ELECTRICAL SOURCES PERFORMANCE IMPROVEMENT OF UNMANNED AIRBORNE VEHILES USING ARTIFICIAL NEURAL NETWORKS BASED SFDIA +

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Abstract :

The occurrence of faults during the flight of unmanned air vehicle UAV is a very critical situation that affects the completion of the mission. It was found that these faults are mainly due to failure in the sender (sensor), it was also found that the rate of failure is high in electrical energy Sensors (ac, dc and battery). This research presents an effective technique to ensure that the electrical power system (.ac, dc, battery) or the sensors are faulting free. This technique using two different approaches. The first approach is Radial Basis Function RBF-NN trained with the Extended Minimal Resource Allocation Network - EMRAN algorithms. The second approach, which is presented in this Paper, is based on Knowledge based Neural Network NN based tool SFDIA (Sensor Failure, Detection, Identification and Accommodation problem). Neural Network ANN based tool SFDIA Sensor Failure, Detection, Identification and Accommodation problem, are used to provide analytical redundancy from which residuals are generated, enabling the detection of failures on sensor signals. Upon detection of failure, the faulty signal is replaced by the neural network based estimate. This technique allows the flight to continue within specified performance limitations. The results achieved from the modeling process showed that the neural network based tool SFDIA is able to show high-resolution results in the behavior of electrical energy Sensors (ac, dc and battery).

Keywords: Unmanned aircraft vehicle UAV, Sensor fault detection SFD,Fault diagnosis, and Aircraft modeling and simulation.

تحسين اداء المصادر الكهربائية للمركبات غير المأهولة المحمولة جوا باستخدام الشبكات العصبية الاصطناعية القائمة على (SFDIA).

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المستخلص :

حدوث الاعطال أثناء طيران المركبة الجوية بدون طيار (UAV) هو وضع حرج للغاية حيث يؤثر على اكمال طيران المركبه الجويه . وقد وجد ان اغلب هذه الاعطال سببها اعطال في المرسلات (المتحسيسات)، وتبين أن نسبة العطل عالية في مرسلات الطاقة الكهربائية (AC، DC والبطارية). يقدم هذا البحث تقنية فعالة ذات نهجين مختلفين لضمان عمل المرسلات الخاصه بنظام الطاقة الكهربائية بكفاءه عاليه. النهج الأول هواستخدام الشبكة العصبية (NN) على اساس الاداه (SFDIA) القائمة على النمذجة، والمحاكاة وتحليل مرسلات الطاقه للطائره

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(الاستشعار، العطل، الكشف، تحديد أماكن العطل و معالجه العطل). النهج الثاني تدريب الشبكه العصبيه على الخوارزميه ((EMRAN) والتي هي مجموعة من القواعد تقرر كيف ينبغي تكييف هيكل RBF–NN لتتناسب مع البيانات من اجل تدريب أفضل.وأظهرت النتائج من عملية النمذجة أن الشبكة العصبية القائمة على الاداء (SFDIA) هي قادرة على أن تظهر نتائج عالية الدقة في سلوك مجسات الطاقة الكهربائية (AC، DC والبطارية).

List of Acronyms

UAV	Unmanned Air Vehicle
SFD	Sensor fault detection
SFDIA	Sensor Failure Detection Identification and Accommodation
NN_s	Artificial Neural Networks
EMRAN	Extended Minimal Resource Allocation Network
RBF	Radial Basis Function

