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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 of internal parameters in office buildings. This method has gained significant importance recently and has also been implemented in the Fuzzy Toolbox of the MATLAB software environment. The Adaptive Neuro Fuzzy Inference System method is a typical Soft Computing approach using Fuzzy Logic for building the initial model and Neural Networks for adaptation of the model parameters [3]. The method is based on a Takagi-Sugeno fuzzy model which has received considerable attention recently because of its suitability for processing information from input-output measurements. This is the case in Building Management Systems where the main on-line information can be obtained from sensor readings connected to the system rather than from expert knowledge as these systems are usually coupled multivariable ones [2], [4]. Another advantage of the Takagi-Sugeno fuzzy model is its capability to 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 algebraic equations in the consequent part. There are two types of parameters in this model: non-linear (in the membership functions in the antecedent part) and linear (in the algebraic equations in the consequent part) which are explained in more details further in this section. The task of the fuzzy model is to determine the initial values of both types of parameters on the basis of the input-output data. There are different methods for this purpose but the one that is most often used with the Adaptive Neuro Fuzzy Inference System is based on the idea of subtractive clustering, i.e. by assuming that each data point is a potential cluster centre and gradually finding the final clustering. The task of the neural adaptation is to adjust the model parameters in order to obtain a better fit to the measured data. There are also different methods for this purpose but the one that is most often used with the Adaptive Neuro Fuzzy Inference System is based on the idea of back-propagation, i.e. by iterative propagating of the error (the difference between the real and the modelled plant output) from the consequent to the antecedent part of the fuzzy rules until a desired accuracy is achieved or a pre-specified number of iterations is reached. The purpose of back-propagation is to reduce the error as much as possible although sometimes this can not be achieved because of divergency during the 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.

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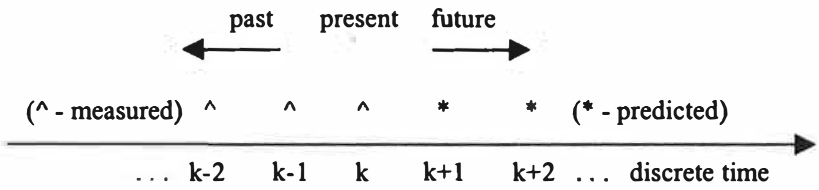

Fig.1. Proactive control strategy.

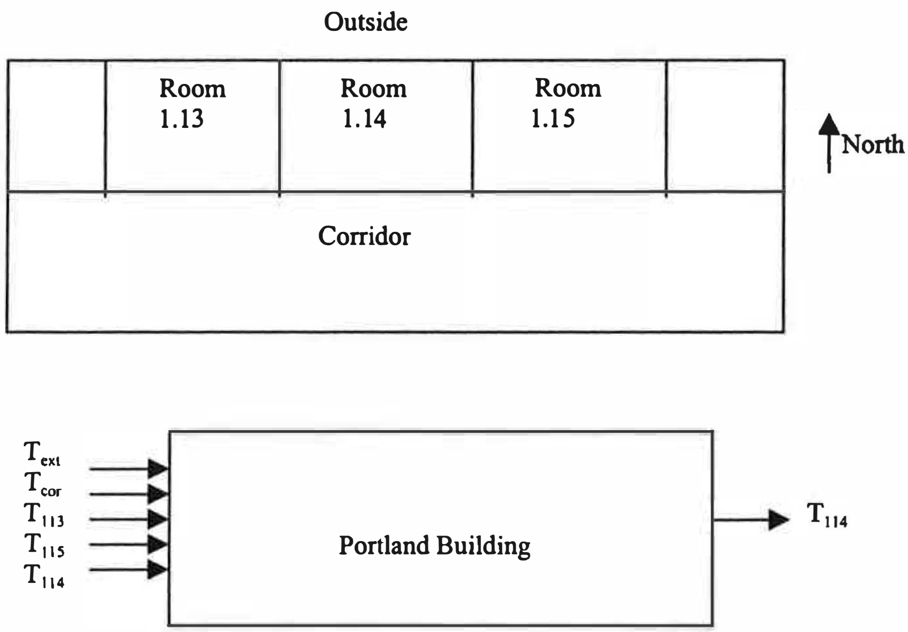

Fig. 2. Monitored zones and black-box model.

