TEMPERATURE PREDICTION FROM REGIONAL SPECTRAL MODEL BY NEUROFUZZY GMDH

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Abstract

New businesses concerned with weather forecast have been emerged recently where the specific climate depending on geographical location and time of season is to be predicted. A neural GMDH (Group Method of Data Handling) family of modeling algorithm emulates the self–organizing activity of the central nervous system, and discovers the structure (functional form) of empirical models that include many input variables. A GMDH model called neurofuzzy (NF-) GMDH, whose partial descriptions (basic building blocks) are represented by the Radial Basis Functions (RBF) network, is applied to temperature forecast from the numerical weather prediction data of the Regional spectral model distributed by the Japan Meteorological Agency and compared with conventional RBF network. It is shown that the hierarchical GMDH type network outperforms the conventional RBF networks.

Keyword: Neural network, Intelligent information processing, Weather Prediction

1 Introduction

The weather forecasts influence the every day decisions of many people. For example, fishermen and ocean voyagers need precise and timely information to avoid storms and save fuel. Farmers depend on the forecasts to know when to plant and harvest their crops, when to apply chemicals to these crops. Aviators, in order to travel safely, need to know detailed weather along their route. Therefore new businesses concerned with weather forecast have been emerged recently where the specific climate depending on geographical location and time of season is to be predicted.

Mathematical models of the multivariable system require a large number of parameters. Group Method of Data Handling (GMDH) [1] is one of the methods of identifying nonlinear systems with many input variables. Its mathematical model is represented by a hierarchical network of the partial descriptions (i.e., the basic building blocks) and discovers the structure of empirical models as well as performing the task of fitting model coefficients to bases of observational data. The GMDH family of modelling algorithms is classified into two categories by Ivakhnenko, that is, (1)the perceptron combination type (we briefly call 'the perceptron type') and (2)the network type.

In the perceptron type GMDH algorithm, we merely take all of the independent variables one or two at a time and construct the partial descriptions. Several partial descriptions are selected by evaluating the mean squared error (MSE) with the checking data set. The outputs of selected partial descriptions are treated as the input in the next layer. These steps are repeated until a termination criterion is satisfied.

The Adaptive Learning Networks (ALN) [2] developed in U.S.A. in the early 1970th are regarded as the network type GMDH in which the successive selections of partial descriptions of the perceptron type are not necessary, and this distinguishes the network type from the perceptron type. Recently new GMDH models, whose partial descriptions are represented by the Radial Basis Functions (RBF) networks or fuzzy models, have been developed [3]. We call them the neurofuzzy (NF-) GMDH.

The RBF network is a technique for interpolating data in multidimensional spaces. The networks have the architecture that uses a single internal layer of locally tuned processing units and are called 'localized receptive fields' [4]. Brown and Harris demonstrated in their book entitled 'Neurofuzzy adaptive modelling and control' [5] that there exists an invertible relationship between fuzzy logic systems and RBF networks, with each inheriting the properties of the other.

In this paper we applied these neurofuzzy GMDH model to temperature prediction by using the numerical weather prediction data distributed from the Regional Spectral Model of the Japan Meteorological

Agency.

2 Multi Layered NF-GMDH

In the perceptron type GMDH algorithm, all partial descriptions with one or two variables chosen from all the input variables in each layer are evaluated and several of them are selected. The fuzzy partial descriptions in this paper is as follows.

Let $A_{ki}(x_i)$ denote the membership function of the k-th fuzzy rule in the domain of the i-th input variables. The compatibility degree of the premise part of the k-th fuzzy rule for an observed system state $\boldsymbol{x}$ is computed with the algebraic product operation of the compatibility degree as:

$$\mu_k = \prod_{i=1}^{I} A_{ki}(x_i) \tag{1}$$

where, $\boldsymbol{x} \in R^I$, and I is 1 or 2 for the partial descriptions of the GMDH. The conclusion part of the fuzzy inference rule which infers output y is simplified as a real number w_k.

$$y = \sum_{k=1}^{K} \mu_k w_k \tag{2}$$

This model is called the simplified fuzzy reasoning. When Gaussian membership function:

$$A_{ki}(x_i) = \exp\left\{ -\frac{(x_i - a_{ki})^2}{b_{ki}} \right\} \tag{3}$$

is chosen, the simplified fuzzy model of Eq.(2) is equivalent to the network of Gaussian RBFs. While the initial values of weights $\boldsymbol{w}$ are chosen from random numbers in the artificial neural networks, those of unknown parameters in the networks of RBFs are usually given a priori, that is, the basis functions are uniformly spaced and their weight coefficients are set to zero.

