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Comparing the Electricity Forecast Performance of the ANFIS and the LSSVM Models for a Case of Suppressed Demand.

[*1]Omogbai Nelson Oyakhilomen; [2]Abonyi Sylvester Emeka.
[*1]*Electrical/Electronic Engineering Department, University of Benin, Benin City, Edo State, Nigeria.*
[2]*Electrical Engineering Department, Nnamdi Azikiwe University, Awka, Anambra State, Nigeria*
Corresponding Author: Omogbai O. N.

Abstract
The amount of electricity to power a city, country or any sizeable load condition, and meet consumers growing electrical needs; can certainly not be cost-effectively stored. The power sector managers need to periodically make a plethora of proactive decisions regarding power system planning and the energy market. Besides, the precision of forecasted loads directly affects the reliability needed for and the financial burden of power system operations. Research to unearth more effective state of-the-art methods to ascertain the present and future load demands, will continue to remain on the front burner. In this article, a comprehensive study of the forecast performance of the Least Squares Support Vector Machine, (LS SVM) and the Adaptive Neuro-Fuzzy Inference System, (ANFIS), is performed on the monthly electricity consumption in Edo state, Nigeria – a region whose electricity consumption is perennially characterized by suppressed demand. A comparison between the models' performances as measured by some choice metrics; was carried out with the aim of ascertaining whether or not the findings of similar studies in literature are herein duplicated despite the nonuniversal attribute of the raw electricity data employed here. This is to further aid power systems managers/researchers with the selection of suitable load forecast models fur that study or that impending critical business deal that requires some informed decision making. The results obtained suggest that while the ANFIS model appears to be more probable to producing a more accurate forecast per trial, the LSSVM displayed a better capacity to regulate the overall forecast error range.
Keywords*: Forecast performance, Electricity consumption, LSSVM, ANFIS, Suppressed demand, Error.*

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I. INTRODUCTION

Modern power system demands an uninterrupted supply of electricity to the load side. This requires a proper idea of predicting present and future load demand with the least amount of error. For achieving this goal, scientists and scholars have been trying to develop the most optimal state of- the-art method for predicting the future demand of electricity consumption by a method known as load forecasting [3].

The amount of electricity to power a city, country or any sizeable load condition is usually not a storable commodity [4], therefore, power sector managers need to periodically make difficult but vital decisions regarding economic load dispatch, unit commitment, fuel allocation, off-line network analysis, purchase or generation of electric power, load switching, infrastructure development etc. [5]. Unfortunately, dynamic factors like demography, weather, economy, power consumption patterns, technological innovation, cultural changes, new products, improved services, stronger competitors, shifts in government priorities, changing social values, unforeseen events, vandalism etc.; complicate this decision-making task [6]. Even in such uncertain circumstances, it is imperative to keep the load forecasting error as minimum as possible because little errors may lead to a huge amount of financial and infrastructural loss.

Demand forecast minimizes the power generation cost and helps to establish an organized power system utility, especially because of the large expense pertaining to power generation. This gives an idea about the future demand of the consumers and sufficient amount of time to equilibrate between the generation capacity and load demand; precluding underinvestment as well as preventing costly overinvestment. [3].

Algorithmically, the ANFIS and LSSVM are very different: The Adaptive Neuro-Fuzzy Inference System (ANFIS)uses a five layered model to learn a system performance from the given data sets so as to automatically procreate fuzzy sets to a pre-specified correctness level, and optimize the values of the equivalent fuzzy with the aid of "if-then" rules, such that it is able to decide the optimal distribution of membership functions in order to obtain the mapping relationship of the input and output data, and the error between the target and the actual output is minimized [8]. On the other hand, the Least Squares Support Vector Machine(LSSVM) reserves the SVM's principle of structural risk minimization, small sample and other outstanding features but transforms the inequality constraints into equality constraints [19]. For a given set of I/O samples the objective is to optimize the generalization ability of the model. This method is capable of locating the nearest minimum to a given initial guess of the parameters to be optimized - the regularization parameter and the parameters defining the kernel function. More about LS-SVM and ANFIS can be found in [25, 26]

In [1], a study was done on the LS SVM and the ANFIS, to estimate biogas production. and it was claimed that the LSSVM model presented a superb performance in terms of validity, accuracy, and generalization. The results of comparing the models in view, among others in [2] also indicate that the LS-SVM model generated superior results than the other investigated models in terms of the mean error criteria, when prediction of suspended sediment concentration for water resources projects was made. This was further supported in [7], a study to determine the aromaticity in biochar from easier accessible parameters. Kaytez et al. [11] applied the LSSVM model for forecasting electricity consumption in Turkey and found that this model performed better than the other models. References [12 – 16] studied the LSSVM model in environmental forecasting, and all but [12,15] found that the LSSVM model performed the best.

