforming the original notion of Soft Computing from a diversity of empirical approaches into a well defined powerful methodology able to address generic problems.

Proactive control phylosophy

The work proposed here is concerned with the efficient control of the internal climate in office buildings and the aim is to develop good predictive models which will allow a proactive control strategy to be produced. In other words, instead of applying a control action only on the basis of the current sensor readings, it is desirable to make use of the system inertia and thus to predict these readings over a certain time interval so that a sensible predictive strategy can be realised. The main advantage of such a proactive strategy lies in the possibility to apply heating and cooling control efforts more efficiently as a result of which state variables are better controlled, with smaller overshoots and undershoots. This, on its turn, leads to decreased energy consumptions and reduced pollution of the environment. However, to obtain predictive models for these buildings is not easy because they are affected by climatic and occupancy effects which are characterised by complex and uncertain processes.

The notion of the proactive control strategy is illustrated in Figure 1. In this case, the control action at the current time instant k is computed not only on the basis of the measurements at k, $k-1$, $k-2$, etc, but also by taking into account the model predictions at future time instants $k+1$, $k+2$, etc. Such a control strategy may be applied for any discrete time increment.

Clearly, such a strategy can only perform well if the model predictions are accurate and hence effort is needed to generate good quality models in a cost effective manner. In this respect, some investigations have recently been carried out in the built sector using separate Intelligent and/or Conventional Techniques but not the Soft Computing methodology as a whole [5], [6], [9], [10]. For this reason, the potential of Soft Computing as a generic modelling approach is well worth exploring. It is expected that it will be able to account for the existing uncertainty in office buildings caused by different unknown stochastic factors and disturbances.

Theoretical background

The so-called Adaptive Neuro Fuzzy Inference System method is used in the paper for predictive modelling o internal parameters in office buildings. This method has gained significant importance recently and has also bee implemented in the Fuzzy Toolbox of the MATLAB software environment. The Adaptive Neuro Fuzzy Inferenc System method is a typical Soft Computing approach using Fuzzy Logic for building the initial model and Neura Networks for adaptation of the model parameters [3]. The method is based on a Takagi-Sugeno fuzzy model whic has received considerable attention recently because of its suitability for processing information from input-outpu measurements. This is the case in Building Management Systems where the main on-line information can b obtained from sensor readings connected to the system rather than from expert knowledge as these systems ar usually coupled multivariable ones [2], [4]. Another advantage of the Takagi-Sugeno fuzzy model is its capability t approximate non-linear input-output mappings by a number of locally linearised models.

The Takagi-Sugeno fuzzy model consists of linguistic *if-then* rules in the antecedent part and linear algebrai equations in the consequent part. There are two types of parameters in this model: non-linear (in the membershi functions in the antecedent part) and linear (in the algebraic equations in the consequent part) which are explained i more details further in this section. The task of the fuzzy model is to determine the initial values of both types c parameters on the basis of the input-output data. There are different methods for this purpose but the one that is mo often used with the Adaptive Neuro Fuzzy Inference System is based on the idea of subtractive clustering, i.e. b assuming that each data point is a potential cluster centre and gradually finding the final clustering. The task of th neural adaptation is to adjust the model parameters in order to obtain a better fit to the measured data. There are als different methods for this purpose but the one that is most often used with the Adaptive Neuro Fuzzy Inferen System is based on the idea of back-propagation, i.e. by iterative propagating of the error (the difference between th real and the modelled plant output) from the consequent to the antecedent part of the fuzzy rules until a desir accuracy is achieved or a pre-specified number of iterations is reached. The purpose of back-propagation is to redu the error as much as possible although sometimes this can not be achieved because of divergency during th iterations.