1. Introduction :

Unmanned air vehicle UAV are complex technical systems. They are out of reach by the pilot. But the name of this aircraft does not fully demonstrate the way in which they are operated. They are in fact not fully self piloted, but also need a pilot sitting at the steering station on the ground, to remotely control it by a wireless manner. The control Process of the UAV is through signals transmitted by sensors. In this respect comes the importance of increasing the efficiency of sensors. Which transmit signals back to ground stations [1] .Sensor fault in UAV is detected by using two different approaches. The first approach is Radial Basis Function RBF- NN trained with the Extended Minimal Resource Allocation Network- EMRAN algorithms.[2-.3] The second approach, which is presented in this Paper, is based on Knowledge based Neural Network NN based tool SFDIA (Sensor Failure, Detection, Identification and Accommodation problem) [4-5]. The tool is based on a SFDIA scheme in which learning NN are used as on-line non-linear approximates of the analytically redundant portion of the system dynamics [6]. This can provide validation capability to measurement devices, allowing sensors failures to be detected, identified and accommodated. Research on fault tolerance based on analytical redundancy has produced a quite mature framework especially for linear systems [7]. But unfortunately, the assumption of linearity is not often valid throughout the whole flight envelope of the aircraft. Thus the performance of a fault tolerance scheme based on such assumption can become inadequate, for example providing a high false alarm rate in a wide portion of the flight envelope. Chow and Willsky (1984) first defined model-based FDI to consist of two main stages; residual generation and residual evaluation [8]. Patton et al.(1989) also outlined the criteria for selecting a suitable FDI approach, two of which were low false alarm rates and fewer missed faults [9]. In this work, SFDIA software has been designed in the Simulink environment. The tool allows evaluating either the open loop or the closed loop performance of the SFDIA scheme that employs different kinds of NN approximators and learning algorithms [10]. The NN structure chosen is based on the Extended-Minimum Resource Allocating Network (EMRAN) Radial Basis Function (RBF), due to its good generalization ability and fast performance [11] Comparisons of a conventional residual generator approach and our novel approach are carried out under different levels of sensor noise and fault classes in order to test their robustness and sensitivity respectively

2. Analytical redundancy-Based SFDIA :

Analytical redundancy implies that some of the system variables are functionally related namely a variable y (k)can be expressed as function of a suitable set of other variables z (k)and input commands u (k) [12]. Figure1 shows a flowchart of the SFDIA scheme.

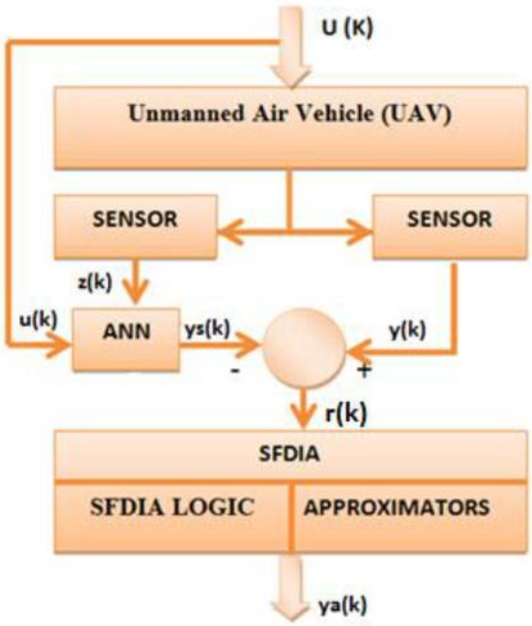

Figure (1): SFDIA Scheme [12]

$\mathbf{y_s\ (k) = f\ [z(k)\ ,\ u(k)]}$ ………………………………………………………….. (1)

Where: u (k) - inputs commands.
y_s (k) -estimation signal provided by estimator (ANN)
z (k) - function of a suitable set of other variables
The residual signal r(k)is the difference between the sensor output y(k)and its estimation y_s(k) provided by a proper estimator (in this work the estimator is a NNs).[13].

$\mathbf{r\ (k) = y\ (k) - y_s(k)}$ …………………………………………………………… (2)

Where: y (k) –sensor output
y_s(k) – estimation signal provided by estimator (ANN)
r (k) – residual signal

When the square of this (filtered) residual exceeds predefined threshold, the state of the corresponding sensor is declared suspect and a suitable procedure is called to decide on the health status of this sensor figure 2 shows a flowchart of the predefined threshold.

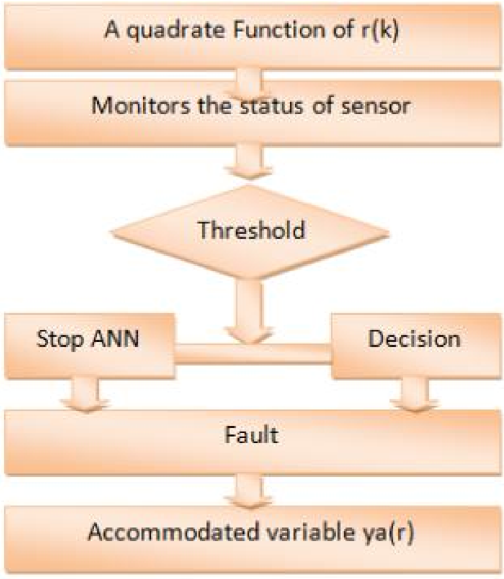

Figure (2): Predefined Threshed [12]

If the state of the sensor is then declared faulty, a procedure is enabled, and an accommodated variable $y_a(k)$is provided as output. In this work the accommodation procedure simply substitutes the faulty measure with the Estimation given by the ANN. Figure 3 Shows the accommodation with the estimation given by the ANN.

