Optimal Decision Maker Algorithm for I2Sim Using ANN, Neuro Fuzzy and Fuzzy

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Abstract

The aim of this paper is to design an optimal decision maker algorithm for I2SIM using Fuzzy, Neuro fuzzy and Artificial Neural Network (ANN). The objective is to minimize the deaths in the system through controlling the distributor outputs. Three controllers are designed that is able to optimize resource usage following an infrastructure disruption. These controllers are designed in MATLAB and then implemented in I2SIM. From the results, the controller which gives the best distribution output will be determined. The goal of the controller is to maximize an output, which in this case is the number of discharged/healed patients from the hospitals. The results of the controller will be compared and analyzed to determine which technique gives the best result.

Keywords

I2SIM, Neuro Fuzzy, Decision Maker, Optimization

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Introduction

Here in this paper we will be using three different techniques to control the output of the distributors. Those techniques are Fuzzy, Neuro fuzzy and Artificial Neural Network. In this paper we describe the modelling of three optimization technique and the simulation of a real world scenario is implemented and the simulation results are analysed. A simulation related to a General Hospital and Health Centre critical infrastructures will be described. An interactive, graphical user interface design to allow the decision makers to get a better understanding of the emergency system behaviour in different operational scenarios. One such scenario is studied by using the I2SIM model, which allows an operator to find the best optimum allocation of a limited resource in order to ensure the best possible operation of the other critical sectors during the event.

This section is a combination of four sections first three sections is for designing controller by

1. Neural network
2. Fuzzy logic
3. Neuro-fuzzy
4. Comparison of controller

First three sections are done independently and the fourth section is dependent on first three sections as in this section we have to compare results of controllers.

The controllers will be implemented in MATLAB; controller will be designed on the basis of available dataset and later it will be compared.

Artificial Neural Network controller

For neural network the training data and training target will have to be defined so that the network is to be trained and network is developed to utilize resources in disaster event.

After development of network, output (Number of patients to be served) is predicted on the basis of input (power, communication, water and gas available) with reference of network.

Fuzzy logic controller

In fuzzy logic controller input data will be mapped on the basis of membership function of fuzzy controller, rules are to be defined for it on the basis of which it will give the output as a resource management.

After defining of rules, output (Number of patients to be served) is predicted on the basis of input (power, communication, water and gas available).

Neuro-fuzzy controller

In controller designed by neuro-fuzzy logic the training data and training targets will be defined and by the help of these training data the controller will be design for prediction of the output. Output (Number of patients to be served) is predicted on the basis of input (power, communication, water and gas available). In the comparison section the results of all the predicted output by different controllers will be compiled in the form of table on the basis of inputs (resources) and output (number of patients to be treated). The final result will be compared to that of previous results and our solution will be defined. The data will be used for the training of ANN and Neuro Fuzzy network. Similarly, Fuzzy rule will be written by memory of the data.

The two hospitals to be modelled are the Vancouver General Hospital (VGH), which is the main hospital, and Saint Paul's Hospital (SPH) (Khouj et al 2014)[1]. The production cell inputs for VGH and SPH come from the electrical power station (electricity), water pumping station (water), natural gas or steam (for heating purpose) and medical gas (for medical use) (Khouj 2014 et al)[1]. The HRT's for the VGH production cell and the SPH production cell is based on prior research done by Khouj et al 2014 in their paper "Decision assistance agent in real-time simulation"[1]. "Based on the availability of these resources, the rate of healed patients is known from experience in operating the hospitals as shown in Table 1-1 and Table 1-2 below. It is assumed that 1/10 of the total hospitals' resources are needed by the ER" (Khouj et al 2014)[1].

Table 1. HRT for the VGH production cell (Khouj et al., 2014)

Physical mode #	RM Emergency room output	**Hospital inputs**			
		Electricity [MW/hour]	Water [KL/hour]	Steam [Ft^3/hour]	Medical gasses [%]
1	10.00	1.00	5.15	1,145.80	10.00
2	7.00	0.75	3.80	853.97	7.50
3	5.00	0.50	2.55	572.92	5.00
4	2.00	0.25	1.28	286.46	2.50
5	0.00	0.00	0.00	0.00	0.00

"For a certain quantity of input resources, the outputs of the hospital depend on number of the patients per hour that can be treated. These outputs are used to determine the maximum output rate for the waiting areas that are represented by storage cells. The input of patients to these waiting area cells come from the modelled venues (GM and BC). At the final step, patients that are input to the storage cells are going to be used to count the total number of patients discharged from the hospitals during a given run of the model" (Khouj et al 2014)[1].