The Takagi-Sugeno fuzzy model for a system with two rules, two inputs (u_1, u_2) and one output (y) is presented by Equation *(1)*. The linguistic labels (membership functions) of the inputs are denoted by A_i, B_i, $i=1,2$ and their parameters are the non-linear antecedent parameters. The coefficients a_i, b_i, $i=1,3$ are the linear consequent parameters used for the computation of the output.

$$\begin{aligned} &\textit{If } u_1 \textit{ is } A_1 \textit{ and } u_2 \textit{ is } A_2 \textit{ then } y = a_1.u_1 + a_2.u_2 + a_3 \\ &\textit{If } u_1 \textit{ is } B_1 \textit{ and } u_2 \textit{ is } B_2 \textit{ then } y = b_1.u_1 + b_2.u_2 + b_3 \end{aligned} \qquad (1)$$

Equation *(1)* represents a static Takagi-Sugeno fuzzy model which does not contain the time argument in the input and the output variables. However, in order to predict the temperature, the time argument should be included in the equation, i.e. the model must be a dynamic one. In this respect, two types of dynamic models are investigated in the paper, namely Regression Delay and Proportional Difference. Examples of such models are represented by Equations *(2)* and *(3)*, respectively.

$$\begin{aligned} &\textit{If } y_{k-1} \textit{ is } A_1 \textit{ and } y_{k-2} \textit{ is } A_2 \textit{ and } u_{1,k-1} \textit{ is } A_3 \textit{ and } u_{1,k-2} \textit{ is } A_4 \textit{ and } u_{2,k-2} \textit{ is } A_5 \\ &\textit{then } y_k = a_1.y_{k-1} + a_2.y_{k-2} + a_3.u_{1,k-1} + a_4.u_{1,k-2} + a_5.u_{2,k-2} + a_6 \end{aligned} \qquad (2)$$

$$\begin{aligned} &\textit{If } y_{k-1} \textit{ is } A_1 \textit{ and } Dy_{k-1} \textit{ is } A_2 \textit{ and } u_{1,k-1} \textit{ is } A_3 \textit{ and } Du_{2,k-1} \textit{ is } A_4 \\ &\textit{then } y_k = a_1.y_{k-1} + a_2.Dy_{k-2} + a_3.u_{1,k-1} + a_4.Du_{2,k-1} + a_5 \end{aligned} \qquad (3)$$

$$\textit{where } Dy_{k-1} = y_{k-1} - y_{k-2},\ Du_{2,k-1} = u_{2,k-1} - u_{2,k-2}$$

It can be seen that Equation *(2)* contains two auto regressive terms of the output y, two regressive terms of the input u_1 and one delay term for of the input u_2. As opposed to this, Equation *(3)* contains one proportional and one derivative term of the output y, one proportional term of the input u_1 and one derivative term of the input u_2. For simplicity purposes, each of the equations includes only one rule, but in general the number of rules is higher. More specifically, it is equal to the number of the linearised submodels applicable to the respective local regions of the whole operating range.

The adaptation of the fuzzy model by a neural network is implemented by a procedure in two phases, namely the forward and backward phases. In each phase, one set of the parameters (antecedent or consequent) is kept constant while the other set is adapted.

Experimental results

This section presents results obtained with the Adaptive Neuro Fuzzy Inference System method for modelling the air temperature in an office in the Portland Building at the University of Portsmouth. The building is of a mixed mode, i.e. based mainly on natural ventilation but involving also the possibility for heating, ventilating and air-conditioning in some parts when the natural ventilation is not able to maintain a satisfactory internal climate for the occupants [1].

The modelled parameter is the internal temperature of a centrally located room (number *1.14*) in the building which has one north facing external wall, one corridor to the south and two other neighbouring rooms (numbers *1.13* and *1.15*) on the same floor. It is intended to install a window actuator for this room in the near future but for the time being the window is opened only manually by the occupant. There are also two other neighbouring rooms – on the floors below and above. A horizontal cut of the monitored offices in the Portland Building and the respective black-box scheme of the model are given in Figure 2 where the following notations are used:

- External temperature (T_{ext}),
- Corridor temperature (T_{cor}),
- Internal temperature of room *1.13* (T_{113})
- Internal temperature of room *1.15* (T_{115})
- Internal temperature of room *1.14* (T_{114}).

Both figures show only the zones and variables which are taken explicitly into account in the analysis presented here. This is a simplified model which includes only the external temperature as a stochastic input but no occupancy effects which are intended to be studied later. All these zones are continuously monitored with temperature and humidity sensors and the readings from these sensors are the ones which seem to have a bigger impact on the behaviour being modelled. The data was recorded during July 1998. The training data comprised a period of four days while the validation was carried out using data covering the last two days of the trial.

