Detection of Climate Crashes using Fuzzy Neural Networks

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***Abstract*—In this paper the detection of the climate crashes or failure that are associated with the use of climate models based on parameters induced from the climate simulation is considered. Detection and analysis of the crashes allows one to understand and improve the climate models. Fuzzy neural networks (FNN) based on Takagi-Sugeno-Kang (TSK) type fuzzy rule is presented to determine chances of failure of the climate models. For this purpose, the parameters characterising the climate crashes in the simulation are used. For comparative analysis, Support Vector Machine (SVM) is applied for simulation of the same problem. As a result of the comparison, the accuracy rates of 94.4% and 97.96% were obtained for SVM and FNN model correspondingly. The FNN model was discovered to be having better performance in modelling climate crashes.**

Keywords*—*Climate crashes; fuzzy neural networks; parallel ocean program; SVM

I. INTRODUCTION

Climate models play important role in the prediction of future climate changes. Tough climate models are offering huge benefits to the pupils. They are suffering from failure which is known as crashes or bifurcations. The failure in climate models is a result of their complex nature [1]-[4]. The scientific representation of this problem is too complex and huge, and the corresponding models involved are considered to be so complex [5]. Another important problem that has been characterised by the use of climate models is related to the software challenges. The software that is used for modelling climate takes time in changing climate conditions [6].

In the paper, the effects of ocean parameter uncertainties on climate simulation are considered. Modern tool such as uncertainty quantification (UQ) is used to solve simulation problems and improve existing climate models. Primary UQ is made up of parameters or coefficients whose values are always changing. However, Sternsrud [7] show that the changing of the parameters leads to difficulties and it became difficult to simulate the climate changes within required conditions. This can be solved by conducting the parameterization process separately [6]. The best way for climate simulation is the use of non-linear climate models. This can lead to huge changes in simulation output. But the models' properties are restricted and model sometimes fails when the adjustable parameters are amplified using small perturbations [8]. Taking into account above-mentioned it is necessary to specify the reasons and causes for climate model simulation failure. It is also needed to define the conditions that can affect the effectiveness of climate models in simulating the climate changes.

There are set of parameters that have impact on climate. The weather conditions are chaotic and affect climate simulation [9]. When the wind blows, the weather is always being in a state of disequilibrium and the climate conditions are being affected. Greenhouse gas forcing is major chaotic effect while volcanoes, sun and weather changes, etc. are smaller chaotic effects. These factors can strongly influence a simulated model. Watanabe et al. in [10] shows that climate modelling is not an easy problem as weather changes cause chaotic behaviour and are characterized by Lorenz non-linearity. This non-linearity is due to unpredictable air oscillation behaviour. Randall et al. in his paper [11] evaluates the use of climate models and their ability to predict future climate changes. The study showed that climate variables such as precipitation have lower predictability than temperature changes. The paper [12] analyzed the use of climate data to forecast future climate changes using a General Circulation Model. The study uses stochastic and generalized downscaling methods to generate the weekly data. Using various simulation models, it is possible to predict potential climate changes and their implications. The paper [13] showed that the integrated climate models could simulate climate changes. The study evaluates environmental policies targeted at reducing emissions and combines uncertainty quantification methods to simulate carbon components. The study recommends that improvements in climate models be extended to cover carbon cycle feedbacks, inertia and climate sensitivity. The paper [2] used distribution models and showed that careful selection of climate models is an important process which must not be done arbitrarily.