We run the three algorithms i.e. Neuro Fuzzy, Fuzzy and ANN on the Vancouver downtown model. The scenario setup in I2Sim blocks is shown in Figure 1-1. For normal operation each hospital requires water, Natural gas and electricity to function. There is a water pump station and an electricity generation station with channels being water pipes and transmission lines. In this scenario, the electricity distributor needs to distribute certain amount of electricity for the pump station to work, creating interdependency problems. During non-disaster times there are enough resources to supply the hospitals but, resources become scarce after a disaster occurs. The optimal decision making algorithm was applied at the distributors for electricity and water with the optimal question being how efficiently the limited resources would be distributed to the two hospitals. We checked the system output by using mean square error (MSE) technique. In this technique first we subtract the actual value from the predicted value and then we divided it on the total number of samples. When we talk about the Simulink implementation of this model, the model which we built for the implementation of neuro fuzzy and fuzzy was approximately same where

Table 2. HRT for the SPH production cell (Khouj et al., 2014)

Physical mode #	RM Emergency room output Rate of treat-ment[people/hour]	**Hospital inputs**				
		Electricity [MW/hour]	Water [KL/hour]	Natural gas [Ft^3/hour]	Medical gasses [%]
1	10.00	2.00	5.15	333.30	10.00
2	7.00	1.50	3.80	249.98	7.50
3	5.00	1.00	2.55	166.65	5.00
4	2.00	0.50	1.28	83.33	2.50
5	0.00	0.00	0.00	0.00	0.00

as for the implementation of the ANN it was different. The models which includes the ANN is shown in figure 1-3. Similarly, models with Fuzzy and neuro fuzzy is shown in figure 1-2 and 1-4 respectively.

The mean square error (MSE) used to check the system output is given by

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value and n is the total number of samples.

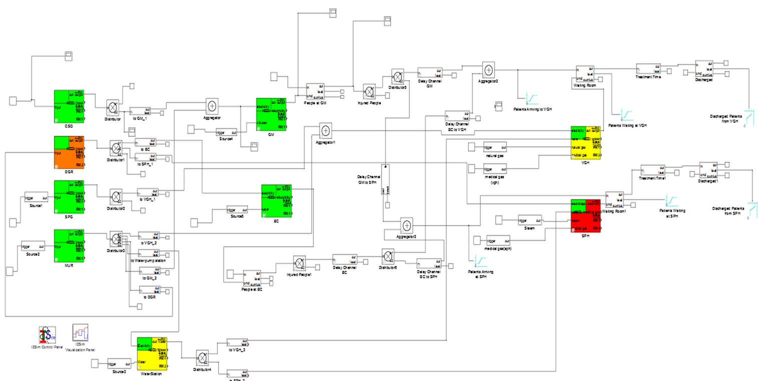

Figure 1. Vancouver Downtown Model I2sim (Khouj et al, 2014)

The first step was to collect the training and the testing data for ANN and neuro fuzzy. The major aim of this project was to optimize output of the distributors. We put the possible optimal dispatch of natural gas and water together. The combined solution table is shown in Table 1-3. The decision maker is faced with resolving conflicts from the two resources. There are three types of resource conflicts, as listed below. The underlying assumption is the PM is at 100% for all the hospitals. For example, as shown in the table 1-3, point A, when Med gas is sufficient and water is insufficient, the electricity supplies of the

