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Abstract: In this paper we report an Artificial Neural Network (ANN) based Nonintrusive Appliance Load Monitor (NALM), which is used to determine when individual appliances switch ON and OFF, measuring only the aggregated load. The NALM consists of an expert system that is an extension of Hidden Markov Models based Nonintrusive Appliance Load Monitors, since it uses both jumps of the aggregated load and time related information. This time related information cannot be used by Hidden Markov Models as their use is based on the Viterbi algorithm. Since modern domestic appliances are known to have similar electrical consumptions, the time related information enhances the performance of the NALM.

The development time of the NALM is kept low by using an ANN to perform the classification of the observed aggregated load into ON/OFF states of the different appliances. The extraction of features that describe the distinct appliances, is based on measurements of the individual appliances during a setup phase. These measurements are also used to artificially generate a large balanced training and validation set.

Keywords: Nonintrusive Appliance Load Monitor, Feedforward neural networks, Electrical End-Uses

I. INTRODUCTION

An Artificial Neural Network (ANN) based Nonintrusive Appliance Load Monitor (NALM) is described, which is used for the investigation of electrical end-uses [1][2][3][4][5][6][7][8]. A NALM is designed to identify the loads of the individual appliances, switching ON and OFF independently, while it measures only the aggregated load. Hence the complex and expensive sensoring and measuring of all individual loads, allowing easy data analysis, is replaced by a cheap data gathering by measuring only the total load, at the expense of a complex data analysis algorithm.

The knowledge of load patterns of the end-uses is important for market analysis applications such as energy efficiency, short term load forecasting [9][10], mid term load scheduling and long term investment planning. The load patterns of the end-uses are estimated by random surveys load monitoring and by inquiries. Fig. 1 gives such an example based on an inquiry carried out by the Belgian energy company Electrabel, asking when the customers put on an important appliance as the dishwasher. Nowadays more attention is paid to continuously load monitoring random surveys. Since a NALM is designed to identify several end-uses measuring only the aggregated load, these cost-savings make it very useful for random surveys. It enables e.g. to enlarge the sample size using a fixed budget.

A lot of research has already been done on Hidden Markov Models based NALMs which use only load jump information [1][2][4][5][6][7][8]. In this paper an ANN based NALM is described which uses both load jump information and time related information. ANNs are universal non-linear approximators used in various fields of applications, including classification [11], non-linear identification and control [12],[13]. In this application, both load jump and time related features of the total load are extracted and are fed to an ANN classifier. The ANN classifies the extracted features into ON/OFF states of the appliances. It is shown that the ANN based NALM is capable of differentiating between appliances with similar load characteristics.

This paper is organised as follows: in section II the problem of subdividing the aggregated (total) load into (known) loads of the appliances is discussed. The ANN based NALM is explained in section III. The NALM consists of two modules: the first module extracts the features that describe the distinct

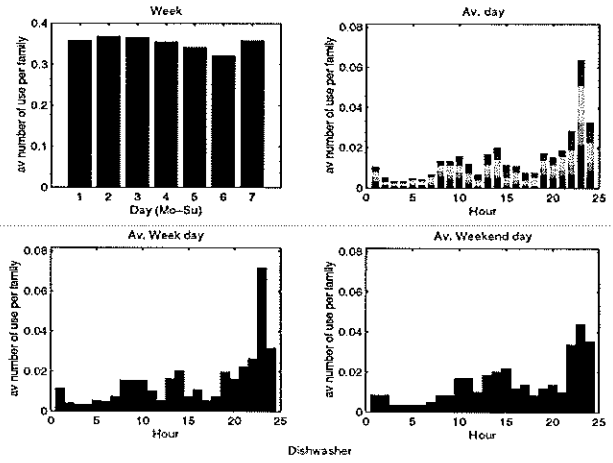

Fig. 1. Results of an inquiry concerning the use of the dishwasher. Top left: average times per day that the dishwasher was used. Top right: average number of times that the dishwasher was used, with respect to time of day. Subsequent days have different gray scales (starting with Mondays at the bottom). Bottom left: average use for an average weekday (Monday - Friday). One can distinguish the peak when the lower tariff period starts. Bottom right: average use for a weekend day. This inquiry was ordered by the direction of the Belgian electricity company Electrabel.

appliances, while the second module is a trained ANN which performs the classification of the extracted features of the observed aggregated load into ON/OFF states of the appliances. Some simulation results are shown in section IV. Conclusions are drawn in section V.