The network type NF-GMDH have been proposed [3], whose partial descriptions are represented by the RBF networks. The NF-GMDH model[3] we adopt here is a kind of adaptive learning network (i.e., a network type of GMDH) in the hierarchical structure. In the net, two input variables are introduced in each partial description. Figure 1 shows the model structure. Let the number of partial descriptions in each layer be M and the number of layers be P. The final output y is the average of outputs in the last layer.

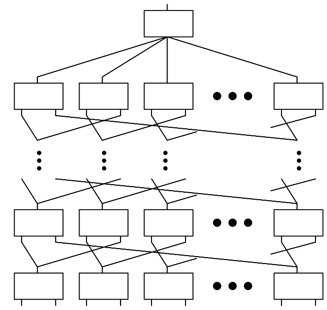

Figure 1: Structure of Neurofuzzy GMDH with six input variables

$$y = \frac{1}{M} \sum_{m=1}^{M} y^{Pm} \tag{4}$$

We apply error-back-propagation-learning using this output value.

3 Temperature Prediction

Numerical weather prediction(NWP) by the RSM at the Japan Meteorological Agency(JMA) has been remarkably progressed during the past decade. The NWP is distributed twice a day from the JMA, which predicts up to 51 hours ahead. Though the forecast of large scale fields have become reliable up to two or three days ahead, it is a common fact that NWP exhibits systematic errors in the forecast of the near surface weather parameters[6, 7]. The 2m-temperatures for example are often systematically biased with geographical location and time of season. Individual mountains or different parts of a large city with their specific climate can hardly be resolved. This bias can be reformed to some extent by using regression models like the multiple linear regression. However, the JMA undergoes a modernization plan occasionally, that will replace the outdated equipment with the most modern technological advances, which includes more sophisticated weather satellites, and a computerized system for the processing and communication of weather information. These tools certainly enable the operational forecaster to more accurately pinpoint the location and timing of severe storms, but cause ill effect since the NWP by the RSM does not have continuity and it is hard to apply regression models for prediction of future weather. In this sense, the adaptive method like Kalman filter or artificial neural network models are indispensable. The NWP statistically processed by using Kalman filter and AMeDAS(Automated Meteorological Data Acquisition System) data is called the guidance, which is also distributed from the JMA.

The guidance is transmitted electronically and local meteorologists prepare forecasts using this information. We used NWP by RSM up to 24 hours ahead and compared the prediction results by the NF-GMDH with that of the guidance by JMA. We used RMSE (Root Mean Square Error) when we compared each regression models with AMeDAS. RMSE is often used as a difference of prediction error.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (F(i) - A(i))^2}{N}} \tag{5}$$

$F(i)$:Prediction value, $A(i)$: Actual measurement, N:Number of Data

We calculated with $\tau = 0.01, \beta = 0.5$ and $P = 3$ by NF-GMDH. 6 features (temperature, cloudiness of mid level, cloudiness of lower level, EAST-WEST wind direction, SOUTH-NORTH wind direction, average temperature of past 10years) are selected. These data are normalized in unit interval $[0, 1]$. We used (24hour×30days=)720 RSM data for training, (24hour×1day=)24 RSM data for checking. Figure 2 shows its schematic representation. We used RSM and AMeDAS data in Osaka Japan between June 1998 and October 1998 for training and we predicted the temperature between July 1998 and October 1998.

The mean RMSE of each month is shown in Figure 4. If the seasonal change of the temperature is not drastic, NF-GMDH produced better result than the guidance by JMA. Figure 5 shows the mean RMSE of each day. Figure 6 shows an example of the changes in temperature on July 1 1998. The mean RMSE at 6 O'clock and 15 O'clock (Japan Standard Time), are almost same as the mean RMSE of each month. The variance of RMSE by NF-GMDH is smaller than that of the guidance by JMA. The result by RBF is the worst among three methods (RBF, NF-GMDH, Kalman filter).

Since kalman filter is the adaptive method, it predicts near future well. NF-GMDH is better for the months when temperature change is not so drastic.

We have studied whether the combinations of paired input variables as shown in Figure 7 have different performances or the model is robust with respect to the combination. Fifteen cases in Figure 7 cover all combinations of the six variables because of symmetricity of the hierarchical model. Table 1 shows the simulation results which indicate both of the training RMSE and checking RMSE does not have much differences depending on the combination of variables.