A long-term prediction interval of up to 12 hours was investigated. This interval is evidently divisible by the logging frequency of the sensor readings which is equal to 30 minutes. This frequency might seem too coarse from a general point of view but it is quite acceptable in this particular case taking into account the slow dynamics of the building in the summer season. The best model was chosen from a set of possible models, representing all combinations of (auto)regressive and (auto)delay terms. The backward (dynamical memory) horizon was chosen equal to 2, i.e. the prediction of the internal temperature at time k is obtained on the basis of measurements at times $k-1$ and $k-2$.

The initial fuzzy model was built by the subtractive clustering method where the number of the membership functions of inputs was defined on the basis of the number clusters of input-output data. These membership functions were chosen to be of the Gaussian type and the model adaptation was carried out by a back-propagation neural network. The selected learning options of the network were 100 iterations, zero error goal, initial step size equal to 0.1, and decreasing and increasing learning rates equal to 0.9 and 1.1, respectively. Further discussions about these aspects can be found in [3], [4].

The best fuzzy model was found on the basis of one step (30 minutes) prediction after exploring all possible combinations of Regression Delay and Proportional Difference model structures. This is equal to 1023 when the model is assumed to have 5 inputs and a backward horizon of 2. In fact, the number of combinations is an exponential function of the number of inputs and therefore the computational time and complexity will increase significantly as the number of inputs increases.

Afterwards, the antecedent and consequent parameters of each of the best model were adapted by the neural network. The plant and the final model outputs (after learning) for this model are shown in Figure 3. It is evident that the model outputs are close to the plant outputs which is a measure of a good quality prediction. The residuals and their autocorrelation for the same model are shown in Figures 4 and 5. It can be observed from the plots that the model incorporates almost all significant inputs and that the residuals are to a great extent white noise related. The long-term prediction performance of the model is given in Figure 6 and it seems to be quite satisfactory.

It should be noted that the prediction properties of the derived model are possibly favoured by the small variation range of the temperature. This phenomenon is typical for the considered building in the summer season not only with respect to the modelled room but also with respect to the two neighbouring ones. In this sense, the purpose of the monitoring of the neighbouring rooms and the corridor is not only to see if they can contribute to the improvement of the model accuracy for the central room but also to model these rooms in the future and thus to extend the conclusions from the small monitored area to the whole building.

Conclusions

The results presented in this paper show that the Soft Computing methodology can be successfully used for the predictive modelling of office internal thermal behaviour. Although the modelled zone is not a very representative one, the same modelling methodology has already been successfully applied to buildings with fast dynamics and a considerable temperature variation range [8]. In this respect, the results seem promising and further effort is worthwhile to fully assess the capabilities of these models. In order to extend the validity of the results and to make the investigation more systematic, the Matlab software is being further extended and improved to handle models corresponding to different buildings, seasons, prediction intervals, modelled parameters, dynamical structures and adaptation / optimisation schemes. This software is intended to be finally built with a suitable Graphical User Interface (GUI) which would significantly facilitate its usage.

Another investigated direction is the application of Genetic Algorithms for tuning of the initial model parameters [7]. This is done in parallel with Neural Networks in order to compare the adaptation / optimisation properties of both approaches.

Acknowledgement

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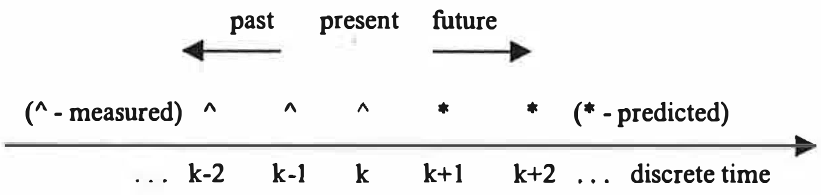

Fig.1. Proactive control strategy.