II. PROBLEM DESCRIPTION

In this section the problem of subdividing the measured aggregated load into the partial loads of the appliances is discussed.

A. Continuous time model

Let $\mathcal{P}(t) = [\mathcal{P}_{Act}(t) \quad \mathcal{P}_{React}(t)]^T$ denote the total multiphase load at the time instant t and let $P_\xi = [P_{Act,\xi} \quad P_{React,\xi}]^T$ denote the vector with the multiphase load[1] of appliance ξ $(1 \leq \xi \leq N)$, then find $a_\xi(t) \quad (1 \leq \xi \leq N)$ such that:

$$\mathcal{P}(t) = \sum_{\xi=1}^{N} a_\xi(t) P_\xi + e(t) \tag{1}$$

with

$$a_\xi(t) = \begin{cases} 1, & \text{if the appliance } \xi \text{ is in the ON state at time } t. \\ 0, & \text{if the appliance } \xi \text{ is in the OFF state at time } t. \end{cases}$$

$$e(t) = \begin{bmatrix} e_{Act}(t) \\ e_{React}(t) \end{bmatrix}, \quad \text{the error term.}$$

The error term $e(t)$ is due to unknown consumptions of (small) appliances and measurement errors.

For each time instant t equation (1) has to be satisfied. This combinatorial optimisation problem can be stated as two multi 0/1 knapsack problems [14] which can be solved by e.g. branch and bound methods. If one uses only one measurement (most likely the measurement of the active consumption), the problem is reduced to two 0/1 knapsack problems (P1) and (P2):

$$\max_{x_\xi} \quad \sum_\xi P_\xi x_\xi \tag{P1}$$

$$\text{s.t.} \quad \sum_\xi P_\xi x_\xi \leq \mathcal{P}, \qquad x_\xi \in \{0, 1\}$$

$$\max_{y_\xi} \quad \sum_\xi P_\xi y_\xi \tag{P2}$$

$$\text{s.t.} \quad \sum_\xi P_\xi y_\xi \leq \sum_\xi P_\xi - \mathcal{P}, \qquad y_\xi \in \{0, 1\},$$

where x_ξ (y_ξ) the decision variables for (P1) ((P2)), with x_ξ=1 (y_ξ=0) if P_ξ is in the subset (the appliance P_ξ is ON) and x_ξ=0 (y_ξ=1) otherwise. These can be solved in a much faster way since the knowledge of the structure of the knapsack problem can be exploited to obtain fast calculations of good bounds [15], however using less information.

Analogously a discrete time model ($t_k = k\Delta t$) can be derived for integrated loads, with $a_\xi(t_k) \in [0, 1]$, due to state changes during the time interval.

[1]For notational convenience, only ON/OFF appliances are considered. Appliances having $\alpha > 1$ ON-states are described as α appliances.

B. Switch continuity principle

The switch continuity principle states [1]: *In a small time interval, we expect only a small number of appliances to change state in a typical load.*

This and other reasons imply that the methods above are not appropriate for this application:

- It is very hard to include the switch continuity principle in the combinatorial optimisation problem.
- The solution of the multi 0/1 knapsack problem can be very noise sensitive.
- The error term can be relatively large, since not all (most likely small) appliances are known and since the slumber consumption (e.g. clocks, leds, stand-by modes of television and radio) can be relatively high.
- The consumption also depends on the fluctuations of the power net and the result of normalisation towards the voltage depends strongly on the linearity of the appliances.

Hence it is impossible to find the "exact" solution with combinatorial optimisation. In the next section an alternative and more robust approach based on ANNS is described.

III. ARTIFICIAL NEURAL NETWORK BASED NONINTRUSIVE APPLIANCE LOAD MONITOR

The NALM consists of two modules: the first module performs feature extraction on the total aggregated load. A description of the setup of this module and three representive examples are given in subsection III-A. Arguments concerning the choice of an ANN classifier instead of Hidden Markov Models are given.