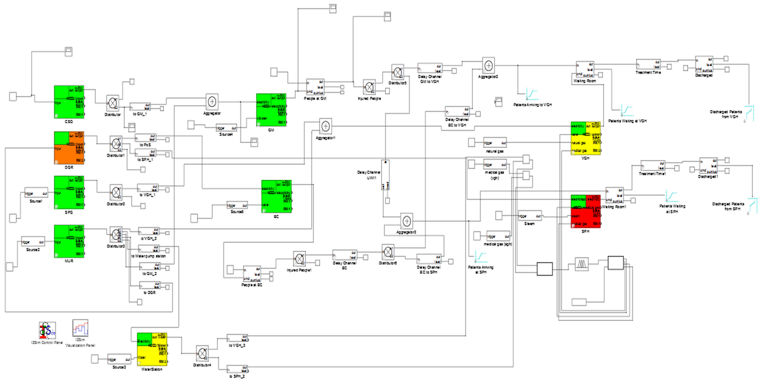

Figure 2. Vancouver Downtown model in I2sim with Fuzzy controller

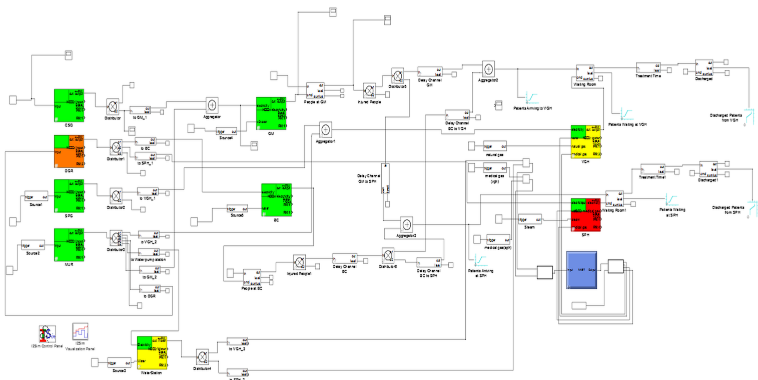

Figure 3. Vancouver Downtown Model I2sim with ANN

hospitals are more than the water supplies. Then just follow the row of water (R4, R5). In this case it is difficult to say which resource is sufficient. We have to adjust the Row of either water or power or both.

Here we are only explaining the two cases. In actual we prepared 82 cases to resolve the conflict. Then those cases were divided by the ratio of 70% to 30% for the training and testing of ANN and Neuro fuzzy. Whereas for fuzzy we written the rules on our own. Another major task was to import the fuzzy rules and Neural network model in Simulink. These rules were to be imported in such a way that the can be implemented on a real time model and it shows us the results with the values changing at every instance and predict the output value. In order to implement this technique two separate methodologies were used. Those techniques were given two different names which are given below:

- SimOut Method
- GENSIM Method

SimOut Method

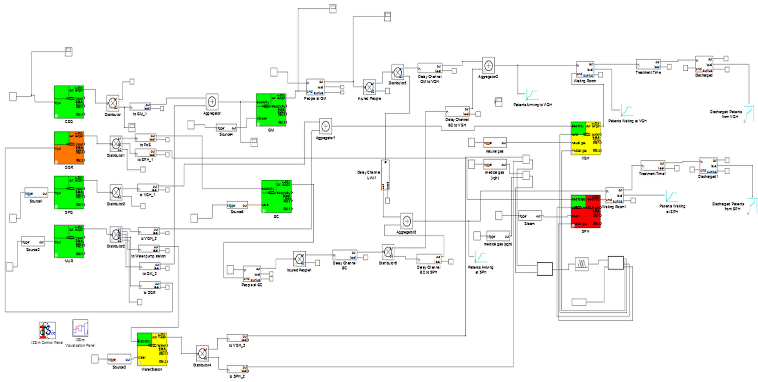

Figure 4. Vancouver downtown model in I2sim with Neuro Fuzzy controller

Table 3. Combined solution table for electricity and water

Point	Available elec. (MW)	Row (Hosp. 1)	Row (Hosp. 2)	Avail. Med gas (KL)	Row (Hosp. 1)	Row (Hosp. 2)
A	25.5	R4	R4	50	R4	R4
B	25.5	R4	R4	75	R3	R4
C	38.5	R3	R4	100	R3	R3
D	38.5	R3	R4	125	R2	R3
E	63.75	R2	R3	150	R2	R2
F	76.5	R2	R1	200	R1	R1

In this method we ran the Simulink model and then exported the variables to the work space. Then we implemented the three models and got the results. But the problem with this method was that we were unable to see the graph at the run time because the controllers were not having any effect on the model at run time. Due to this we rejected this model went for a new technique known as GENSIM Method.

GENSIM Method

In this method we divided it in further two parts. In order to implement the fuzzy and neuro fuzzy we used one technique where as in order to implement it on ANN we used other technique. In order to incorporate the ANN network to Simulink I2sim model we used a "GENSIM" command. Fist we got the output from the distributors then passed its values to the function in order to arrange it in a specific format. In the next step we passed that value to the ANN model. Finally, that output value is passed to the two hospitals. That model is shown in the figure 1-3.