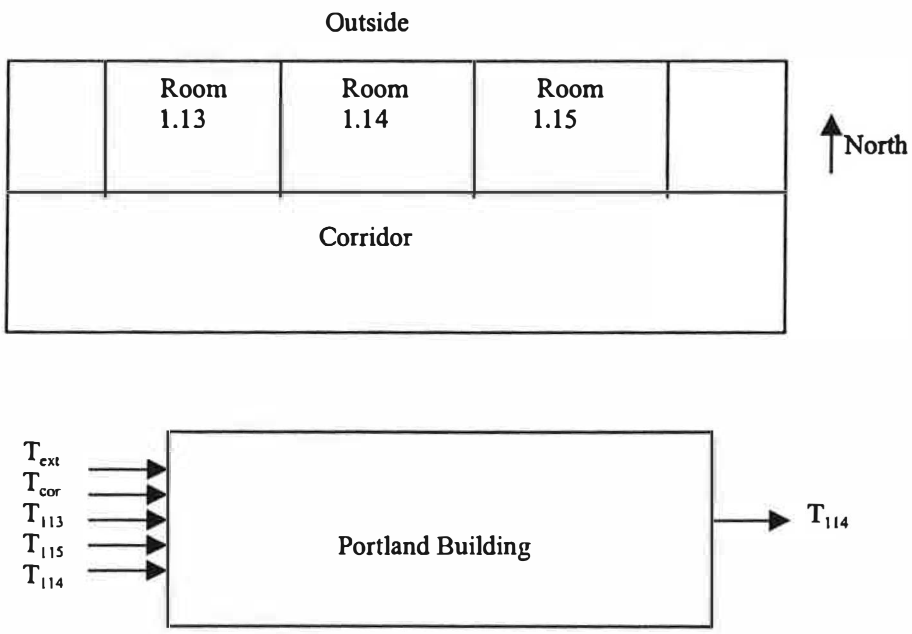

Fig. 2. Monitored zones and black-box model.

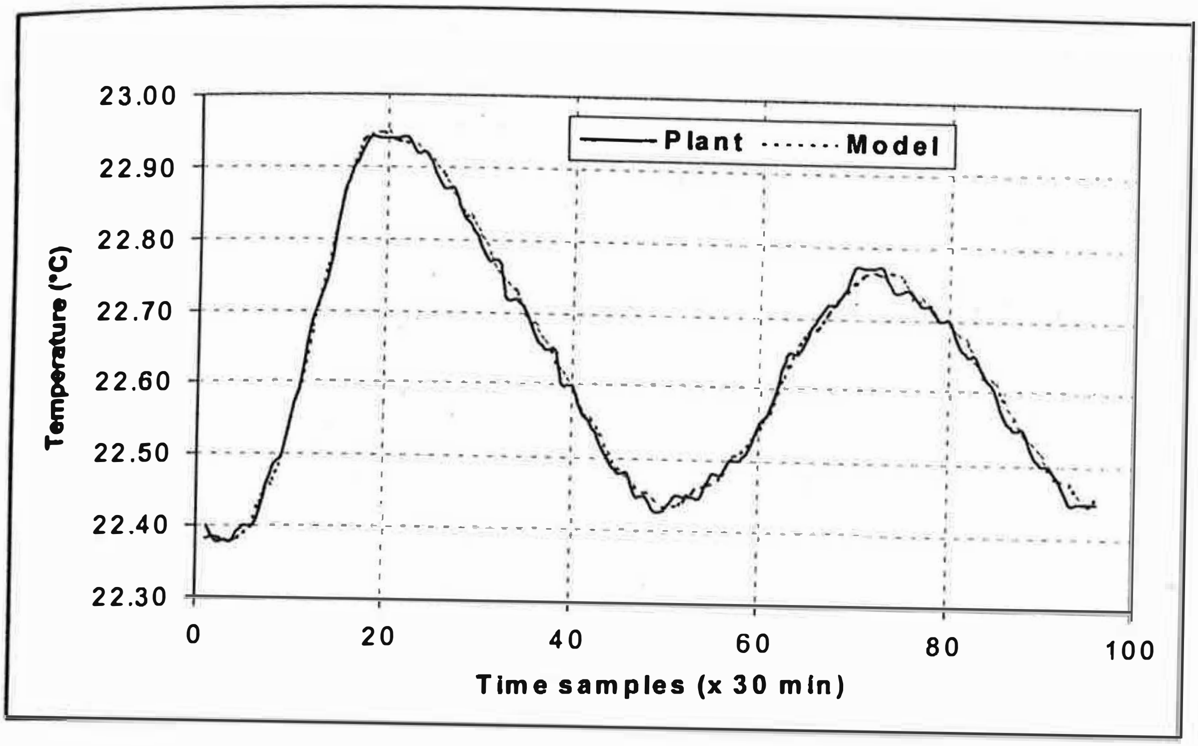

Fig. 3. Plant and model outputs.