The climate models differ in complexity and success perspectives. These climate models consist of various subroutines, functions, algorithms (geologic, climate and biological), huge number lines of codes [11]. All these are used to describe conservative laws and equations related to momentum, energy and flow of matter within the earth's reservoirs, between the land, oceans and atmosphere. All these ideas are based on views that climate models are not always reliable and effective, and are bound to fail [3], [14]. There are no concrete reasons and concurrences about failure in climate models. For instance, [15] mentioned that the use of numerous algorithms of anthropogenic, geologic, chemical and biological nature that are used in the simulation of climate-related issues and greenhouse gases, ozone, aerosols, Sulphur, nitrogen, and cycles of carbon is the main reason of climate model failure. Such algorithms are used in a set of circumstances and time and have solid, liquid and gaseous elements [16], [17] showed that crashes occur at a high rate. Lucas et al. have considered predictions of climate models [18]. A research is required to add and refurbish existing information about crashes in climate models. Bifurcations or crashes are common in any situation irrespective of its complexity and went to establish that intermediate climate models are also prone to crashes. This study aims to examine and predict the failure of parameter-induced simulation crashes in climate models. The accurate prediction of climate crashes is very important. For this purpose, in this paper, FNN is used to predict the failure probability and improve prediction results. The paper is organised as follows. Section 2 presents fuzzy neural networks used for detection of climate crashes. Section 3 presents simulation study. Section 4 gives conclusions.

II. Fuzzy Neural Networks for Detection Climate Crashes

The Fuzzy neural networks (FNN) model conducts a fuzzy reasoning process using the neural network structure [19]-[22]. Here, problem is to determine the accurate values of the parameters of the FNN model. This is obtained through evaluation of the error response of the designed classification system. TSK-type fuzzy rules are basically used for designing the fuzzy systems. TSK fuzzy rules include fuzzy antecedent and crisp consequent parts. These fuzzy systems approximate nonlinear systems with linear ones and have the following form:

If x_1 is A_{11} and x_2 is A_{21} and … and x_m is A_{m1} Then

$$y_1 = b_1 + \sum_{i=1}^{m} a_{i1}x_i$$

if x_1 is A_{12} and x_2 is A_{22} and … and x_m is A_{m2} Then

$$y_2 = b_2 + \sum_{i=1}^{m} a_{i2}x_i \qquad (1)$$

If x_1 is A_{1n} and x_2 is A_{2n} and … and x_m is A_{mn} Then

$$y_n = b_n + \sum_{i=1}^{m} a_{in}x_i$$

where x_i and y_j are input and output signals of the system respectively, $i=1,...,m$ is the number of input signals, $j=1…r$ is a number of rules. A_{ij} are input fuzzy sets, b_j and a_{ij} are coefficients. Fuzzy sets are applied for the description of A_{ij} parameters of the antecedent parts of the fuzzy rules.

The structure of FNN used for prediction of the climate crushes is given in Fig. 1. The input layer (block) is used for distributing of the coming x_i signals. In next block the membership degrees of input signal for ach linguistic value are calculated. Linguistic values are represented by Gaussian membership functions that are characterized by the width and center parameters.

$$\mu 1_j(x_i) = e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}}, \quad i=1..m,\ j=1..r \qquad (2)$$

where, c_{ij} *and* σ_{ij} are centre and width of membership functions, correspondingly. These signals are inputs for the next rule layer.

The output signals of the rule layer are computed through the use of t-norm min (AND) operation:

$$\mu_j(x) = \prod_i \mu 1_j(x_i), \quad i=1,..,m,\ j=1,...,r \qquad (3)$$

where, Π is the min operation. These $\mu_j(x)$ signals are input signals for the output layer. The consequent layer includes n linear systems. In this layer, at first the values of the rules' output are determined as

$$y1_j = b_j + \sum_{i=1}^{m} a_{ij}x_i \qquad (4)$$

The output signals of the rule layer are multiplied by the output signals of the consequent layer. The output of j-th node is calculated as $y_j = \mu_j(x) y1_j$

After calculating y_j, the output signals of FNN are determined as

$$u_k = \frac{\sum_{j=1}^{r} w_{jk} y_j}{\sum_{j=1}^{r} \mu_j(x)} \qquad (5)$$

where, u_k are the output signals of FNN, ($k=1,..,n$). After calculating the output signal, the training of the parameters of the network starts. The algorithm described in [23]-[25] is used for learning the parameters of FNN.

