

EVOLUTIONARY MULTIOBJECTIVE DESIGN OF RADIAL BASIS FUNCTION NETWORKS FOR GREENHOUSE ENVIRONMENTAL CONTROL

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Abstract: In this work a *multiobjective genetic algorithm* is applied to the identification of *radial basis function* neural network coupled models of humidity and temperature in a greenhouse. Models are built as one-step-ahead predictors and then used iteratively to produce long term predictions. The number of neurons and input terms used in both models define the search space. Two combinations of performance and complexity criteria are used to steer the selection of model structures, resulting in distinct sets of solutions. It is shown that minimisation of one-step-ahead prediction errors negatively influences long term prediction performance. Long term prediction results are presented for a pair of models selected from sets of models obtained in the experiments. *Copyright © 2005 IFAC*

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1. INTRODUCTION

The main purpose of greenhouses is to improve the environmental conditions in which plants are grown. The aim of *greenhouse environmental control* (GEC) is to provide means to further improve these conditions in order to optimise the plant production process. Methods aimed at efficiently controlling the greenhouse climate environment and optimising the crop must take into account the influences of the outside weather, the actuators and the crop, which is achieved by the use of models. For the great majority of crops, production is mainly affected by greenhouse temperature, humidity and CO_2 concentration. This work deals with the identification of *radial basis function* (RBF) neural network (Broomhead and Lowe, 1988) models of the greenhouse temperature and humidity. These models

are to be used in a predictive GEC strategy as depicted in Figure 1.

1.1 Previous work

Previous work conducted by the authors investigated the application of RBF neural networks (NNs) to greenhouse air temperature modelling (Ferreira *et al.*, 2000a). A new RBF training method was proposed (Ferreira and Ruano, 2000; Ferreira *et al.*, 2002) and its on-line application compared to other on-line methods (Ferreira *et al.*, 2000b). The RBF ability to perform long term prediction was evaluated (Ferreira and Ruano, 2001) and compared with ARX models previously obtained (Ferreira *et al.*, 2000c). The input structure of the RBF model used in those studies was selected from a previous work (Cunha *et al.*, 1996), in the context of dynamic discrete-time model identification, where several hypothesis were tested and the *best* model was chosen by means of the Akaike

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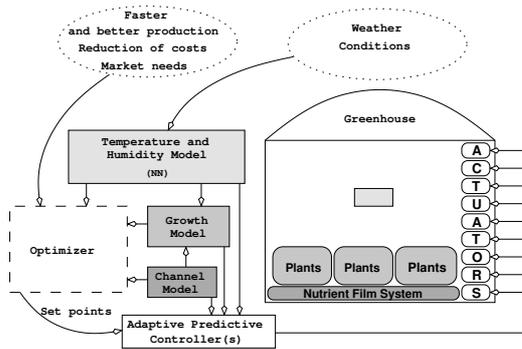


Fig. 1. Predictive greenhouse environmental control strategy

information criterion. It is obvious that this model input structure can not be considered optimal or sub-optimal in any sense when applied to a RBF NN. This fact raised several questions about designing NNs, particularly RBF: given a set of available variables in the form of data, which should be used as inputs to the NN? Having made this decision, are lagged input and output values important? What lags should be considered? How many neurons should be used in the network hidden layer? The answers are problem dependent and often very unlikely to have trivial solutions. In (Ferreira and Ruano, 2002; Ferreira *et al.*, 2003) two approaches were tested with the aim of selecting a better model structure.

2. PROBLEM CHARACTERISATION

As mentioned above, greenhouse temperature and humidity are two of the environmental quantities which most affect crop production, and it is known from the literature that these two variables are strongly coupled. Identifying long term predictive models of coupled variables, can be cast as the problem of finding a set of coupled models satisfying some pre-specified criteria. As long as *auto-regressive* (AR) model structures are to be selected based on long term prediction errors, both models must be determined prior to evaluation. Having these considerations in mind the problem can be stated as the search for a pair of coupled humidity-temperature models which is best in some sense. For the problem at hand the notion of *best* is regarded as the minimisation of both long term prediction error and number of parameters. In the framework of RBF NN modelling, searching for model structures corresponds to searching for both the number of neurons in the hidden layer and the network input terms, given a set of available variables. Improving prediction performance while reducing model complexity easily becomes conflicting, giving rise to a multiobjective optimisation problem. Evolutionary multiobjective optimisation (EMO) algorithms have been successfully applied (Fonseca and Fleming, 1996a; Rodríguez-Vázquez *et al.*, 2004) to this type of system identification problems. In particular, the multiobjective genetic algorithm (MOGA) (Fonseca and Fleming, 1998a)

has been applied by the authors to greenhouse inside air temperature prediction (Ferreira *et al.*, 2003), and is considered in this work.