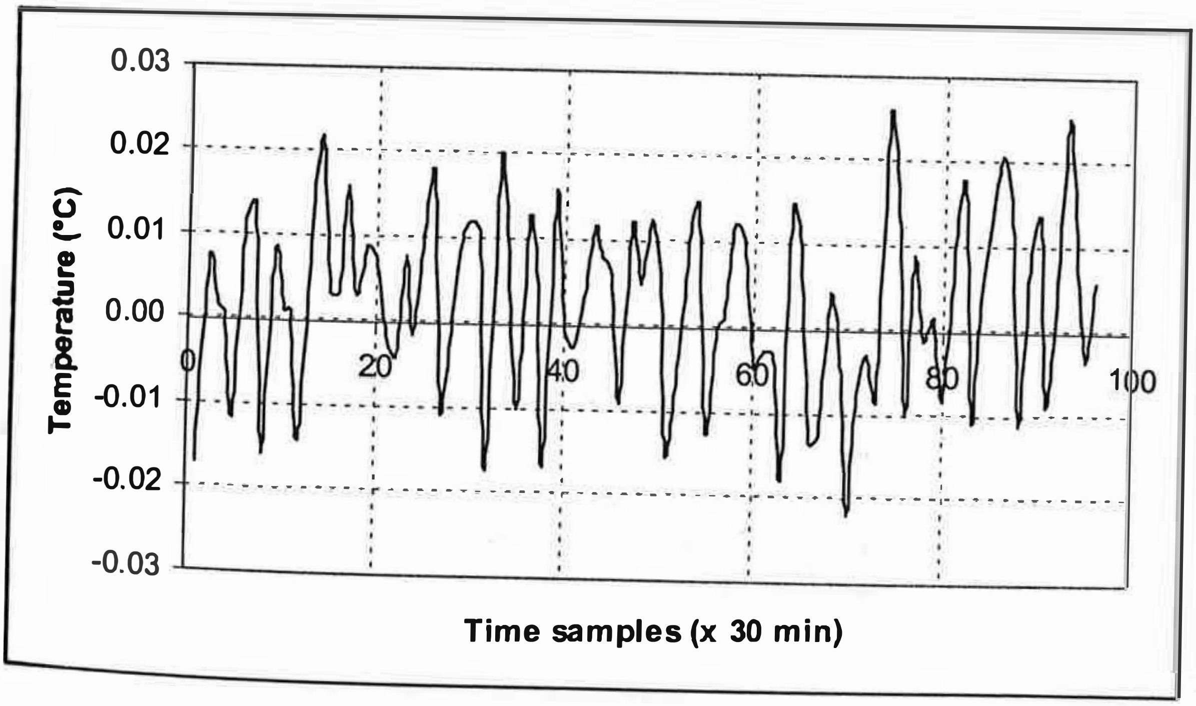

Fig. 4. Residuals (difference between plant and model outputs).