However, in [8] the ANFIS, LSSVM and two other models were used to forecast the electricity consumption for ten years and for seven selected countries. The four models showed differing performances in different forecasting periods and in the forecasting of electricity consumption for the different countries. The LSSVM model, was shown to produce the highest average forecasting error for quite a lot of forecasting periods and for different countries. Reference [9] studied the application of the ANFIS model in forecasting short-term electricity load, while [10] used the ANFIS model to forecast the long-term peak electricity loads of Gulf Cooperation Council member countries, and all of these studies found that the ANFIS model tends to perform better than the other investigated models.

One of the important decisions of the managers of the power industry is the selection of a reliable model for load forecast. This usually depends on the problem and the situation under consideration. Therefore, from practice and available literature, there exists neither a blanket solution nor a silver bullet as far as forecast techniques are concerned.

In Nigeria, the annual power consumption pattern varies between dry and rainy seasons. Maximum peak demand occurs between January and April when the weather is extremely hot and dry. Minimum annual load demand occurs between June and September, mid-November and early January with extreme wet period of the year and harmattan period respectively; when most heavy loads like air conditioners are switched off [17].

Conventional load forecasting methods assume that the current demand of customers connected to the power grid is precisely reflected by their levels of electricity consumption. However, in many third world countries, diverse inefficiencies, create an inequality between demand and consumption [27]. Reference [20] notes that the unmet latent demand for basic services is termed "suppressed demand". This occurs where there is insufficient power supply facilities, depressed voltages, load shedding, insecurity of power supply, etc. [24], - conditions that are not uncommon in Edo State, Nigeria. The case is such that consumers who are prepared to pay for electricity end up receiving none, or they receive less than the desired quantity. In view of the foregoing, the data obtained from this unique and nonuniversal demand condition is employed in this study to ascertain if the findings in literature concerning the standalone forecast performance between the LSSVM and ANFIS models, stay corroborated or not, under a monthly periodicity; and in any case outline contributions and recommendations derivable therefrom.

II. METHODOLOGY

The electricity data (dependent variable) deployed for the entire study is the monthly electricity consumption of Edo state as estimated and aggregated with the aid of the load duration curves, load shedding profiles and the monthly summary logs from the local electric utility company. The sample spans from January 2013 through September 2016, a total period of forty-five (45) months. The independent variables include: Energy sent into the grid per month, Average monthly temperature, Real GDP and Population. These raw data is plotted in figure 1.

The ten test data for assessing and comparing the forecast performance of the two chosen methods were selected at strategic points from different quarters of the different years under study. The remaining thirty-five data points were used for developing the two different models. Ten checking data points were used for the ANFIS. Before the commencement of model development, the datasets were arranged such that a column matrix of each variable is inputted separately to each of the two selected forecasting toolboxes.

The LS-SVM model was built on the training dataset with the Radial Basis Function (RBF) kernel. The functional interface was chosen and then the function *tunelssvm* was used to search for suitable tuning parameters i.e. the regularization parameter (gamma) and the squared bandwidth (sig2), as determined by the leave-one-out cross-validation technique. With these parameters, the model was trained using the function *trainlssvm* to obtain the support values (alpha) and the bias term (b). The parameters and the variables relevant for the LS-SVM were passed as one cell to allow for consistent default handling of LS-SVM parameters and syntactical grouping of related arguments. This routine was repeated several times while monitoring the learning error each time, until the desired tolerance is got. To evaluate model predictions the Matlab code was used as culled from [19]:

simlssvm({X,y,'f',gam,sig2,'RBF_kernel','preprocess'},{alpha,b},U).

Where, X,U are the matrix of all x & u respectively; and x ,u are the column matrix of the input variable of the training & testing dataset respectively.