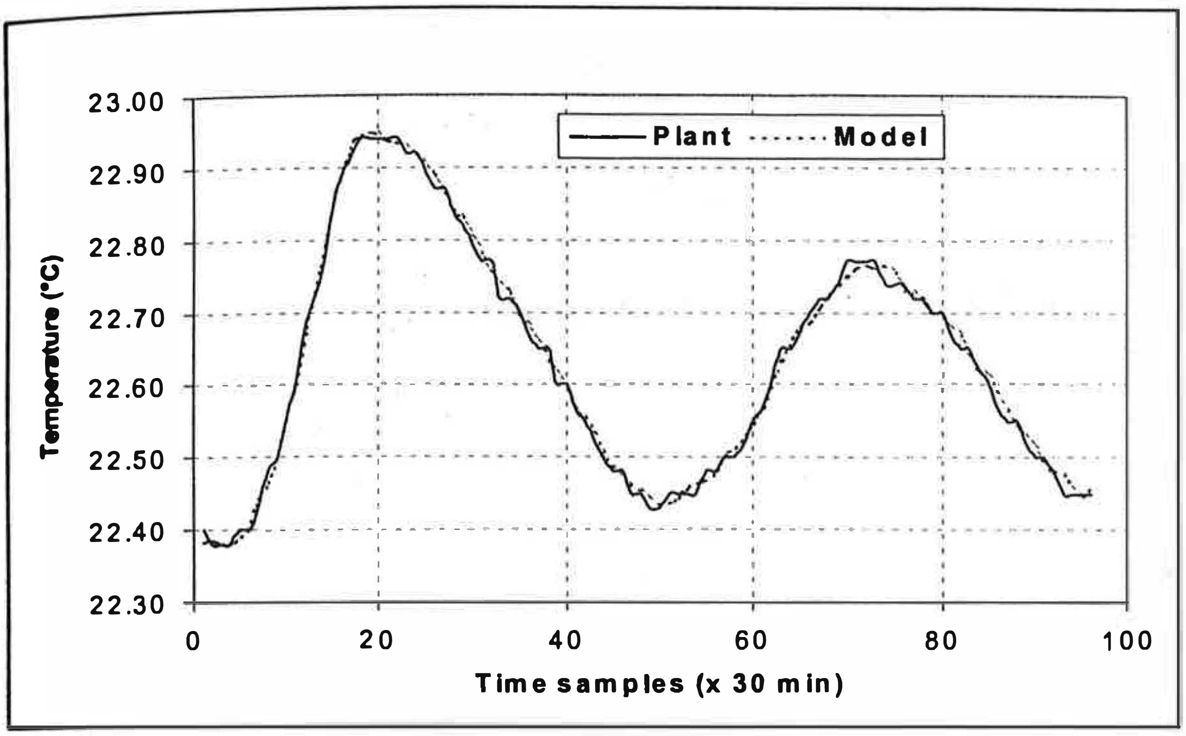

Fig. 3. Plant and model outputs.

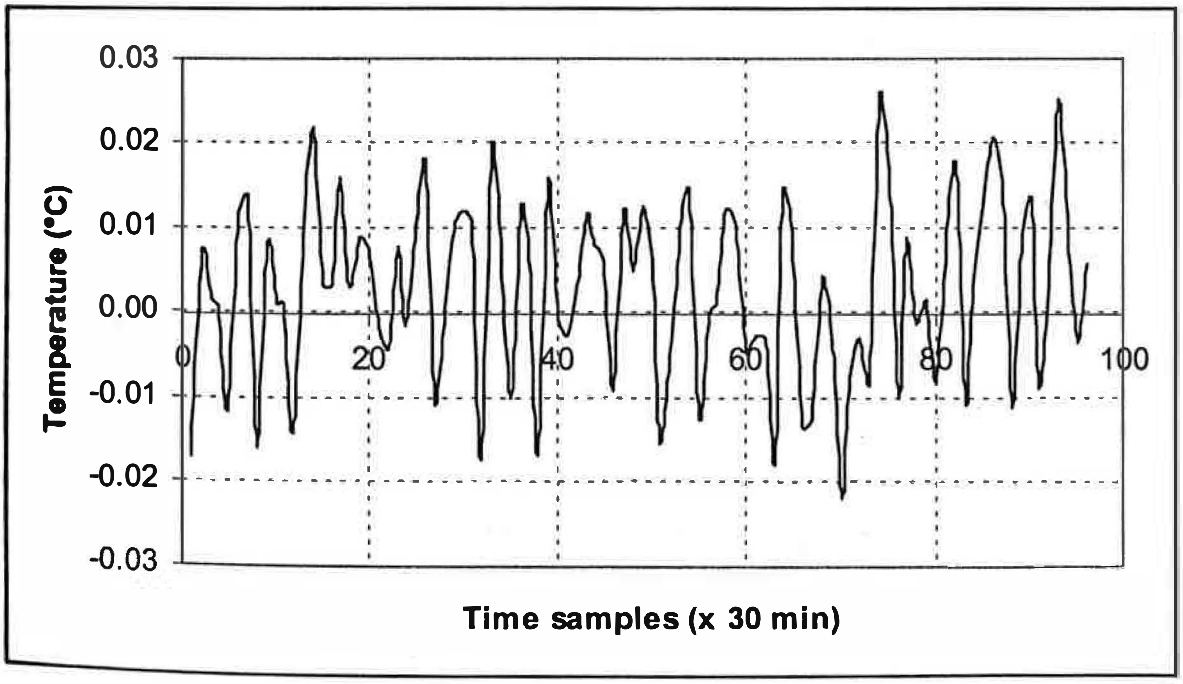

Fig. 4. Residuals (difference between plant and model outputs).