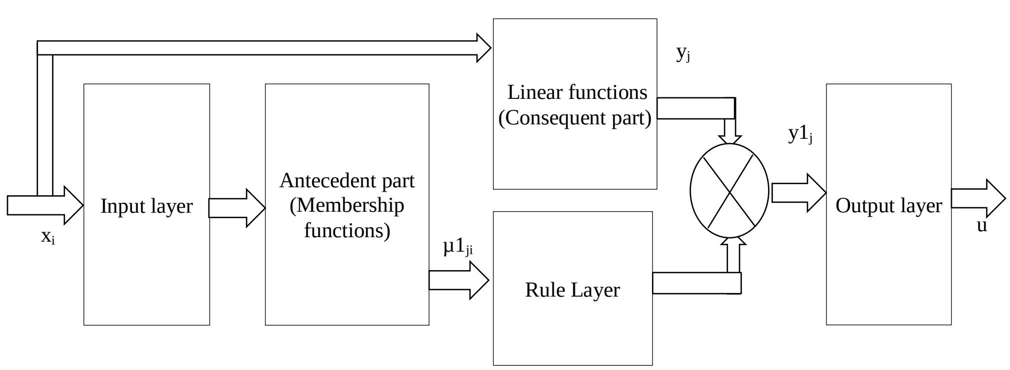

Fig. 1. The structure of FNN based prediction system.

III. Simulation

In the paper, POP2 model is used to select ocean model parameters. These model parameters were subjected to different parameterizations on a sub-grid scale. The main emphasis behind such parameterization was to determine the resultant outcome of vertical and horizontal oceanic turbulent after simulation [18], [26], [27]. Table I provides details of the uncertainty ranges of the model parameters used in this study.

The parameters are taken according to the [18]. These are: spatial anisotropic viscosity that was used to determine the horizontal momentum and was represented by the parameters 13 to 18, isopycnal eddy-induced transport of the horizontal mixers that were for parameters 10 to 12, the parameters 7 to 9 that can be used to simulate mixed layer eddies and submesoscale, and were used for the abyssal tidal mixing. Further prescriptions were K-profile parameterization associated with vertical mixing and convection and these corresponded to parameters 1 to 6. The examination of the ensembles was done in three different stages with simulations amounting to 180. The first and second studies were used to program machine learning algorithms so that they can track and analyze simulation crashes. The third study was conducted so as to determine their potential to forecast simulation crashes. 46 failures were observed out of the 540 simulations that were done. The recorded failures were observed at different intervals of the integration phase. 18 POP2 parameter values were examined using a Latin hypercube method. This was also important as it resulted in the establishment of an ensemble. In addition, normalized log-uniform probability functions were also employed to represent the model parameters' high and low values.

Statistical data were collected as a result of 540 simulations. During simulation, 494 successes and 46 failures occurring at the various times were observed. During simulation, Latin hypercube method is used to sample the values of the 18 POP2 parameters (Table I). The parameters of the model are represented with standard uniform and log-uniform probability distribution functions normalised in the interval [0,1],

Using statistical data, the training of FNN was performed. The problem is the accurate prediction of failures. The fragment of data set is given in Table II. In the table, the data from 1 to 18 are the values of input parameters. The data of number 19 are the values of output, that are 1 is the success, 0 is the failure.

The data sets include 18 inputs and one output. FNN is used for prediction purpose. At first, the parameters of FNN system is initialised randomly, then gradient descent algorithm is applied for training. The training is carried out using 10 fold cross-validation approach. During the design of FNN prediction system training, evaluation and test results are obtained. During training, evaluation and test stages root mean square error and recognition rate are used to measure FNN performance. RMSE is computed as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i^d - y_i)^2} \qquad (6)$$

where y_i^d and y_i are the target and current output signals, the number of samples is represented by N. RMSE is applied for the training of the network. Accuracy rate is used to measure the performance of FNN using test data set.