As It can be seen that we have a neural network. In the figure it is named as "Function Fitting Neural network". Basically the model consists of three blocks, the first block known as "MATLAB function" concatenates the data in certain format whereas the last block known as "Neuro fuzzy" block disassociate the predicted output. Then this output was given to the two hospitals known as VGH and SPH.

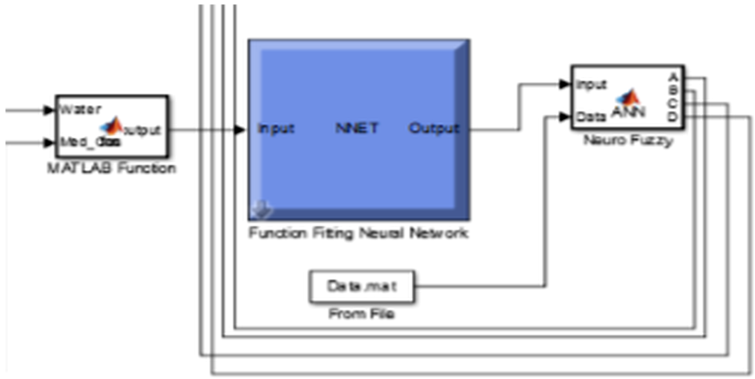

Figure 5. ANN model in Simulink

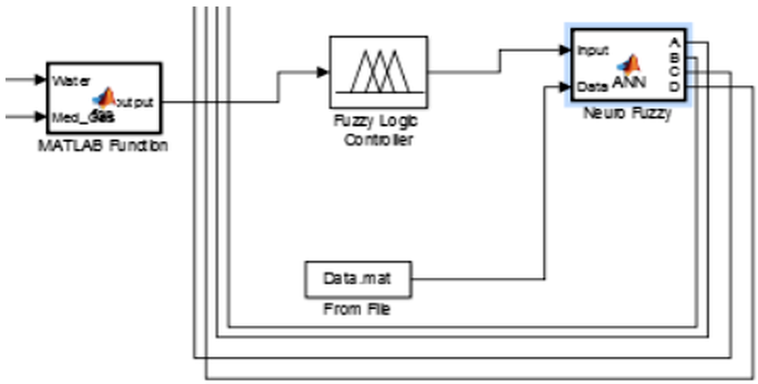

Figure 6. Fuzzy model in Simulink

In order to implement the fuzzy and neuro fuzzy in the Vancouver downtown model, we incorporated these blocks in it. As rules for both the cases were stored in the ".fis" file. This file was read by the Fuzzy Logic Controller. The purpose of other two blocks was same as in the case of ANN. Their functionality has been discussed earlier.

After making the rules for fuzzy and training our system for fuzzy and neuro fuzzy the we got are shown in the Figure 1-5 and figure 1-6. Before running the simulations, we checked the accuracy of the system. By mean error square method which has already been discuss before. By using this method, we got following values for the accuracy of the three methods as shown in table 1-4 below.

We kept the values constant and then found that, there was not patient was discharged from the either hospital without the optimization algorithm whereas when the optimization algorithm was applied we were able to allocate the resources accurately and at least one hospital was able to operate. This also shows that our algorithm was able to resolve the sources conflict which was the requirement of the project.