Also, in MATLAB, the ANFIS Editor was called with the *anfisedit* command. Next, the training and checking datasets were loaded into the ANFIS Editor GUI from the workspace. The fuzzy inference system (FIS) was then initialized and generated by choosing the partitioning method, number of membership functions, MFs, the type of input and output membership functions, parameter optimization method, error tolerance, and the number of training epochs so as to produce the FIS structure and fuzzy rules. Extensive training was then done with repeated but informed adjustment of parameters until minimum training and checking errors were attained for model parameter training convergence, using the grid partitioning method. The trained FIS-matrix was saved to the workspace as the ANFIS model to be used for the forecast. The code below was used to evaluate model predictions by using the already generated and saved FIS-matrix and forming matrix U: *evalfis([U],fiss).* Where, 'fiss' is the saved FIS-matrix.

The ten test data points were fed as predictors to each developed model in turn, to get two different sets of predictions. With the aid of the actual monthly load; the Sum of Errors, standard deviation of Errors, Coefficient of determination, Coefficient of Variation (CV), Squared Error (SE), Mean Absolute Percentage Error (MAPE), and the root mean squared error (RMSE) of forecast for each model were then computed and analyzed. To conduct a reliable test/validation procedure, an untrained test dataset was utilized. The dataset was fed as input into each of the developed model to get their individual forecasts. The test results were subjected to various performance metrics. The results from the various test forecasts were also plotted with the actual load to accentuate their goodness of fit. The residual plot was also done and analyzed inter alia.

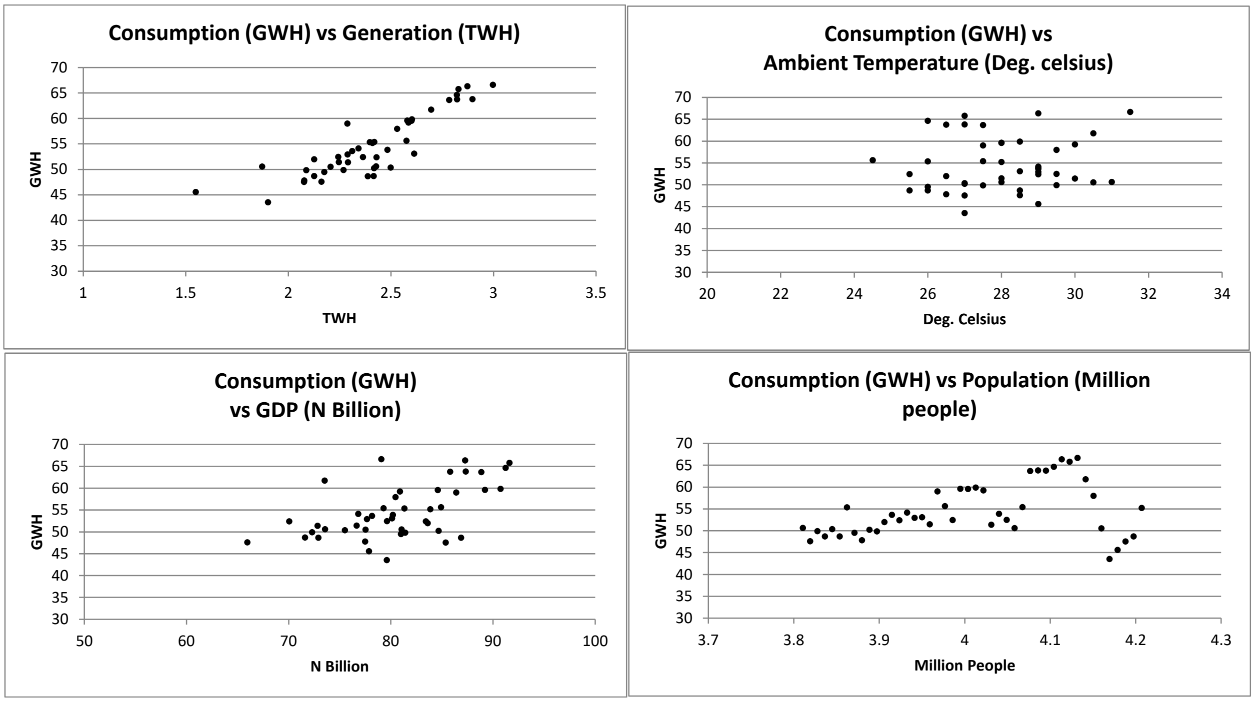


Figure 1: Plots of the original data

III. RESULTS AND DISCUSSION

3.1 LS SVM MODEL

In the functional interface, the Radial Basis Function (RBF) was called to compute the kernel value, and suitable tuning parameters (gamma γ and sig2 σ) were automatically searched for using a combination of Coupled Simulated Annealing (CSA) and a standard simplex method.