The second module performs the classification given the extracted features. It is a trained ANN and decides whether the appliance was ON (positive, corresponding output 1) or OFF (negative, corresponding output 0). This module is described in subsection III-B. Fig. 2 gives a flowchart of the NALM. The results are presented in the next section.

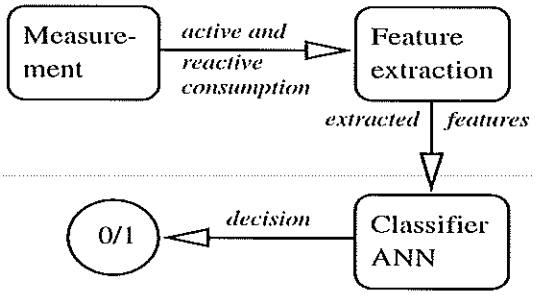

Fig. 2. Flowchart of the ANN based NALM: both the total active and reactive consumption are measured with time intervals of 1 minute. Features are extracted from these measurements (module 1) and are passed to the Artificial Neural Network (ANN) (module 2) which classifies the different appliances as ON or OFF.

A. Feature extraction

Feature extraction is based on heuristics, identifying discriminating features from the given dataset of each appliance. This dataset can be constructed during the setup phase by intrusive

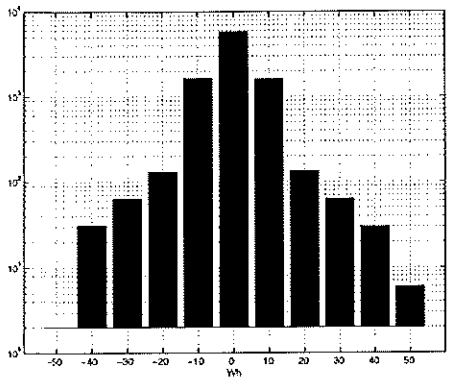

Fig. 3. Histogram of the load jumps of the total consumption (in Wh). The measurement period is about 6 days. It is clear that also other appliances which are not known or not taken into account can cause similar load jumps for the appliances under consideration. This indicates that other (e.g. time related) information is necessary to enhance the performance of the NALM.

monitoring of the load when the appliance is ON or may consist of nonintrusive monitoring when basically only the investigated appliance is ON.

The most important features are the load jumps at the beginning and the end of the work cycles. Using only this information results into the use of Hidden Markov Modelling techniques. Extra information is based on interjacent ON/OFF jumps and time related information such as the elapsed time between different ON/OFF jumps. Using this information, it is impossible to instantaneously decide whether an appliance is turned ON/OFF. This is not seen as a drawback since, in the case of the random surveys, data is stored in local RAM and is typically read out once a day (during the night). In the next three paragraphs, three examples of feature extraction are given. We consider the case of a dishwasher, a washing-machine and a tumble drier.

These three appliances have similar load characteristics, which causes problems for Hidden Markov Model based NALMs [1][2], which use Viterbi algorithm [16][17][18]. The main restriction is that the Viterbi algorithm does not allow to take time information into account. Fig. 3 shows the histogram of the load jumps of the total active consumption in a time period of about 6 days. From this it should be clear that the number of jumps of 30 Wh or 40 Wh is far too high to allocate them to the three applications considered here (see also Fig. 1). Besides the fact that the considered appliances can have similar load characteristics, the fact that also unknown appliances can cause similar load jumps is a clear indication for using other (e.g. time related) information. The features for each of the three appliances are:

- *The dishwasher:* Fig. 4 shows the active (full line) and reactive (dashed line) consumption of the dishwasher. It is characterised by two peaks of the active power consumption, due to the heating of the water, which yield the main features. Only jumps occurring in fixed time windows after the first ON jump are taken into account.
- *The washing machine:* The load of a washing machine is shown in Fig. 5. It is characterised by an initial active power peak, caused by the heater, and a continuous high consumption of reactive power, due to the transient behaviour of the motor.
- *The tumble drier:* The load of the tumble drier is shown in Fig. 6. It takes the form of a single block of active power consumption, with sharp edges, and some high frequency ON/OFF jumps at the end of the cycle.