$\mathbf{y_a(k)=r(k)}$ .... (3)

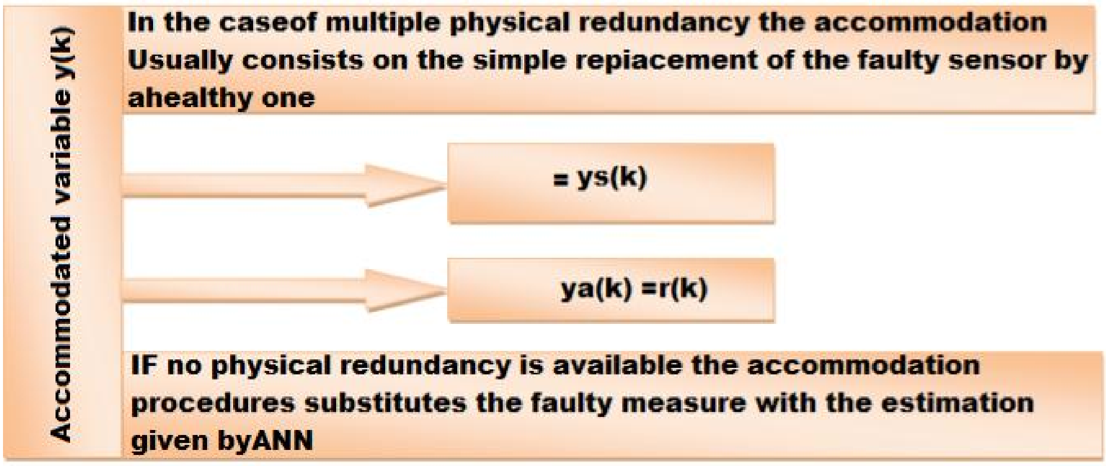

Figure (3):The accommodation with the estimation given by the ANN

Several options can be added to this basic scheme to increase robustness in presence of noisy measurements and/or intermittent sensor failures [14].Thus, the accommodation procedure substitutes the faulty measurement with the estimation given by the NN [15]. As for any SFDIA approach, the following capabilities are critical:

- Failure detect ability and false alarm rate (the sooner the fault is detected and the least the number of false alarm it is, the better is the SFDI system [16].
- Estimation error(The least is the estimation error; the better is the quality of the accommodation) [17].

3. The Simulation :

The Neural Network based SFDIA modeling and simulation toolbox was built under the Math lab and simulink for Technical computing (by The Math worksInc) [18]. In particular the freely available aircraft Sensor Failure, Detection, Identification and Accommodation SFDIA toolbox for Mat lab provides powerful tools for aircraft power system simulation, electrical fault analysis, and electrical fault control system design [19-20]. In figure 4 shows the graphical interface of the proposed aircraft SFDIA tool.