During training, the input data sets are fed to the FNN input. Using formulas (1)-(5) the output of the network is computed. On the output, the deviation of current output from target signal is determined. This value is used to determine RMSE. Using RMSE, the training of FNN system is performed. The training is performed for 500 epochs. The simulation is performed using 8, 16, 24 fuzzy rules (hidden neurons). Root mean square errors (RMSE) indicate the difference between the actual values and the predicted values. Fig. 2 depicts the plot of RMSE values of FNN based system for 500 epochs. The simulation results for three cases are given in Table III. In all of the cases of the fuzzy neural algorithm that were conducted, success rates were observed to be averaging high above 93.15% for 8 rules. The accuracy rate for 16 rules 96.11%, for 24 rules 97.96% were obtained. The RMSE values for test data were 0.3607, 0.3146 and 0.2609 for 8, 16 and 24 fuzzy rules correspondingly. The highest accuracy rate can be observed to be associated with the activity of 24 rules with a success rate of 97.96% and is composed of 16 neurons. The obtained results are obtained by averaging of the simulations.

FNN with the 24 neurons was established to be the best model in terms of accuracy and this follows a recorded accuracy rate of 97.96% while model FNN with 8 neurons had the lowest accuracy rate of 93.15%.

The performance of FNN classifier is evaluated using Sensitivity, Specificity and Precision. These factors can be computed using true positive, true negative, false positive and false negative parameters. The FNN classifier that correctly predicts successes and failures are denoted true positives (TP) and true negatives (TN), respectively. The classifier that incorrectly predicts current output failures and successes are denoted as false negatives (FN) and false positives (FP), respectively. Using these parameters we can determine true positive rate (TPR), true negative rate (TNR) and positive predictive value (PPV). These variables are used to evaluate sensitivity, specificity and precision, correspondingly. Here,

$$TPR = \frac{TP}{(TP+FN)}; \quad TNR = \frac{TN}{(TN+FP)}; \quad PPV = \frac{TP}{(TP+FP)} \qquad (6)$$

When classifiers are predicting all output values perfectly then the values TPR and TNR (or sensitivity and specificity) become equal to 1. The values of TPR, TNR and PPV for FNN classifier for climate crashes prediction are given in Table IV.

For comparative analysis, the same problem is solved using support vector machine (SVM). Table V includes a fragment from the set of simulations. Six cases were used for the SVM algorithm with a 10-fold cross-validation and all the cases have attained accuracy rates that are above 91%. The highest accuracy rate of 94.1% can be noted to be in line with a quadratic SVM while the lowest rate of 91.5% is recorded for Fine Gaussian SVM and Coarse Gaussian SVM. The best one is Quadratic SVM, Accuracy with 10-Fold Cross-Validation is 94.4%.

As shown in Tables III and V, the recognition rates of the FNN system with 16 and 24 rules are better than SVM.

After training, the models' performances are estimated to show which model has the best overall score. Such a score is termed the root mean square error (RMSE) on the validation set alternatively, it can be said to be useful in estimating the performance of the trained model on new data. Response plots were used to determine which model offers the best performance in terms of the predictability power. The decision criteria is to accept that the model is a good model and can forecast or predict the actual when the resultant distance or margin between the actual and predicted values is small.