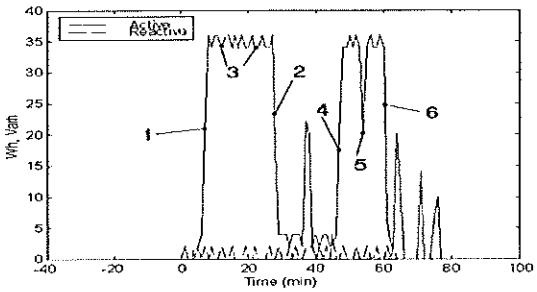

Fig. 4. Active (full line) and reactive (dashed line, below) consumption of the dishwasher. The extracted features are: 1) Height of the first ON jump. 2) Height of the first OFF jump. This OFF jump has to occur within a fixed time window after the ON jump. 3) Consumption during the first ON/OFF period is higher than 30 Wh. 4) Height of the second ON jump, which also has to occur within a certain time window after the OFF jump (2). 5) Dip in the consumption. 6) Height of the second OFF jump, within a certain time window after the ON jump (4.).

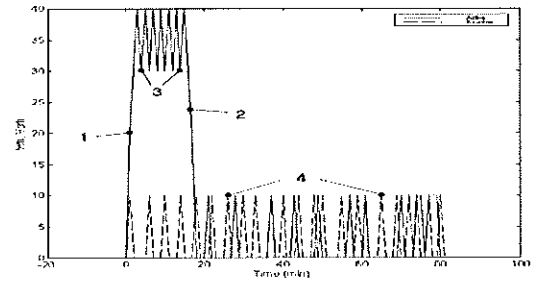

Fig. 5. Active (full line) and reactive (dashed line) consumption of the washing machine. The extracted features are: 1) Height of the ON jump. 2) Height of the OFF jump of the heating element, within a fixed time window after the ON jump. 3) Consumption is higher than 30 Wh from the ON jump till the OFF jump. 4) Reactive consumption is high.

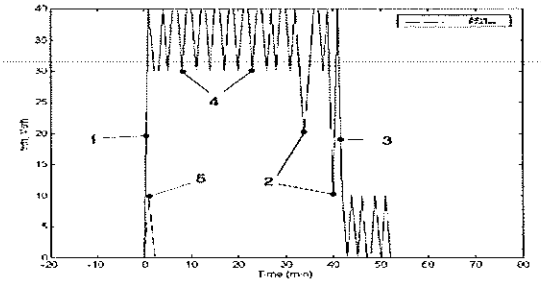

Fig. 6. Active (full line) and reactive (dashed line) consumption of the tumble drier. The extracted features are: 1) Height of the ON jump. 2) High frequency ON/OFF jumps at the end of the heating, within a fixed time window after the ON jump. 3) Height of the OFF jump, within a fixed time window after the ON jump. 4) Consumption is equal to or higher than 30 Wh during the ON/OFF period, except for the ON/OFF jumps. 5) Reactive consumption is rather low. 6) No second ON jump (to differentiate with the dishwasher); this feature is obviously not shown.

B. Use of Artificial Neural Networks

The main engine of the NALM is a multilayer perceptron (MLP) [12][13]. For each appliance an ANN is trained by supervised learning to determine whether the appliance is ON/OFF. In other words, the ANN is a classifier with 2 classes: ON (1) and OFF (0) [11].

The inputs H_i^0 ($i = 1 \ldots n^0$) of a R-layer MLP are multiplied by the connection weights W_{ij}^0 and passed to the neurons $j = 1 \ldots n^1$ of the first hidden layer (Fig. 7). The neurons of the hidden layers have a tanh activation function. The output neuron has a purely linear transfer function, to speed up the training. The equations for the hidden layer nodes and the output node are:

$$H_j^r = \tanh\Big(\sum_{i=0}^{n^{(r-1)}} W_{ij}^{(r-1)} H_i^{(r-1)}\Big), \quad (2)$$

$$Y = \sum_{i=0}^{n^R} W_{ij}^R H_j^R, \quad (3)$$

where H_j^r is the output of the hidden layer node j ($1 \le j \le n^r$) of the rth hidden layer ($1 < r \le R$), and $H_i^{(r-1)}$ is the output of node i ($1 \le i \le n^{(r-1)}$) of the previous hidden layer connected to H_j^r via the weights W_{ij}^{r-1}. The bias is introduced by $H_0^{(r-1)} = 1$. The output Y of the output node is given by (3). Fig. 7 shows an MLP with 3 input nodes, 1 hidden layer with 4 hidden nodes and 1 output node.