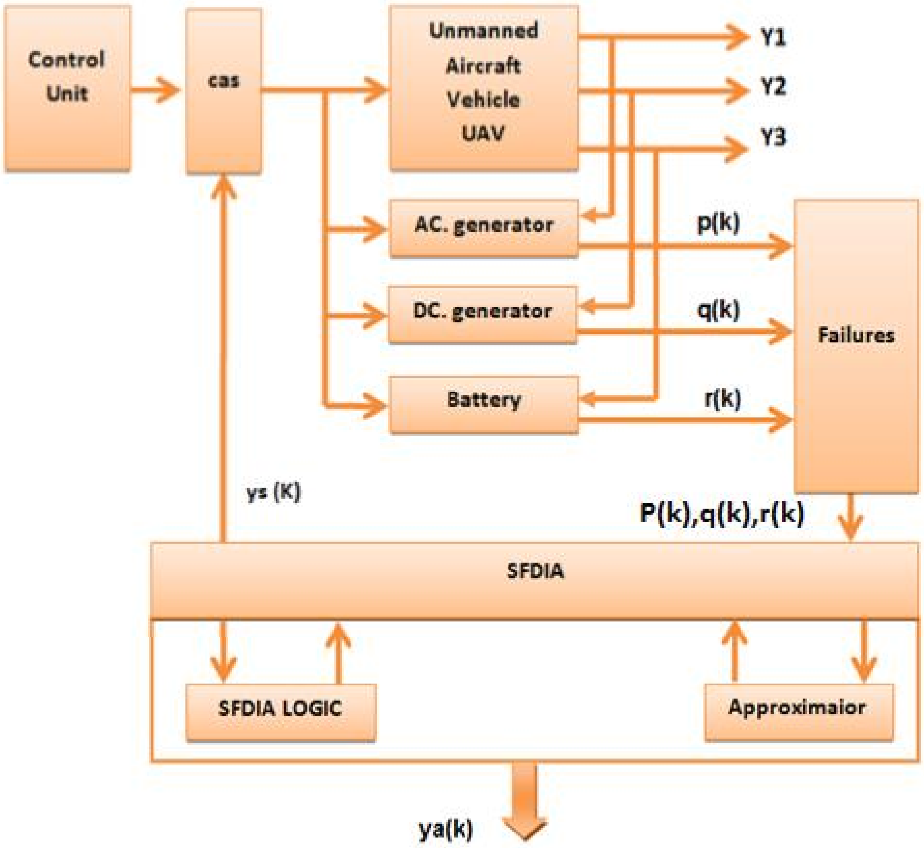

Figure (4): Modeling and simulation the proposed aircraft SFDIA.

The main blocks of the scheme are the following:

- **Unmanned air vehicle UAV electrical model.**
  The tool has been built around a generic nonlinear unmanned air vehicle UAV model, which has a modular design that provides maximum flexibility to the user. The unmanned air vehicle UAV model has been implemented as Simulink block-diagram (Ac-channel, Dc channel, Battery channel).The model is adapted for many different kinds of airplanes as required. [21-22].
- **Control Augmentation System CAS.**
  The block is implemented with a Stochastic Optimal Feed forward and Feedback controller[23].
- **The substitute pilot control unit.**
  The block in this paper allows the generation electric energy sensors commands (Ac-channel, Dc channel, Battery channel). [24]
- **Hard and soft sensor failure**s.

The block injects soft and hard sensor failures to the desired measured signals [25].

- **(SFDIA)group**.
  It is the core of the tool that performs the main SFDIA procedures. It is constituted by two main sub-blocks: [26]

i. Approximators.
The block contains the Neural Network based function estimators. In figure 5 is showing (p(k) ac generator channel ,q(k) dc generator channel, and r(k) Battery channel) [27-28].