TABLE I. CCSM4 OCEAN MODEL PARAMETERS

	Description	**Module**	**Scale[1]**	**(low, default, high)**	**Parameter[2]**
1	Ration of background diffusivity and vertical viscosity	Vmix_kpp	Log	(4.0, 10.0, 20.0)	Prandt1
2	Max PSI induced diffusion	Vmix_kpp	Log	(0.1, 0.13, 0.5)	Bckgrnd_vdc_psim
3	Equatorial diffusivity	Vmix_kpp	Log	(0.01, 0.01, 0.5)	Bckgrnd_vdc_cq
4	Banda sea diffusivity	Vmix_kpp	Lin	(0.5, 1.0, 0.5)	Bckgrnd_vdc_ban
5	Base background vertical diffusivity	Vmix_kpp	Log	(0.032, 0.16, 0.8)	Bckgrnd_vdc1
6	Mixed diffusion coefficients	Vertical_mix	Log	$(1.0, 10.0, 50.0) \times 10^3$	Convect_corr
7	Convect_visc (momentum) and convect_diff (tracer)	Tidal	Log	$(2.5, 5.0, 20.0) \times 10^4$	Vertical_decay_scale
8	Tide induced turbulence's vertical decay scale	Tidal	Log	(25.0, 100.0, 200.0)	Tidal_mix_max
9	Tidal mixing threshold	Mix_submeso	Lin	(0.05, 0.07, 0.01)	Efficiency_factor
10	Submesoscale eddies' efficiency factor	Hmix_gm	Log	(0.05, 0.03, 0.03)	Slm_corr
11	Slm_r (redi terms) and slm_b bolus' maximum slope	Hmix_gm	Lin	$(2.0, 3.0, 4.0) \times 10^7$	Ah_bolus
12	Bolus mixing's diffusion coefficient	Hmix_gm	Lin	$(2.0, 3.0, 4.0) \times 10^7$	Ah_corr
13	Ah_bkg_srbl (horizontal diffusivity within the surface boundary) and Ah (redi mixing's diffusion coefficient and background)	Hmix_aniso	Lin	(30.0, 45.0, 60.0)	Vconst_7
14	Variable viscosity parameter	Hmix_aniso	Lin	(2, 3, 5)	Vconst_5
15	Variable viscosity parameter	Hmix_aniso	Log	$(0.5, 2.0, 10.0) \times 10^{-8}$	Vconst_4
16	Variable viscosity parameter	Hmix_aniso	Lin	(0.16, 0.16, 0.02)	Vconst_3
17	Variable viscosity parameter	Hmix_aniso	Log	(0.25, 0.5, 2.0)	Vconst_2
18	Variable viscosity parameter	Hmix_aniso	Lin	$(0.3, 0.6, 1.2) \times 10^7$	Vconst_corr

[1] Logarithmic and linear scales were applied for parameters whose ratios were between the range high/low ≥ 5 and high/low <5,
[2] Individual correlated pair of parameters were denoted by numbers 1, 7, 9 and 13

TABLE II. FRAGMENT FROM DATA SET

No	**Input parameters' values**													
1	0.8590	0.6060	0.9976	0.7834	0.4062	0.0414	0.1611	0.4153	0.1668	0.6556	0.5900	0.8819	0.9610	0.1725
2	0.9278	0.4577	0.3732	0.1041	0.5132	0.6290	0.5488	0.8987	0.3530	0.4139	0.2937	0.4249	0.9769	0.0136
3	0.2529	0.3594	0.5174	0.1975	0.0618	0.3034	0.1536	0.9318	0.9881	0.8053	0.4235	0.9032	0.8579	0.6234
4	0.2988	0.3070	0.5050	0.4218	0.6358	0.8134	0.6544	0.9166	0.2871	0.1635	0.3298	0.1733	0.6150	0.5191
5	0.1705	0.8433	0.6189	0.7421	0.8448	0.2228	0.1403	0.3991	0.5636	0.8619	0.4578	0.7910	0.6155	0.2545
6	0.7359	0.9349	0.6056	0.4908	0.4415	0.9712	0.7966	0.0094	0.4027	0.9476	0.8298	0.4762	0.3528	0.3669
7	0.4283	0.4446	0.7462	0.0055	0.1919	0.6098	0.4058	0.8463	0.3809	0.5466	0.4978	0.6812	0.8340	0.0557
8	0.5679	0.8280	0.1959	0.3921	0.4875	0.6478	0.6626	0.6838	0.4792	0.4261	0.1594	0.9058	0.0951	0.5185
9	0.4744	0.2966	0.8157	0.0100	0.3585	0.7379	0.0494	0.3973	0.0602	0.4171	0.9711	0.8284	0.2309	0.3713
10	0.2457	0.6169	0.6794	0.4715	0.5515	0.4409	0.5785	0.8868	0.2365	0.9456	0.4923	0.0837	0.9548	0.8538
11	0.1042	0.9758	0.8034	0.5979	0.7439	0.0360	0.2649	0.5224	0.2905	0.3254	0.0843	0.5206	0.5772	0.3470
12	0.8691	0.9143	0.6440	0.7617	0.3123	0.6159	0.9592	0.6948	0.3918	0.6665	0.9743	0.0729	0.7835	0.9473
13	0.9975	0.8452	0.7184	0.3628	0.6502	0.0175	0.6981	0.8865	0.2549	0.3743	0.9264	0.9481	0.5304	0.5973
14	0.4486	0.8642	0.9248	0.9128	0.5223	0.9323	0.4674	0.4117	0.4884	0.1003	0.2954	0.9996	0.1752	0.4288
15	0.3075	0.3467	0.3154	0.9780	0.0435	0.3293	0.6371	0.4811	0.0537	0.2133	0.8042	0.7285	0.5445	0.4014
16	0.8583	0.3566	0.2506	0.8459	0.3767	0.9541	0.0113	0.9265	0.8622	0.2229	0.8708	0.2859	0.0814	0.8204
17	0.7970	0.4384	0.2856	0.6994	0.2801	0.1354	0.1473	0.0264	0.4151	0.0073	0.5463	0.2109	0.7330	0.5996
18	0.8699	0.5123	0.3659	0.4760	0.1323	0.2948	0.2138	0.0927	0.4871	0.4200	0.8849	0.8336	0.5314	0.1357
19	0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0	1.0000