The training sets are artificially generated by using nonintrusive measurements of the setup phase. This also balances the training set size for not frequently used appliances, which is necessary for a good performance [19]. The weights are initialised by the Nguyen-Widrow method and the Levenberg-Marquardt optimisation algorithm [20] is used to train the MLP's. It has faster convergence than the error back propagation method [21], at the expense of higher memory requirements. Learning is stopped when the error for the test set starts to increase, since further training will then deteriorate the generalisation ability of the ANN [22]. To avoid the "curse of dimensionality", we consider separate MLP's for each appliance.

The following terminology has been used to measure the performance:

- *False Positive (FP):* the output of the NALM is 1, the true output is 0.
- *True Positive (TP):* the output of the NALM is 1, the true output is 1.
- *False Negative (FN):* the output of the NALM is 0, the true output is 1.
- *True Negative (TN):* the output of the NALM is 0, the true output is 0.

The performance is evaluated by the following ratio's:

$$\begin{aligned} \text{TPratio} &= \text{TP}/(\text{TP}+\text{FP}) \quad (4)\\ \text{FPratio} &= \text{FP}/(\text{TP}+\text{FP}) = 1 - \text{TPratio}\\ \text{TNratio} &= \text{TN}/(\text{TN}+\text{FN})\\ \text{FNratio} &= \text{TP}/(\text{TN}+\text{FN}) = 1 - \text{TNratio}. \quad (5) \end{aligned}$$

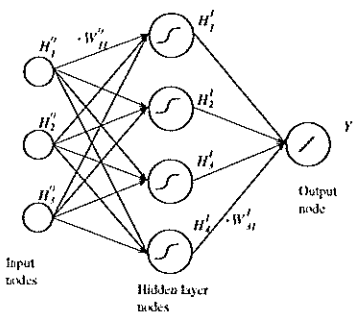

Fig. 7. An multilayer perceptron with one hidden layer, 3 input nodes, 4 hidden layer nodes and 1 output node.

IV. SIMULATION RESULTS

A. Description of the data

The data consist of active and reactive consumption measurements. The length Δt of the sampling interval is chosen equal to 1 minute. This approach differs from [3] where the NALM is based on transient behaviour of the appliances.

At each time instant $t_k = k\Delta t$ the integrated active and reactive consumption of the total load are read out and rounded down. The remainder of this quantisation step is held for the next minute.

Since also high consumptions (due to heating during the winter months) are measured, the quantisation step is quite high being 10 Wh and 10 VARh, for the active and reactive consumption respectively.

A balanced data set of 20.000 samples was artificially constructed by using datasets of the individual appliances and of the total load of the setup phase. From this data set, 2/3 was used for training, 1/3 for validation. The ANN was developed by means of the Matlab Neural Networks Toolbox, using the Levenberg-Marquardt learning rule. Learning is stopped when the error on the test set starts to increase. Three different starting points were used. For all three appliances different structures for the ANN were investigated. An ANN with 2 hidden layers gave the best performance. The number of hidden neurons per hidden layer varied from 4 to 6, depending on the application.

B. Performance evaluation of ANNs

The results of the ANN based expert system are given in table I. It is obvious that the performance for the dishwasher (DW) is much better than the performance for the washing machine (WM) and the tumble drier (TD). This can be explained by the better quality of the features that have to be recognised. The difference between the washing machine and the tumble drier is explained by the fact that the feature of low reactive power is not very discriminative.

V. CONCLUSIONS

In this paper we presented an Artificial Neural Network (ANN) based Nonintrusive Appliance Load Monitor (NALM). It is a logical extension of Hidden Markov Model based algorithms [1][2], which use only load characteristics, to a system which takes time related information into account as well.