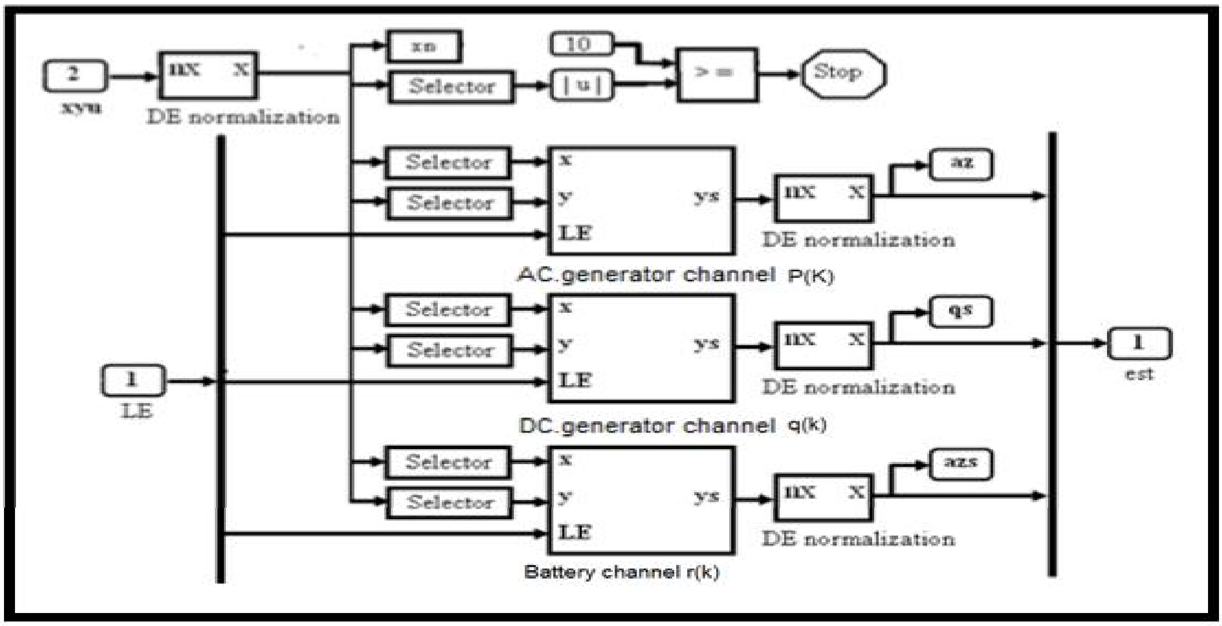

Figure (5): Estimators for AC-Generator channel p (k), Dc-Generator channel q (k), Battery. – channel r (k)

ii. SFDIA Logic:
The block performs the main threshold based sensor failure detection identification and accommodation operations Figure 6 Two filtered residuals (derived by filtering the absolute approximation error with both a "fast" low pass filters and a "slow" low pass filter) are contemporary evaluated for each sensor. When the fast filter output is bigger than a threshold, the corresponding NN learning is preventively stopped (LE=0), in order to prevent the possibly wrong signal from being learnt. When the slow filter output is bigger than a threshold, the corresponding sensor is declared failed (AE=0), so the accommodation logic is enabled, and the estimated signal is fed back through the controller instead of the faulty one.[29]

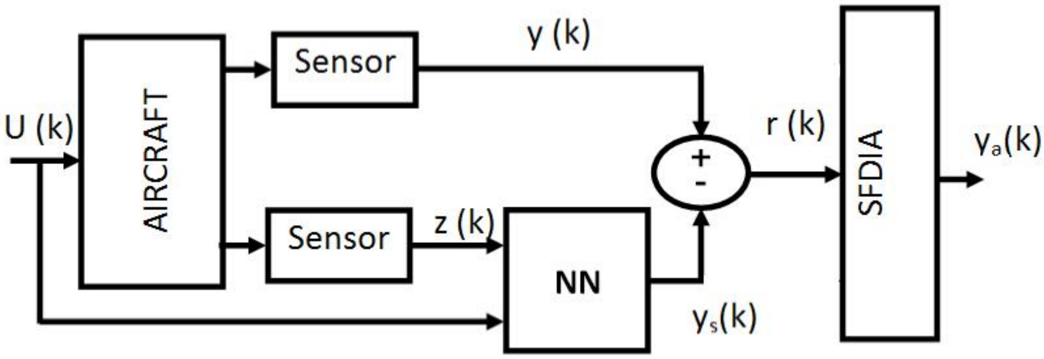

Figure (6): SFDIA Logic

4. Results :

In order to apply this technique (artificial neural networks based SFDIA to improvement electrical sources performance of unmanned airborne vehicles in this research were taken three cases which follows:

4.1 The voltage sensor ac generator :

Figure 7 shows a typical time of Y_1-(sensor ac generator) and its estimation, during the occurrence of a simulated failure on it at (t_f =168sec) using the EMRAN algorithm, which is a set of conditions decide how the RBF-NN structure should be adapted to better suit the training data.[30-31]. The results show that EMRAN-algorithm is well suited for fast on-line identification of nonlinear plants

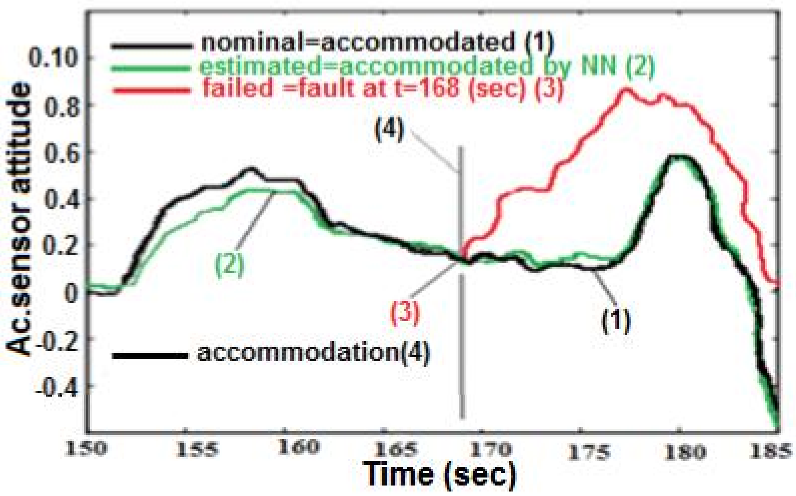

Figure (7): Sensor ac gen. (accommodated nominal, accommodated estimated, failed) at t_f=168sec.