Next, we studied to find optimum duration of days whose NWP data are used for training. The bias against AMeDAS temperature can be reformed by using relatively recent data of the NWP, the aver-

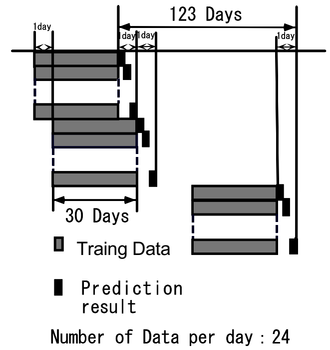

Figure 2: Schematic representation of temperature prediction by Neurofuzzy GMDH

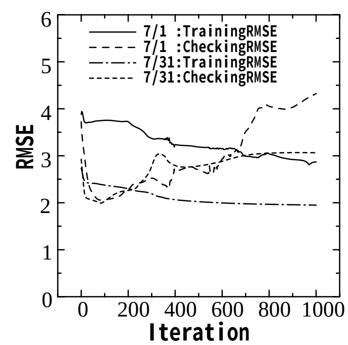

Figure 3: Learning curves

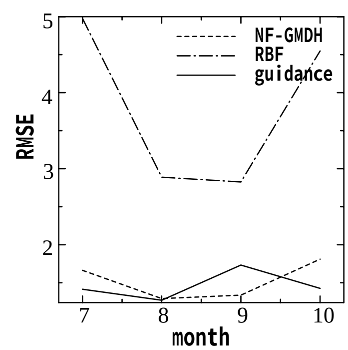

Figure 4: Means RMSE of the months (July,August,September and October 1998)

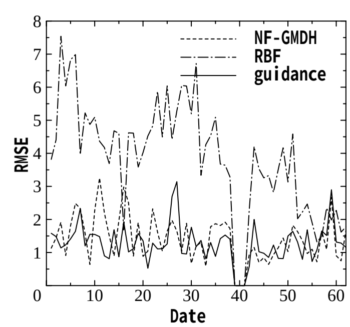

Figure 5: Mean RMSE of the days (July and August 1998)

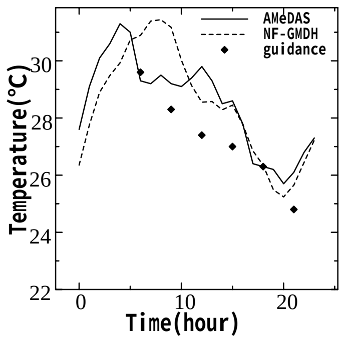

Figure 6: Changes in temperature on July 1 1998

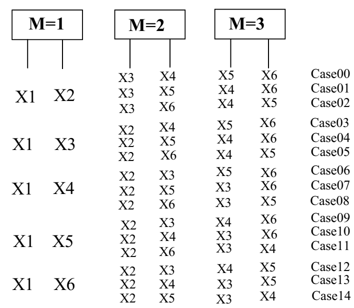

Figure 7: Combinations of input variables

	RMSE(Training)	RMSE(Checking)
Case00	2.064	0.566
Case01	2.101	0.562
Case02	2.098	0.581
Case03	2.103	0.557
Case04	2.101	0.568
Case05	2.107	0.555
Case06	2.097	0.548
Case07	2.103	0.611
Case08	2.108	0.575
Case09	2.103	0.547
Case10	2.110	0.579
Case11	2.085	0.573
Case12	2.079	0.558
Case13	2.099	0.568
Case14	2.066	0.585

Table 1: Simulation result

	Training Data					
	10 Days		20 Days		30 Days	
Months	Training	Checking	Training	Checking	Training	Checking
July	1.553	1.689	2.417	1.824	2.767	1.664
August	1.245	1.302	1.453	1.277	1.763	1.292
September	1.107	1.404	1.343	1.358	1.436	1.337
October	1.442	1.693	1.884	1.647	1.974	1.810

Table 2: RMSE of each month when the duration of training data are changed as 10, 20 and 30 days

age temperature of past 10 years and the AMeDAS. Three cases as 10, 20 and 30 days were compared as shown in Table 2 which indicate that the RMSE for checking data (prediction errors) changes with the duration but the case of 30days is relatively better than other cases.

4 Conclusion

This paper proposed the use of RBF neural network and the numerical weather prediction(NWP) by the RSM at the JMA for temperature prediction. We compared the prediction of the guidance with that of the multi-layer RBF and single-layer RBF. We showed some improvement can be achieved by the NF-GMDH model compared with the Kalman filter, when the seasonal change is moderate.

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