Table 4. Accuracy of different methods

Method name	Accuracy (%)
ANN	94.4
Neuro Fuzzy	96.5
Fuzzy	99.1

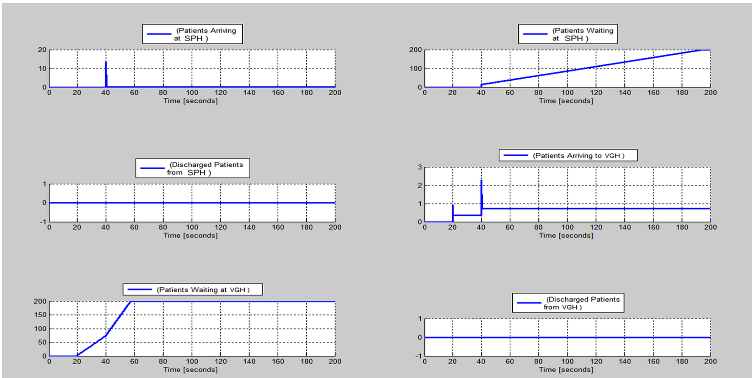

Figure 7. Without optimization algorithm

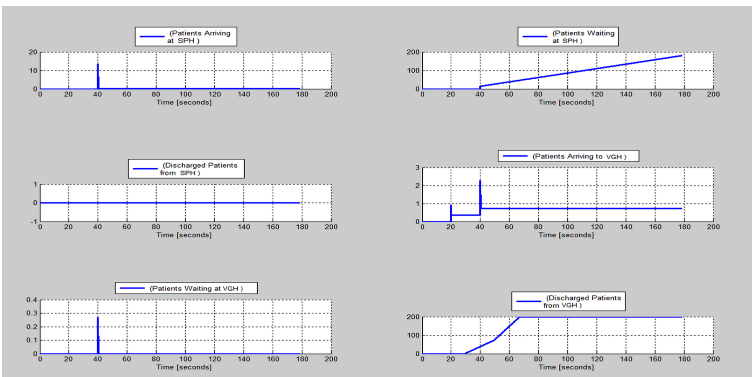

Figure 8. With optimization Algorithm

Neuro-fuzzy models have a proven record of successful application in finance. Forecasting future values is a crucial element of successful decision making in trading. In this paper, a novel ensemble neuro-fuzzy model is proposed to overcome limitations and improve the previously successfully applied a five-layer multidimensional Gaussian neuro-fuzzy model and its learning. The proposed solution allows skipping the error-prone hyperparameters selection process and shows better accuracy results in real life financial data[23,24].

Conclusion

In this research we used multiple techniques to implement the decision making algorithm on the Vancouver downtown I2sim model. This algorithm can be used to solve the multiple type of problems. Our major task was to find that which algorithm has the best accuracy. We used three different techniques i.e. Neuro Fuzzy, Fuzzy and ANN on the same model. The I2sim toolbox can be used to solve any number of cells. Every cell that is used from the I2sim toolbox depends upon the multiple resources and sometimes these resources are shared between the multiple blocks. With these resources interdependencies the infrastructure of any city or town gets exposed after the disaster occurs. The decision maker algorithm is used to solve this problem and it is assign with the task to solve the resources allocation problem and increase the efficiency of the system. The main aim of this algorithm is to get the maximum patients treated by controlling the outputs of the distributor in the system.

In this project we used three different techniques to check that which one gives the most accuracy. ANN and Neuro Fuzzy were used in regression mode whereas in case of fuzzy we wrote its rule by using a certain format. In the ends the results shown that fuzzy gave us the most accuracy. Its accuracy was about 99%. This high percent of accuracy shows that these techniques can be used to resolve the conflict of resources in the future on practical systems. This type of system optimization technique becomes even more important when we talk about a disaster situation.

Future work

In future we can use the other artificial intelligence techniques for the optimizations of input of hospital resources. We can use the optimization techniques such as Genetic algorithm and particle swarm optimization. We can also use some other techniques that are used as regression like SVM. We can also make some specific test cases, in which the disaster will occur at different locations and then by applying different techniques we can also figure it out that which are the distributed generators who are more sensitive to the resources allocation at this time. Then we can develop more fast and more accurate algorithms for the resources allocation.

References

1. Khouj, M.T, Sarkaria, S and Marti, J.R (2014). Decision assistance agent in real-time simulation. Int. J. Critical Infrastructures. The University of British Columbia (Vancouver) 2014
2. Khouj, M (2014) Resource Allocation Optimization of a Disrupted Interdependent System using Machine Learning
3. Bai, M (2012). Optimization Decision Maker Algorithm for Infrastructure Interdependencies with I2sim Applications. The University of British Columbia (Vancouver) July 2012
4. Wang, K., Bai, M., Marti, J and Srivastava, K.D. (2012). Optimal Decision Maker Algorithm for Disaster Response Management with I2Sim Applications. Proceedings of the 9th International ISCRAM Conference – Vancouver, Canada, April 2012.
5. Khouj, M., Lopez, C., Sarkaria, S., and Marti, J. (2011) Disaster Management in Real Time Simulation Using Machine Learning, Canadian Conference on Electrical and Computer Engineering, 1507-1510
6. I2Sim. (2007) Infrastructure Interdependencies Simulation (I2Sim) Team[Internet 2007] Available from: <www.i2sim.ca> Date Accessed: March 05, 2013.