3. RBF NN REPRESENTATION AND THE MOGA

The MOGA is an evolutionary computing approach, inspired by the theory of natural selection and the notion of survival of the fittest, which performs a population-based search by employing operators such as selection, mating and mutation. One of the advantages of EMO techniques over other techniques is that they can provide a diverse set of non-dominated solutions to problems involving a number of possibly conflicting objectives, in a single run of the algorithm. One run consists of a sufficiently large number of generations to allow the evolution of individuals meeting certain pre-specified requirements.

3.1 Chromosome representation

The structure of a multiple-input single-output RBF NN can be represented by the number of neurons in the hidden layer and the number of inputs. The chromosome for one such network can be represented by a string of integers, the first of which corresponds to the number of neurons, and the remaining represent a variable number of distinct input terms. Input terms are represented by their position in a lookup table of the lagged terms considered for each available variable. For the case of the humidity-temperature models, each individual chromosome is constructed by concatenating two such strings of integers.

3.2 Recombination

After the individuals in a generation are evaluated, the population is ranked using the preferability relation (Fonseca and Fleming, 1998a) and then, the individuals selected are mated to produce two offspring from each pair of parents. Parent recombination is done in such way that offspring respect the maximum model length with no loss of input terms (Fonseca and Fleming, 1996a). The resulting offspring may be longer, shorter or equally sized as their parents.

3.3 Mutation

The mutation operator is implemented by three basic operations: substitution, deletion and addition of one element. The number of neurons is mutated, with a given probability, by adding or subtracting one neuron to the model, verifying boundary conditions that no NN can have fewer or more neurons than pre-specified values. Each model input term in the chromosome is tested and, with a given probability, is either replaced by a new term not in the model, or deleted. Finally a new term may be appended to the chromosome.

4. METHODOLOGY

4.1 Data sets

The data employed in this work was acquired with a sampling rate of 1 minute, in a plastic covered greenhouse, and is composed of 12 days of data. Variables used are: greenhouse inside relative humidity (rh_i) and temperature (t_i), outside temperature (t_o) and solar radiation (sr_o). Other variables (inside solar radiation and outside wind speed and direction) are available but were not considered, as they were discarded by the MOGA when modelling greenhouse inside air temperature in a previous experiment (Ferreira *et al.*, 2003). Although wind speed and direction could be of importance for the humidity model, there is no data regarding the greenhouse openings state, and the fact they were not selected in previous work may mean that they were almost always closed at the time the data was acquired. The number of points is reduced by applying a 5 minute average over the entire data set and then, due to the different scales in the variables considered, all data is scaled to the $[0, 1]$ interval. The resulting data is split up into three equally sized (4 days) data sets, DS_r , DS_g and DS_v , for model training, generalisation testing, and validation, respectively. For each variable in the data sets, lagged terms up to 24 hours are computed, resulting in 288 possible input terms per variable. In order to reduce the size of the search space, a subset of all possible input terms is selected according to the following reasoning. Consider the fact that climate values at a given time instant are strongly related to their most recent values, and also, to a certain extent, to their values 24 hours before. So that recent values predominate and a smaller number of not so recent values, including those from one day before, are present, per-variable lagged term subsets are chosen as follows:

$$\begin{aligned} L_i &= \text{round}(l_i), i = 1, \dots, N \\ l_i &= l_{i-1}h, i = 2, \dots, N \\ l_1 &= 1 \end{aligned}$$

where N is the desired number of terms and the value of h is such that $L_N = 288$. As an example, for $N = 10$, the lagged terms considered would be:

$$L = [1, 2, 4, 7, 12, 23, 44, 82, 154, 288]$$

and $h = 1.8761$. In this work, for each variable considered N is set to 144 and $h = 1.0404$.

4.2 RBF NN training

Networks are trained as *one-step-ahead* (OSA) predictors by an algorithm (Ferreira and Ruano, 2000; Ferreira *et al.*, 2002) based on unconstrained deterministic optimisation employing Levenberg-Marquardt methods. RBF NNs are structurally simple layered

feed-forward NNs characterised by a nonlinear-linear topology in the parameters. The referred algorithm exploits this feature on the minimisation of a single explicit training criterion (Ferreira and Ruano, 2000). Early stopping is used to terminate training.