Table 1:Optimization routine generated from the *tunelssvm* function

Iterations	Func-count	Min f(x)	Log (gamma)	Log(sig2)	Procedure
1	3	6.52E+00	6.1333	2.9318	initial
2	5	6.52E+00	6.1333	2.9318	contract outside
3	7	6.40E+00	5.6833	3.0068	contract inside
4	11	6.40E+00	5.6833	3.0068	shrink
5	13	6.40E+00	5.6833	3.0068	contract inside
6	15	6.36E+00	5.7771	3.0911	reflect
7	19	6.35E+00	5.6927	3.2552	shrink
8	21	6.34E+00	5.7396	3.2974	reflect
9	25	6.34E+00	5.7583	3.1943	shrink
10	27	6.33E+00	5.8146	3.1849	expand

First, CSA finds good starting values with search limits set to [exp(−10), exp(10)]. The starting values are:
Regularization parameter [gamma] = 460.9649;
Squared bandwidth [sig2] = 18.7608.
The starting point for the local minimum of the function is: F(X) = 6.5167.
These values were then passed to the Simplex optimization algorithm in order to fine tune the result. Using the leave-one-out-lssvm cost function, the simplex results are:
X = 335.147856, 24.164805; F(X) = 6.327427e+00 i.e., with optimization terminated successfully (Max-Fun-Evals criterion) the obtained tuning-parameters to carry out training is: [gamma, sig2]: 335.1479, 24.1648.
After training, the solutions of the linear system i.e., the support values (alpha), are:
alpha = [-19.66, -3.92, 7.02, -10.8, -31.12, 3.11, 180.26, -59.28, -60.74, -229.57, 66.90, 28.37, 97.48, 33.12, -174.01, 33.35, 213.09, -12.02, 77.40, -60.82, 54.45, -53.31, -104.66, -26.70, -68.53, 81.74, 23.06, 34.92, 35.19, 6.64, 9.46, 26.25, -104.59, -49.01, 56.91].
While the bias term b = 0.17.

3.2 ANFIS MODEL

In the ANFIS GUI environment; the training, checking and testing datasets were loaded from the workspace together with the following parameters, to get the initial FIS.

Table 2: ANFIS Information

ANFIS INFORMATION				
Type	'sugeno'		**Number of nodes**	25
and Method	'prod'		**Number of linear parameters**	15
or Method	'probor'		**Number of nonlinear parameters**	24
DefuzzMethod	'wtaver'		**Total number of parameters**	39
ImpMethod	'prod'		**Number of training data pairs**	35
AggMethod	'sum'		**Number of checking data pairs**	10
Input	[1x4 struct]		**Number of fuzzy rules**	3
Output	[1x1 struct]		**Number of input MFs**	3 1 1 1
Rule	[1x3 struct]		**MF plot points**	181
Optim method	Hybrid		**ANFIS training completed at epoch**	10

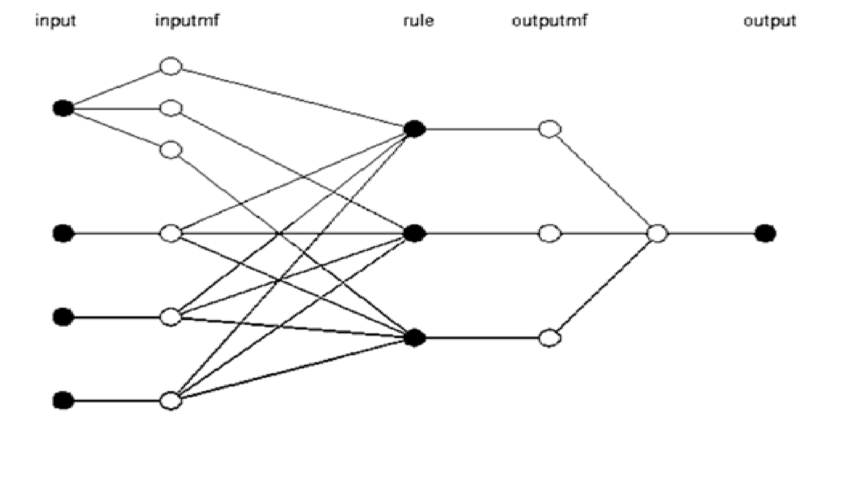


Figure 2: ANFIS structure

3.3 TEST RESULT

The test results on an untrained dataset are shown in Table3 with selected metrics used to compare the models of forecast.