7. Marti, J.R., Hollman, J.A., Ventura, C and Jatskevich, J. (2006). Design For Survival Real-Time Infrastructures Coordination. University of British Columbia, Department of Electrical and Computer Engineering.
8. Jain, S and McLean, C. (2003) A Framework for Modeling and Simulation for Emergency Response. [Internet 2003] Available from: <http://www.informs-sim.org/wsc03papers/132.pdf> Date Accessed: March 14, 2013.
9. Rahman, H.A., Armstrong, M., Mao, D and Marti, J.R. (2008) I2Sim: A Matrix-partition based Framework for Critical Infrastructure Interdependencies Simulation. 2008 IEEE Electrical Power & Energy Conference.
10. Ventura, C.E., Juarez Garcia, H., Thibert, K.M, Martí, J. and Hollman, J. (2008). Mapping of Interdependencies through Integrated Hazard Analysis: study case of a Canadian University Campus. The 14th World Conference on Earthquake Engineering October 12-17, 2008, Beijing, China.
11. Stergiou, C and Siganos, D (2010). Neural Networks. [Internet 2010] Available from: <http://www.doc.ic.ac.uk/∼nd/surprise_96/journal/vol4/cs11/report.html> Date Accessed: November 2014.
12. Paplinski, A (2005). Neuro-Fuzzy Computing. [Internet 2005] Available from: <www.csse.monash.edu.au/courseware/cse5301/2006/Lnts/L12fz.pdf > Date accessed: November 2014>
13. Sheu, J.-B. 2007. "An emergency logistics distribution approach for quick response to urgent relief demand in disasters". Transportation Research E: Logistics and Transportation Review 43 (6): 687–709.
14. W. Wang, M. Liu and L. Wang, "The dynamic optimal method of emergency resources deployment planning based on markov decision processes," Acta Scientiarum Naturalium Universitatis Nankaiensis(Natural Science Edition), vol. 43, no. 3, pp. 18-23, June 2010.
15. Yanfeng Wang, James R. Perkins (2002), "Optimal Resource Allocation in New Product. Development Projects: A Control- Theoretic. Approach.", IEEE transactions on automatic control, Vol. 47, pp 1267-1276.
16. Vieira, J, Dias, F.M, and Mota, A (2001). Neuro-Fuzzy System- A Survey. [Internet] Available from: <www.cee.uma.pt/morgado/down/483-343.pdf> Date accessed: Jan 2016
17. C. A. Arboleda, D. M. Abraham, J.-P. P. Richard and R. Lubitz, "Vulnerability assessment of health care facilities during disaster events," Journal of infrastructure system, vol. 15, no. 3, pp. 149-161, 2009.
18. S. Wu, L. Shuman, B. Bidanda, M. Kelley, K. Sochats and C. Balaban, "Agent-based discrete Event simulation modeling for disaster responses," in The Proceeding of the 2008 Industrial Engineering, 2008.
19. Eusgeld, C. Nan and S. Dietz, "System-of-system approach for interdependent critical infrastructures," Reliability Engineering and System Safety, vol. 96, no. 6, pp. 679-686, 2011.
20. G. M. Atanasiu and F. Leon, "Agent-based risk assessment and mitigation for urban public infrastructure," Forensic Engineering 2012, pp. 418-427, 2013.
21. . Fiedrich, F. Gehbauer and U. Rickers, "Optimized resource allocation for emergency response after earthquake disasters," Safety Science, vol. 35, no. 1, pp. 41-57, 2000.
22. H. Das, B. Naik, and H. S. Behera, "Classification of diabetes mellitus disease (DMD): a data mining (DM) approach," in Progress in Computing, Analytics and Networking, pp. 539–549, Springer, Singapore, 2018.
23. S. K. Meher, "Efficient pattern classification model with neuro-fuzzy networks," Soft Computing, vol. 21, no. 12, pp. 3317–3334, 2017.
24. I. Škrjanc, J. A Iglesias, A Sanchis, D. Leite, E. Lughofer, and F. Gomide, "Evolving fuzzy and neuro-fuzzy approaches in clustering, regression, identification, and classification: a survey," Information Sciences, vol. 490, pp. 344–368, 2019.