TABLE III. FNN MODEL RESULTS

No.	**Neurons**	**epoch**	**SSE_{Train}**	**$RMSE_{Train}$**	**$RMSE_{Evaluation}$**	**SSE_{Test}**	**$RMSE_{Test}$**	**Accuracy**
1	8	500	635.8686	0.3617	0.3614	70.2851	0.3607	93.15%
2	16	500	477.7429	0.31353	0.321350	53.4488	0.3146	96.11%
3	24	500	333.2924	0.261875	0.261879	36.7607	0.2609	97.96%

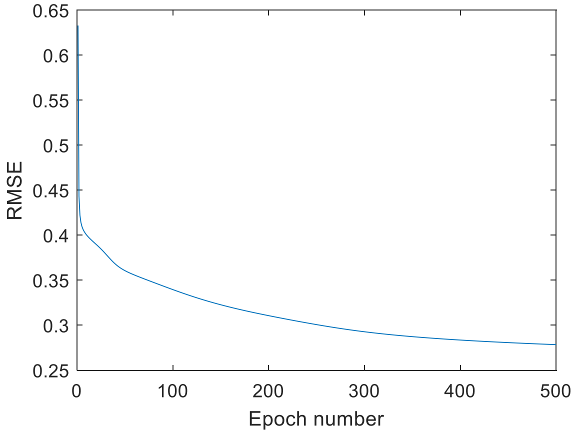

Fig. 2. Plot of RMSE.

TABLE IV. FNN MODEL RESULTS

No.	Neurons	Sensivity	Specifity	Precision
1	8	0.93032	1	1
2	16	0.96673	1	1
3	24	0.97821	1	1

TABLE V. SVM RESULTS

No.	Types SVM	Cross-Validation	Accuracy
1	Linear SVM	10-Fold	93.1%
2	Quadratic SVM	10-Fold	94.4%
3	Cubic SVM	10-Fold	94.1%
4	Fine Gaussian SVM	10-Fold	91.5%
5	Medium Gaussian SVM	10-Fold	91.7%
6	Coarse Gaussian SVM	10-Fold	91.5%

IV. CONCLUSIONS

The main emphasis of the study was to determine if there are any crashes or failure that are associated with the use of simulation models as well as conditions that can cause climate models to fail by determining the chances that POP2 simulation will fail. For this purpose, the fuzzy neural network was applied to determine chances of failure of the models. The simulation crashes were based on the idea that they may either succeed or fail (binary problem) and failure probabilities were quantified using FNN based machine learning classification. The quantification process was based on the 18 model parameters and the simulations based on cross-validation techniques. Conclusions can be made that the occurrence of the crashes is as a result of several numerical reasons which are caused by changes in the combination of parameter values used in the simulation process. Based on the obtained accuracy rate, conclusions can be made that climate models have a high predictive capacity to simulate climate changes. It can also be finally concluded that the fuzzy-neural network performs better in modelling climate crashes as compared to SVM.

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