4.2 The voltage sensor dc generator :

Figure 8 shows a typical time of Y_2-(sensor dc generator) and its estimation, during the occurrence of a simulated failure on it at (t_f =168sec) using the EMRAN- algorithm.

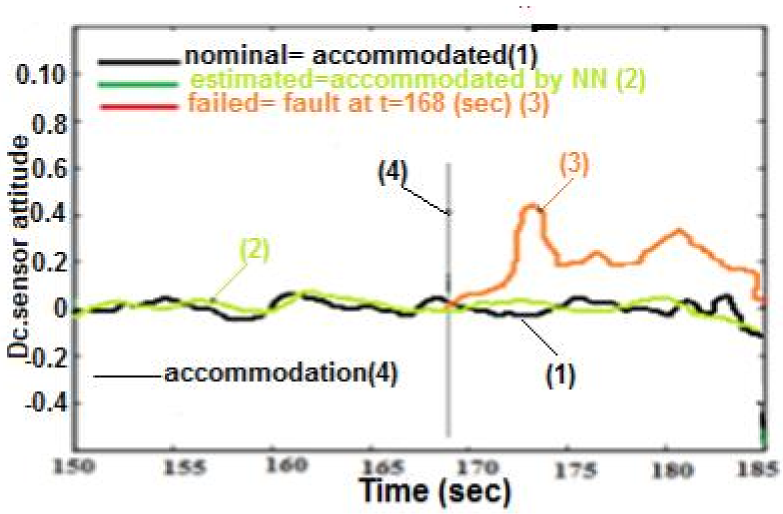

Figure (8): Sensor dc gen. (accommodated nominal, accommodated estimated, failed) at t_f=168sec

4.3 The voltage sensor Battery :

Figure 9 Shows a typical time of Y_3.(sensor Battery) and its estimation, during the occurrence of a simulated failure on it at (t_f=168sec) using the EMRAN-algorithm.

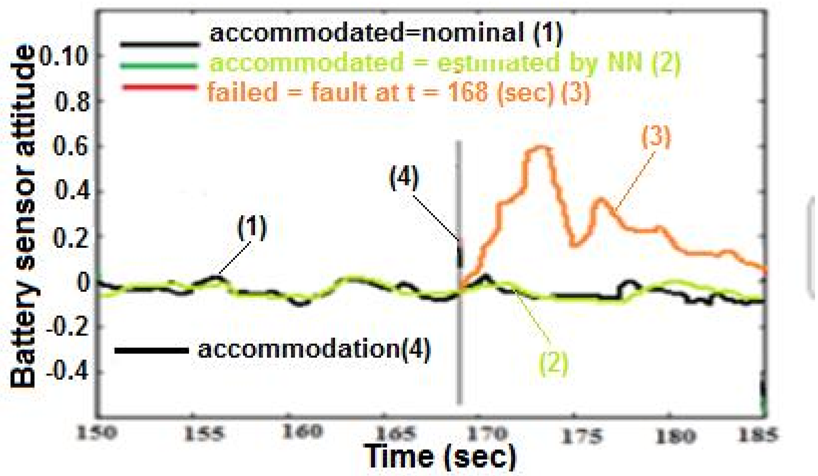

Figure (10): Sensor Battery. (Accommodated nominal, accommodated estimated, failed) at t_f=168 sec.

5. Conclusions :

In this paper unmanned air vehicle UAV, Neural Network NN based tool scheme (SFDIA) for the Sensor Failure, Detection, Identification and Accommodation problem too laws discussed. The scheme was implemented with neural architectures (RBF-EMRAN NN algorithms). The use of NN for sensor estimation of a parameter of interest has been studied. Observed by studying the results of applying the technique used in this research, the results of the application showed high-resolution for the process of replacing the faulty sensor by using the NN estimated value itself for further usage (as a feed back), close match between estimation and actual sensor output has been established. In addition the capabilities of SFDI Sachems exploiting different kinds of neural networks as nonlinear approximate. This capability is a consequence of the extensive modularity of the whole simulation tool, and allows an easy change of unmanned air vehicle UAV, dynamics and feedback control law as well as NN estimators and SFDIA scheme.