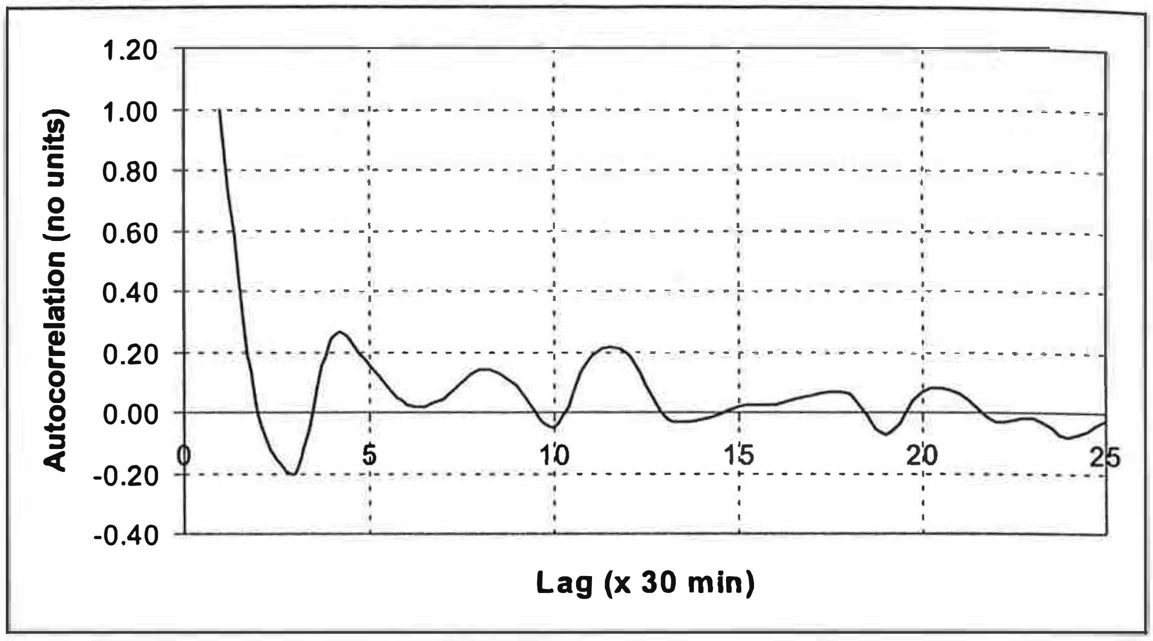

Fig. 5. Autocorrelation function.

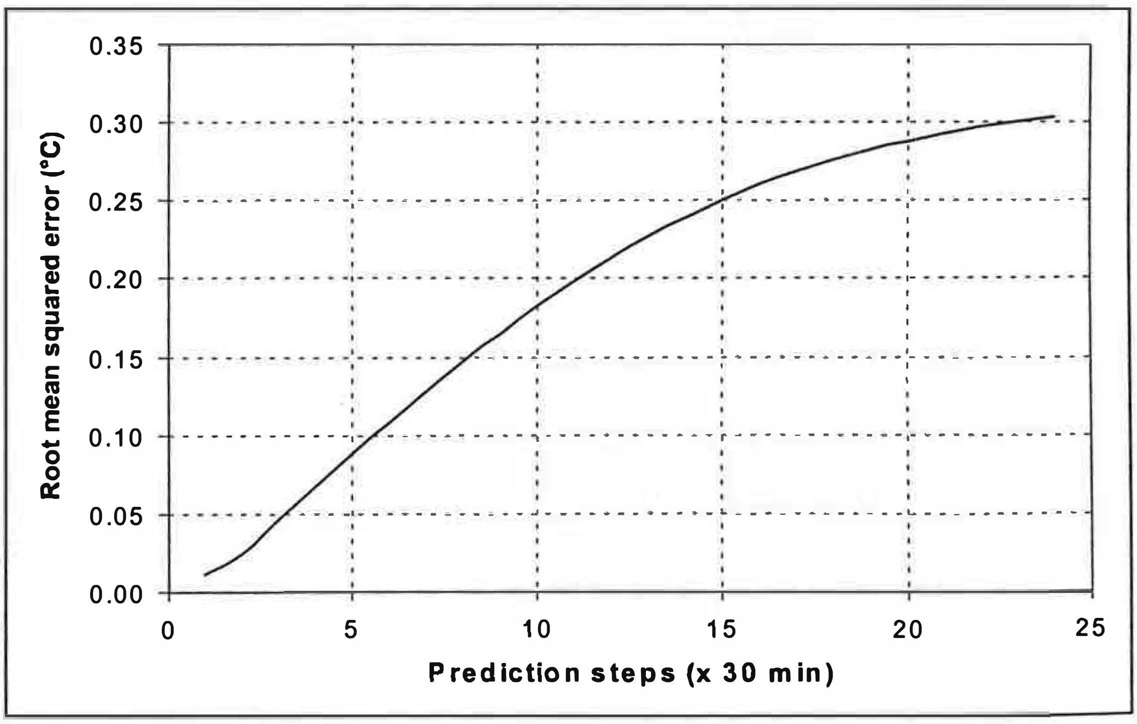

Fig. 6. Long term prediction error.