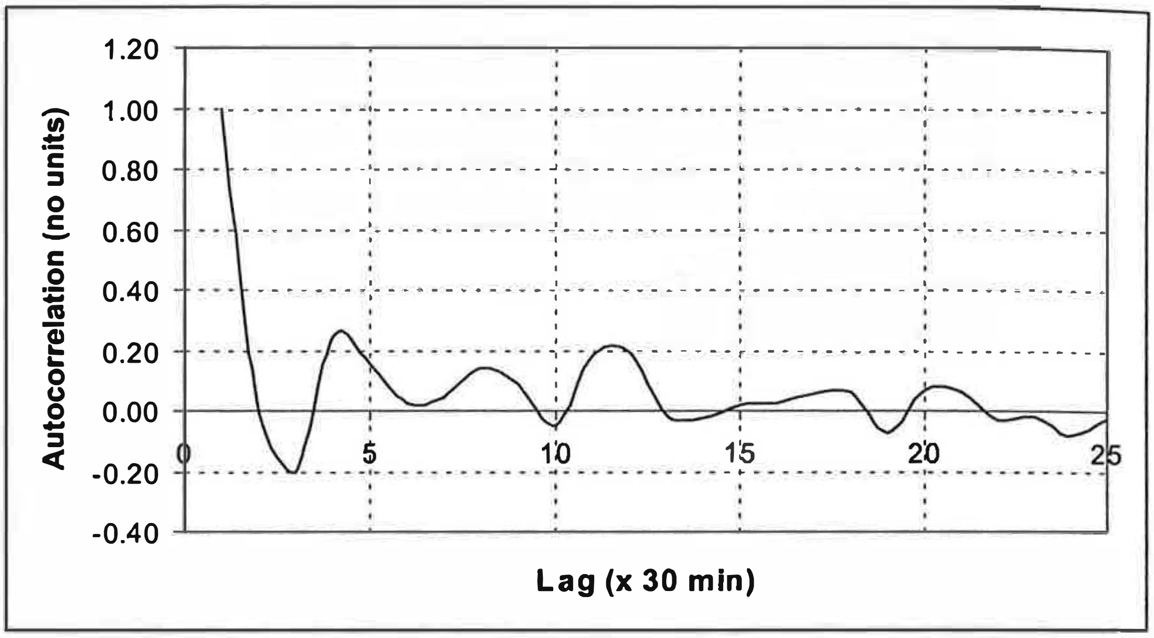

Fig. 5. Autocorrelation function.

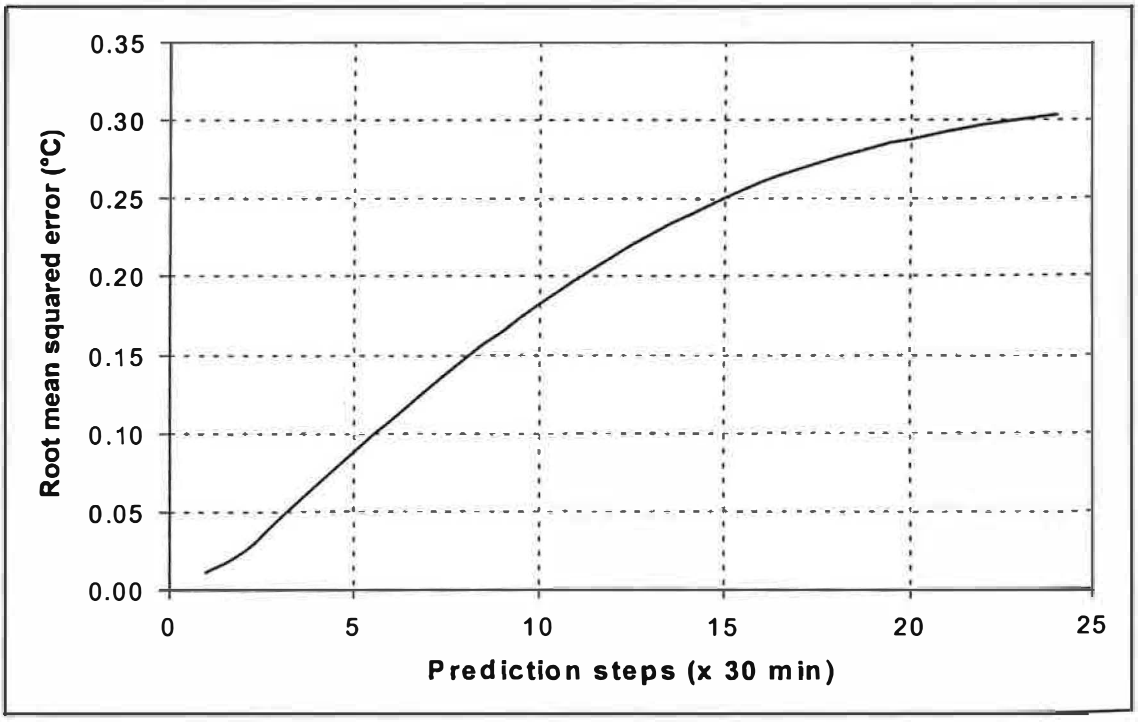

Fig. 6. Long term prediction error.