4.3 Model search space

Each individual in the MOGA is a pair of humidity-temperature models. The structure for both models is a *Non-linear auto-regressive model with exogenous inputs* (NARX) with the following general form:

$$\hat{r}h_i(k+1) = RBF_1\{rh_i(k), \dots, rh_i(k-n_{rh}), t_i(k), \dots, t_i(k-n_{ti})\} \quad (1)$$

$$\begin{aligned} \hat{t}_i(k+1) &= RBF_2\{t_i(k), \dots, t_i(k-n_{ti}), \\ &rh_i(k), \dots, rh_i(k-n_{rh}), \\ &t_o(k), \dots, t_o(k-n_{to}), \\ &sr_o(k), \dots, sr_o(k-n_{sr})\} \quad (2) \end{aligned}$$

The number of neurons for each network is required to be between 2 and 15. RBF_1 and RBF_2 may have 16 and 32 inputs, respectively. These limits spawn a search space of about 2.5750×10^{129} model pairs.

4.4 Long term prediction

When predicting $rh_i(k+j)$ or $t_i(k+j)$, any lagged model input terms for which no measured values are available are replaced by the corresponding predictions, $\hat{r}h_i$ and \hat{t}_i . For the t_o and sr_o variables, two independent auto-regressive RBF NN models were selected using a similar MOGA approach and are used to predict the necessary input values. The quality of each trained NN is assessed by its prediction performance over an horizon of 3 hours (36 steps) using the DS_g data set. To reduce computational time, prediction is computed starting at one hour intervals, resulting in 96 prediction horizons. For each starting point, the prediction error e_k is taken over the prediction horizon. Consider the matrix,

$$\mathbf{E} = \begin{bmatrix} e_{(1,1)} & \cdots & e_{(1,36)} \\ \vdots & \ddots & \vdots \\ e_{(96,1)} & \cdots & e_{(96,36)} \end{bmatrix}.$$

where each row corresponds to the errors obtained over each prediction horizon. Let $R(\cdot)$ be the *root mean square error* (RMSE) function operating over the rows of a matrix. In this way, $R(\mathbf{E})$ and $R(\mathbf{E}^T)$ are vectors denoting the RMSE over the full predicted horizon for every time instant, and the RMSE over all the horizons, for each prediction instant within the considered horizon, respectively.

Table 1. MOGA runs objectives.

Objective	Case 1	Case 2
$OSATE_{(t_i+rh_i)}$	×	minimise
$OSAGE_{(t_i+rh_i)}$	×	minimise
$\max\{R(\mathbf{E}^T)\}_{rh_i}$	minimise	minimise
$\max\{R(\mathbf{E}^T)\}_{t_i}$	minimise	minimise
$\ \mathbf{W}\ _{rh_i}$	7	7
$\ \mathbf{W}\ _{t_i}$	7	7

Table 2. MOGA runs results.

	Case 1	Case 2
Generations	350	500
PS (#)	19, 24.4, 33	123, 134.8, 157
Distinct pairs of models (PS)	16, 20.8, 25	113, 125, 148
Distinct humidity models (PS)	15, 19.8, 25	67, 84.2, 110
Distinct temperature models (PS)	12, 17.4, 25	101, 116, 140

4.5 MOGA parameters

The MOGA population size was set to 250 individuals, each with a maximum chromosome length of 50 (see sections 3.1 and 4.3). At the end of each generation 25 (10% of population) random immigrants are introduced. The selective pressure, crossover rate and mutation survival rate are, respectively, 2, 0.7 and 0.5. The objectives used in the experiments can be classified into two groups: model complexity and model performance. For the former, the norm of the RBF NN output linear parameters, $\|\mathbf{W}\|$, is used, with subscripts rh_i and t_i denoting humidity and temperature models, respectively. Model performance objectives are the sum of the OSA training error for both models ($OSATE_{(t_i+rh_i)}$), the sum of the OSA testing or generalisation error for both models ($OSAGE_{(t_i+rh_i)}$), and the maximum value of $R(\mathbf{E}^T)$ taken individually for each model. Table 1 shows how the two case studies considered in this work were setup in terms of objectives. The × symbol means the objective was ignored. The measures $\|\mathbf{W}\|_{rh_i}$ and $\|\mathbf{W}\|_{t_i}$ were setup as restrictions with equal priority. For each case, 5 MOGA runs were executed.