TABLE I

RESULTS OF THE RECOGNITION OF THE ANN BASED EXPERT SYSTEM. FOR BOTH THE TRAINING SET (TR.) AND THE VALIDATION TEST SET (VAL.), THE PERCENTAGES (4),(5) OF FALSE ON AND FALSE OFF CLASSIFICATIONS ARE GIVEN; FOR THE DISH WASHER (DW), THE WASHING MACHINE (WM) AND THE TUMBLE DRYER (TD).

Appl.	Set	FNratio	FPratio
DW	Tr.	1,3 %	1,8 %
	Val.	1,5 %	2,1 %
WM	Tr.	0,1 %	1,0 %
	Val.	0,2 %	4,5 %
TD	Tr.	0,3 %	5,2 %
	Val.	1,0 %	7,1 %

Since the use of time information prohibits the use of the Viterbi algorithm as in [1][2], an expert system NALM was developed. During a setup phase the work cycle of each appliance is characterised by a number of features, including information of the time evolution of the cycle. To keep the development time low, an ANN was used to do the classification of the extracted features.

The results of this paper are a clear indication that using time information enhances the discrimination between different appliances with similar power consumptions. In general, as the classification is based on the extracted features, the performance of the ANN based NALM depends strongly on the discriminative power of the extracted features.

Further research is focused on alternatives for the intrusive setup phase and on improving the discriminative power by better measurements. In this last phase, a more sophisticated measurement system will be installed in a relatively large number of houses.

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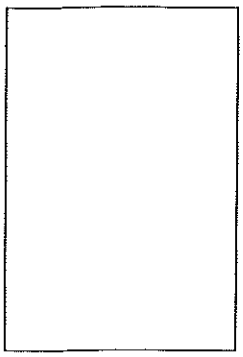
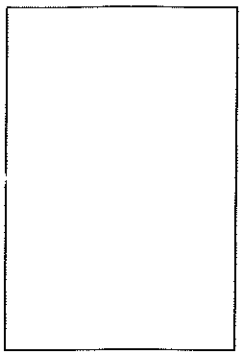
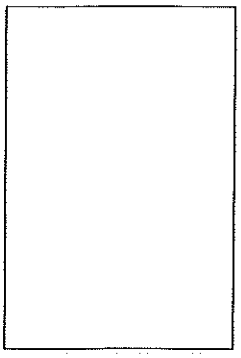
VIII. BIOGRAPHIES



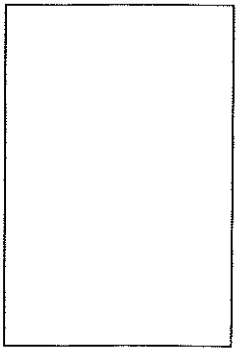
Tony Van Gestel was born in Geel, Belgium, on Thursday November 14, 1974. He obtained the degree in Electro-Mechanical Engineering in 1997 at the Katholieke Universiteit Leuven. The subject of his masters thesis was the identification of ATM-traffic with Hidden Markov Models. Presently he is working towards his doctoral degree at the Department of Electrical Engineering at the Katholieke Universiteit Leuven. He is a research assistant with the Fund for Scientific Research Flanders (FWO-Flanders). His research interests include linear and non-linear modelling, neural nets and time series prediction.



Johan Suykens was born in Willebroek Belgium, May 18 1966. He obtained the degree in Electro-Mechanical Engineering in 1989 and the doctoral degree in Applied Sciences in 1995 at the Katholieke Universiteit Leuven. In 1996 he has been a visiting postdoctoral researcher at the University of California Berkeley. Presently, he is a postdoctoral researcher with the Fund for Scientific Research FWO Flanders. His research interests are mainly in nonlinear systems and neural networks, both theory and applications. He is author of the book "Artificial Neural Networks for Modelling and Control of Nonlinear Systems" and editor of the book "Nonlinear Modeling: Advanced Black-Box Techniques", published by Kluwer Academic Publishers. He is serving as associate editor for the IEEE Trans. on Circuits and Systems-I and for the IEEE Trans. on Neural Networks.



Lieven De Lathauwer was born in Aalst, Belgium, on November 10, 1969. He obtained the degree in Electro-Mechanical Engineering in 1992 and the doctoral degree in Applied Sciences in 1997 at the Katholieke Universiteit Leuven. The subject of his Ph.D. thesis was signal processing based on multilinear algebra. He is currently working as a post-doctoral researcher at the Katholieke Universiteit Leuven. His research interests include linear and multilinear algebra, statistical signal and array processing, higher-order statistics (HOS), independent component analysis (ICA) and blind source separation (BSS), identification, blind identification and equalisation.