Table 3: Closeness of Models' Forecast to Actual Electricity consumption.

PARAMETERS	RMSE	COEFFICIENT OF DETERMINATION	MAPE	STANDARD DEVIATION OF ERRORS	COEFFICIENT OF VARIATION OF ERRORS	PEARSON CORRELATION COEFFICIENT
ANFIS MODEL	1.536333297	0.9136	2.118981	5.904710323	91.90372781	0.9737
LSSVM MODEL	1.651907988	0.9001	2.369333	5.764980139	78.31381142	0.9613

Taking a close look at table 3, it does appear that most of the metrics are trending in favor of the ANFIS model. That is, with reference to the actual monthly GWH consumption, the ANFIS tends to display a better goodness of fit (figure 3), lower RMSE, higher coefficient of determination, a lower MAPE and a higher correlation coefficient; its explanatory powers seem superior to that of the LSSVM. However, the remaining metrics do not support the foregoing trend. The errors of forecast seem to be more predictable and more regulated to a smaller range in the LSSVM results; as may be observed in figure 4 and in the lower numbers of both the standard deviation and coefficient of variation in table 3. The zero residual line of fig 4 seems more in the LSSVM like a line of symmetry in terms of error polarity. A smaller dispersion of errors as observed would make the LSSVM a less risky forecast tool; and the apparently better predictability of its errors recommends its forecasts as a better candidate to be subjected to finetuning via forecast error compensation techniques.

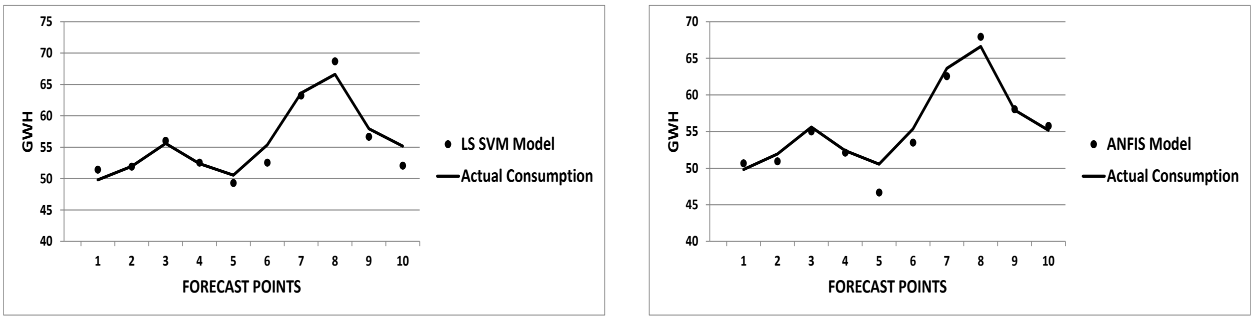
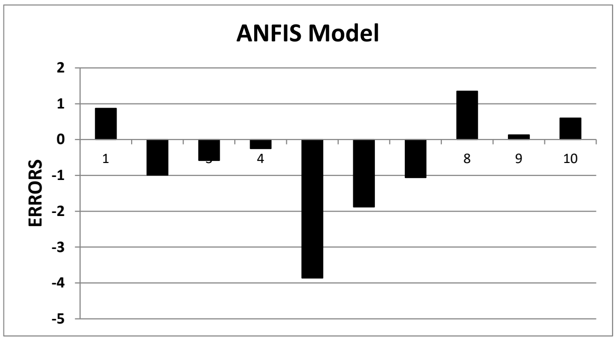


Figure 3: Goodness of fit.