5. RESULTS AND DISCUSSION

Table 2 presents some general results regarding the two case studies. PS is an abbreviation *preferable set*. Where the notation x,y,z is found, x , y and z correspond to the minimum, mean and maximum values obtained over the 5 MOGA runs. Case 2 has a larger objective space, and originating a PS with more individuals than the case 1 PS. The numbers of distinct models indicate greater humidity model similarity in case 2, whereas for case 1 this is verified by the temperature models (see also figure 2). Table 3 shows the distribution of the number of neurons in the preferred humidity and temperature models found in the 5 MOGA runs. The numbers show a greater dispersion in case 2, probably due to the presence of the OSA

Table 3. Frequencies of the number of neurons in distinct humidity and temperature models in the PS.

Neurons	Case 1		Case 2	
	Hum.	Temp.	Hum.	Temp.
2		82	56	67
3			86	264
4	2	2	31	11
5	24		114	38
6	33		42	37
7	24	1	15	23
8	2	2	6	6
9			14	5
10	5		6	8
11			7	3
12			13	20
13			11	59
14	9		17	19
15			13	20

Table 4. Frequency of the number of inputs in distinct humidity and temperature models in the PS.

Inputs	Case 1		Case 2	
	Hum.	Temp.	Hum.	Temp.
1			5	
2			10	
3			6	
4			13	
5	1		37	3
6			38	2
7			37	2
8			53	4
9			41	2
10	2		43	11
11	4		43	18
12	10		34	23
13	11		22	20
14	20		19	24
15	32		15	21
16	19		5	27
17				47
18		1		35
19				39
20				29
21		1		32
22				37
23		8		37
24		3		37
25		8		38
26		5		30
27		4		28
28		5		15
29		11		11
30		10		5
31		11		3
32		20		

prediction error objectives, which favour a larger number of neurons. Clearly, networks with fewer neurons are favoured, and better long term prediction results were observed for such networks in general. Table 4 presents the distribution of the number of inputs in the humidity and temperature models found in the five runs. Shaded areas indicate numbers of inputs not allowed for the model in the corresponding column. Again the results for case 2 show much greater diversity. As opposed to the number of neurons, networks

Table 5. MOGA objectives in the two runs, regarding distinct pairs of models in the PS.

Measure	Minimum		Mean		Maximum	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
$OSATE_{(t_i+rh_i)}$	0.0238	0.0085	0.0360	0.0197	0.0552	0.2281
$OSAGE_{(t_i+rh_i)}$	0.0338	0.0123	0.0622	0.0304	0.1030	0.3191
$\max\{R(\mathbf{E}^T)\}_{rh_i}$	4.1857 %	5.4598 %	6.7105 %	8.8150 %	24.3699 %	32.1086 %
$\max\{R(\mathbf{E}^T)\}_{t_i}$	1.1843 °C	1.1738 °C	1.4103 °C	1.9989 °C	2.7042 °C	9.8666 °C
$\ \mathbf{W}\ _{rh_i}$	1.0492	0.6025	1.8663	2.9753	5.0475	6.9696
$\ \mathbf{W}\ _{t_i}$	1.0723	0.9138	2.5793	3.0127	4.2869	6.8532
$OSAVE_{(t_i+rh_i)}$	0.0521	0.0129	0.1122	0.0445	0.1577	0.3502

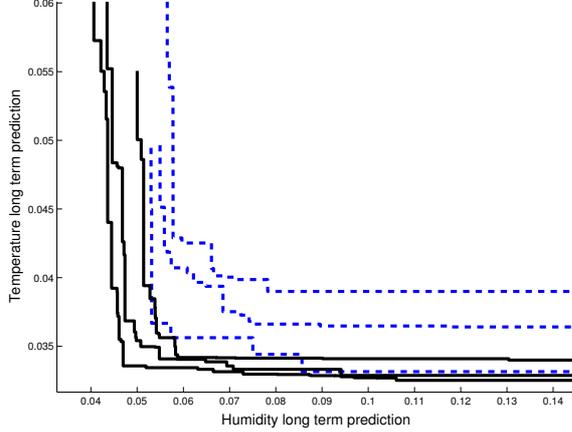


Fig. 2. Attainment surfaces for the two case studies. (Solid line: case 1. Dashed line: case2)