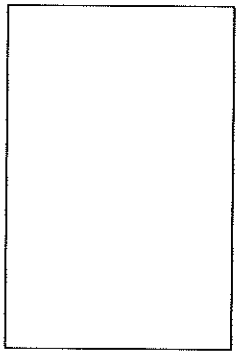


Bart De Moor was born in Halle, Brabant, Belgium on Tuesday July 12, 1960, is married to Hilde Devoghel and has two children, Thomas and Hannah. He received his doctoral degree in Applied Sciences in 1988 at the Katholieke Universiteit Leuven, Belgium. He was a visiting research associate (1988-1989) at the Dept. of Computer Science (Gene Golub) and Electrical Engineering (Thomas Kailath) of Stanford University, California, USA. Since October 1989 he is a senior research associate of the National Fund for Scientific Research of Belgium (FWO-Flanders) and associate professor at the Department of Electrical Engineering of the Katholieke Universiteit Leuven.

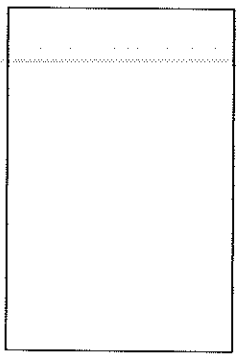
His research interests include numerical linear algebra (generalised svd, complementarity problems, structured total least squares, tensor algebra), system identification (subspace methods), control theory (robust control, neural nets) and signal processing. He has more than 200 papers in international journals and conference proceedings. He received the Leybold-Heraeus Prize (1986), the Leslie Fox Prize (1989), the Guillemin-Cauer Best Paper Award (1990) of the IEEE Trans. on Circuits and Systems, the bi-annual Siemens prize (1994) and became a Laureate of the Belgian Royal Academy of Sciences (1992).

He is a member of several boards of administrators of (inter)national scientific, cultural and commercial organisations, including the Belgian Institute for Control and Automation, the Flemish Interuniversity Institute for Biotechnology and ISMC NV (Intelligent Systems, Modelling and Control), a spin-off company who is specialized in modelling and control of multivariable industrial processes and mechatronics analysis and design. He is also a founding member of the philosophical think tank 'Worldviews'.

In 1991-1992 he was the chief of staff of the Belgian federal minister of science Ms.Wivina Demeester-DeMeyer and later on of the Belgian prime minister Wilfried Martens. Since 1994 he is the main advisor on science and technology policy of the Flemish minister-president Luc Van den Brande.



André Deprêter was born in Ukkel, Belgium, April 4 1952. He graduated from the "Hoger Rijksinstituut te Anderlecht" as Engineer in Control Theory. He joined the energy laboratory Laborelec (Electrabel) in 1978 and started his research on heat pumps for residential and tertiary applications. From 1984-1998 he worked on industrial electro-thermal applications, especially on drying processes. In 1988 he became the Head of Residential and Tertiary Applications Research Group in the Electrotechnology Department of Electrabel. His research interests include heating applications, Demand Side Management (DSM) and the Rational Use of Energy. He is currently working at the headquarters of Electrabel, the largest Belgian electricity company.



Marc Crepel was born Zwevegem, Belgium, on 14 October 1949. He obtained the degree in Electro-Mechanical Engineering (power current) in 1973 at the Katholieke Universiteit Leuven. In 1974 he obtained the degree in Nuclear Sciences at the same University. He also followed the Belgian seminary on Business Management in Brussels (1989). From 1975-1977, he worked at the Nuclear Power Plant of Tihange. From 1977-1983, he worked at Electrobel Engineeringfor the building and start-up of the nuclear power plants Tihange II and Tihange III. He had a technical and marketing position at Sibelgaz from 1983-1988. From 1988-1990 he had a marketing position at Intercom Distribution Nord (Mechelen-Brussel, Belgium). From 1991, he is the head of the market analysis Dept. of the Belgian energy company Electrabel. His main research interest is the market analysis for all clients of the inter-municipalities of the Belgian gas and electricity market.