The FIS structure from Fig. 23 has 6 inputs with 3 membership functions for each input.

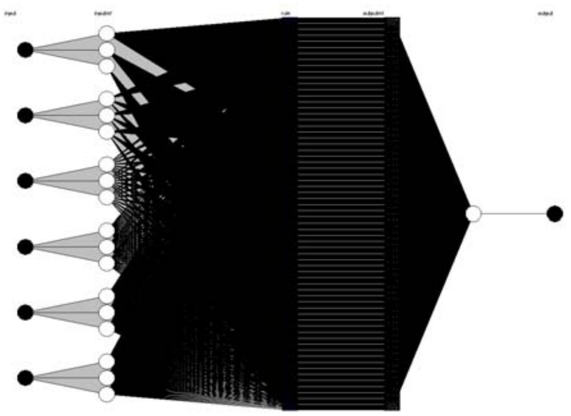

Fig. 23 The FIS structure for the hyperbolic case

Number of training epochs was 3. The compared outputs and error for ANFIS for the 3rd estimation algorithm test is presented in Fig. 24.

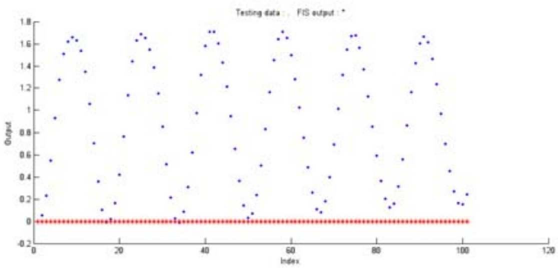

Fig. 24 FIS testing output and error for the 3rd algorithm

The compared outputs and error for ANFIS for the 4th estimation algorithm test is presented in Fig. 25.

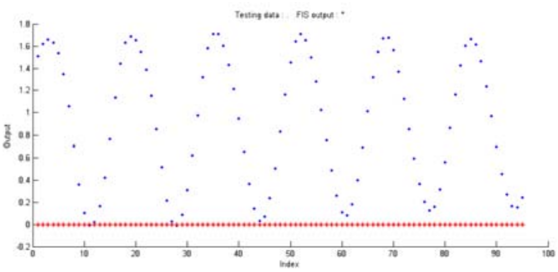

Fig. 25 FIS testing output and error for the 4th algorithm

In both cases, for the 3rd and 4th algorithms small errors at tests were obtain. The comparison characteristics are the same, according to the experiments.

7 Conclusion

The paper presents four algorithms for estimation of state variables in distributed parameter systems of parabolic and hyperbolic cases. Also, a method for monitoring distributed parameter systems based on these algorithms, sensor networks and ANFIS for non-linear system identification is presented. The sensor network is seen as a distributed sensor. The algorithms are two based on regression using the values provided by the adjacent nodes of the sensor network and the other two are based on autoregressive relation with the values from anterior time moments of the same node.

The method described the way how to use all these concepts for fault detection and diagnosis in distributed parameter systems, using the measured values provided by the sensor and the estimated values computed by the ANFIS estimator, calculating an error and detecting the fault based on a decision taken after a threshold comparison.

Four case studies for all four algorithms are presented for parabolic type and for hyperbolic type of equations. A comparison between the algorithms is made. Good approximations were obtained.

Developing of the algorithms and the method are taken in consideration in the future, in other applications, considering all the capabilities of the sensor nodes to measure physical variables. This approach allows treatment of large and complex systems with many variables by learning and extrapolation. Estimations methods may be applied in the case of discovery of malicious nodes in wireless sensor networks. An interesting application could be the monitoring of earth environment at low and high altitudes, based on new types of sensor networks specialized for this purpose.

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