with more inputs are favoured and generally presented better long term prediction results. Table 5 compares both cases in terms of the MOGA objectives and the OSA validation error ($OSAVE_{(t_i+rh_i)}$). It is clear that case 2 models are generally better OSA predictors, although some exhibit worse $OSATE_{(t_i+rh_i)}$ and $OSAGE_{(t_i+rh_i)}$ values. This is caused by hill conditioned models as it can be seen by the results in $\|\mathbf{W}\|_{rh_i}$ and $\|\mathbf{W}\|_{t_i}$. The fact that case 1 models are not as good OSA predictors is justified by the absence of small lag terms, namely $t - 1$ appearing only in about 10% of the humidity models obtained and never in temperature models. Considering this, it is not surprising that the relation between $OSAVE_{(t_i+rh_i)}$ and the other OSA measures favours case 2 models. On the other hand, case 1 models present the best results regarding long term prediction. Figure 2 compares the *attainment surfaces* (ASs) (Fonseca and Fleming, 1996b) obtained in both case studies, regarding the long term prediction objectives only. For each case study, the three lines (from the lower left to the upper right corner) depict the estimates of the 0%, 50% and 100% ASs. The region attained in case 2 is almost entirely covered by that of case 1, with the exception of a small region of very good temperature models but poor humidity predictors. It is important to note that the models obtained in case 1 are generally non-dominated with respect to those obtained in case 2. This is an indication that in case 2 the MOGA was unable to cover the tradeoff surface to its full extent, possibly due to the increased dimensionality of the objective space. However, goal levels for each objective could be provided to the

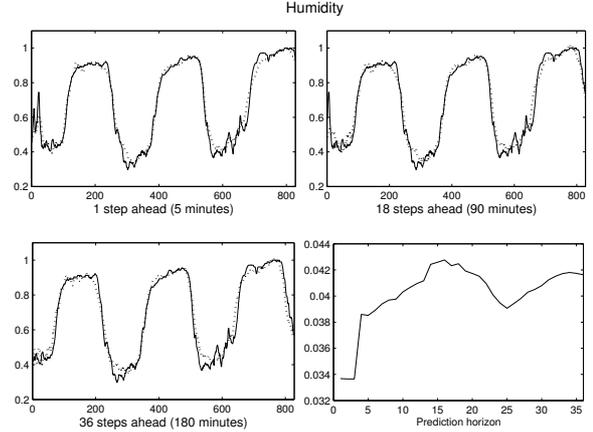


Fig. 3. Humidity prediction for a selected model pair.

MOGA, which would reduce the size of the preferred region and focus the search, eventually providing better performance (Fonseca and Fleming, 1998b).

Regarding input term selection, good agreement could be found for a considerable number of either specific terms or terms with very similar lags. Certainly, input term selection would gain from a reduction in search space dimension by further restricting the number of neurons and inputs. Such restrictions can be guided by the results obtained regarding those parameters.

Long term prediction capabilities over the DS_g data set, for a model pair with a good compromise between humidity and temperature prediction, selected from a run in case 1, are shown in figures 3 and 4. The networks have 6 neurons and 11 inputs for the humidity model, and 2 neurons and 29 inputs for the temperature model. Good fittings are obtained for the prediction in 1, 18 and 36 steps ahead. Both figures show also the evolution of $\max\{R(\mathbf{E}^T)\}$ over the prediction horizon. The mean and maximum absolute error values obtained for humidity and temperature are 3.0383 %, 24.5791 %, 0.8434 °C, and 6.1402 °C.

6. CONCLUSIONS

In this work a strategy was presented for the identification of coupled long term predictive humidity-temperature RBF models, using an evolutionary multiobjective algorithm. The models obtained showed a good level of agreement regarding the number of neurons and inputs, and significant input term selectivity,

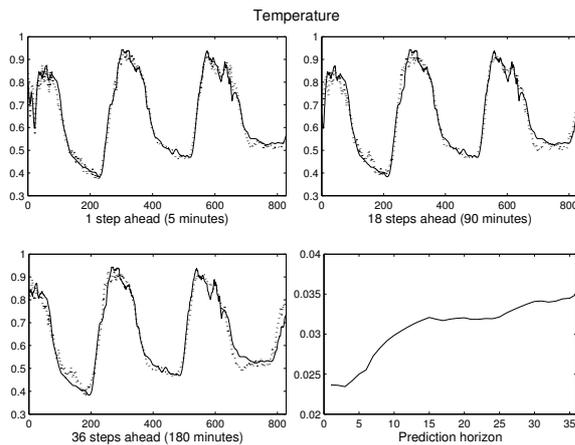


Fig. 4. Temperature prediction for selected model pair.

both within and between runs, which suggests consistent behaviour of the MOGA. Two experiments with difference sets of performance criteria were discussed, and it was shown how minimising one-step-ahead prediction errors does not lead to the best long term prediction performance. A good compromise between model complexity and performance was achieved with networks with just a few neurons and greater input dimension. The methodology presented here is suitable for the design of predictive RBF models, providing the designer with a good number of well performing solutions with varying degrees of complexity.

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