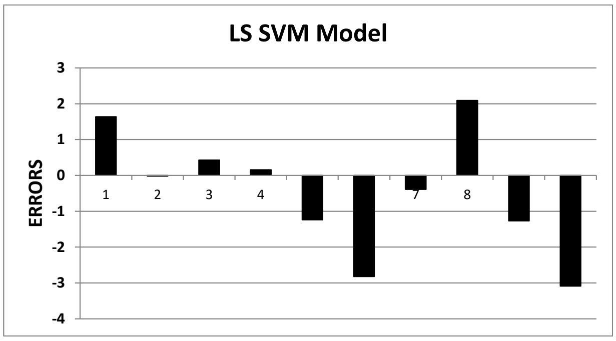


Figure 4: Residual plots.

It may also be observed from Table 4 that based on the forecast error from ten separate test trials, the probability of the ANFIS model coming up with a more accurate forecast is 0.6, besides its lower Mean Absolute Error (MAE) value; giving it a posture of a more precise model. However, taking a close look at the dispersion of the models' forecast errors from their respective MAE's, shows that the maximum deviation of error from the MAE was larger in the case of the ANFIS – indicating a more erratic forecast error trend.

Table 4: Evaluating the superior forecast count and the Error dispersion

Actual Monthly Consumption in GWH	Absolute Forecast Error in GWH (LSSVM)	Absolute Forecast Error in GWH (ANFIS)	More Accurate Model per Trial by Absolute Forecast Error
49.81	1.78	0.92	ANFIS
51.95	0.13	0.92	LSSVM
55.61	0.62	0.51	ANFIS
52.39	0.25	0.31	LSSVM
50.55	1.12	3.8	LSSVM
55.37	2.66	1.86	ANFIS
63.63	0.32	1.15	LSSVM
66.61	2.28	1.4	ANFIS
57.94	1.15	0.11	ANFIS
55.17	2.95	0.6	ANFIS
Mean Absolute Error in GWH (MAE)	1.326	1.158	
Max. deviation from MAE in GWH	1.624	2.642	

Therefore, whereas the ANFIS model seem to be slightly more inclined to delivering a more precise forecast per trial, the LSSVM is not doing badly in terms of accuracy, coupled with the fact that the LSSVM tends to display better tendency to keep the overall forecast error within a narrower spread about the MAE. This latter performance index connotes better curtailment and predictability of model error, which may prove useful in cases where error compensatory actions become necessary; and further signifies some appreciable level of relative reliability.

The findings from this study, though emanating from data sourced from a region experiencing suppressed demand as far as electricity as a commodity is concerned; is not quite far flung from that available inrelevant literarture; some of whicharementioned in the introductory section. Neither of the techniques is an outright underdog relative to the other. However, due to the obvious drawbacks inherent in both investigated models when deployed as standalone forecast tools, neither may be recommended as an optimal solution for use in practical deployments as in the energy market or power system planning. The paper actually goes to unveil more of the pros and cons of both tools relative to each other, for the benefit of researchers and industry players who may advisedly deploy them, preferablyin an hybridized or error compensated configuration, some of which have beendemonstrated in [3, 21, 22, 23].

IV. CONCLUSION

Due to the complex nature of electricity consumption, which involves many different factors, it is a challenging task to compare the performance of different models/methods that are used in forecasting electricity consumption. Hence, this study, which compared the performances of the ANFIS and LSSVM models, is just adequate, as it focuses on the context of electricity consumption with raw data sourced from a region experiencing suppressed demand. The study contributes to the continuous efforts of the research community to assess the performances of various Machine Learning models to develop accurate data-driven forecasting models for the forecasting of electricity consumption. A cursory observation of the overall results may suggest that the ANFIS offers a more precise forecast model, but the model residuals show that the LSSVM isn't an underdog after all, in terms of generalization and overall reliability. The ANFIS model appears to be more inclined to producing a more accurate forecast per trial, while the LSSVM displayed a better capacity to curtail the overall forecast error dispersion. The results do not appear quite far-flung compared to that of a number of similar studies, even though the raw data represents an exclusive case of suppressed electricity demand. However, the shortcomings of both investigated forecast techniques show that their strengths could perhaps be better harnessed under a hybrid deployment (e.g., wavelet-LSSVM, GA–LSSVM, ANFIS-PSO, ANFIS-SC etc.), as against their standalone rendering.

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