Future Work :

The NN estimation of this research can be applied to this research on other aircraft systems such (Flight performance, Engine performance, Control surface situation, Aircraft system status, Environmental data, Sounds, Air-to-ground communications) sensors outputs can be used.

References :

1. Stevens B.L, Lewis F.L. "Aircraft Control and Simulation", John Wiley & Sons, New York, 1987.
2. Kerr, T.H., False Alarm and Correct Detection Probabilities over a Time Interval for Restricted Classes of Failure Detection Algorithms, IEEE Transactions of information Theory, IT-28, No. 4, pp. 619-6318, 1982.
3. Powell M.J.D. "Radial Basis Function for Multivariable Interpolation: a Review", Algorithms for approximation. J.C. Mason and M.G. Cox, Eds. Oxford U.K. Oxford Univ. Press pp. 143-167, 1987.
4. Vemuri A., Polycarpou M., Diakourtis S. "Neural Network Based Fault Detection and Accommodation in Robotic Manipulators", IEEE Transaction on Robotic sand Automation; Vol. 14, no. 2, pp. 342-348, 1998.
5. M.R.Napolitano,Y.An,B.Seanor,Afault tolerant flight control system for sensor and actuator failure using neural networks, Aircraft Design, vol. 3, pp. 103128, 2000.
6. Polycarpou M. "On-Line Approximates for Nonlinear System Identification: A Unified Approach". Control and Dynamic Systems Series, Volume 7, Neural Network Systems Techniques and Applications (Academic Press, January, 1998.
7. P. M. Frank, "Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy. A survey and some new results,"Automatic, pp. 459-474, 1987.
8. E. Y. Chow and A. S. Willsky, "Analytical redundancy and the design of robust detection systems," IEEE Trans. Automat. Contr., vol. 29, pp. 603-614, 1984.
9. R. J. Patton, P.M. Frank and R. N. Clark, "Fault diagnosis in dynamic systems, theory and application," London, Control Engineering Series, Prentice Hall, 1989.
10. J. C. Platt, A Resource Allocation Network for Function Interpolation, Neural Computation3 (2), pp.213-225, 1991.
11. Y. Li, N. Sundararajan and P. Saratchandran, "Analysis of minimal radial basis function network algorithm for real time identification of nonlinear dynamic systems," IEEE Contr. Theory and Application vol. 4, pp 476-484, 2000.
12. M. L. Fravolini, G. Campa, M. Napolitano and Y. Song, "Minima resource allocating networks for aircraft SFDIA," Advanced Intelligent Mechatronics, vol. 2, pp. 1251-1256, 2001.
13. Frank P.M., Ding X. "Survey of Robust Residual Generation and Evaluation Methods in Observer-Based Fault Detection Systems", Journal of Process Control; Vol. 7, no 6, pp. 403-424, 1997.
14. R. Isermann, "Process fault detection based on modeling and estimation methods, A survey,"Automatics, pp.387-404, 1984.
15. Q. Zhang and Y. Zhang, "A method for fault detection and isolation using neuralNetworks," presented at Neural Networks, 1996. IEEE International Conference on, 1996.
16. Cai, G., Lum, K.-Y., Chen, B. M., and Lee, T. H., "A Brief Overview on Miniature Fixed-Wing Unmanned Aerial Vehicles," in Proc. 8th IEEE International Conf. on Control and Automation, Xiamen, Chinapp. 285–290, 2010.

17. A. Alessandri and T. Parisini, "Neural state estimators for direct model-based fault Diagnosis," presented at American Control Conference, Proceedings of the 1998, 1998.
18. MATLAB Help Documentation, Math works,www.mathworks.com, 2011.
19. Rauw, M.O.: A Simulink Environment for Flight Dynamics and Control analysis - Application to the DHC-2 *"Beaver"* (MSc-thesis, Delft University of Technology, Faculty of Aerospace Engineering, Delft, the Netherlands, 1993.
20. Esposito, F.; Accardo, D.; Moccia, A.; Ciniglio, U.; Corraro, .;Garbarino,LReal-Time Simulation and Data Fusion of Navigation Sensors for Autonomous Aerial Vehicles. In Advances and Innovations in Systems, Computing Sciences and Software Engineering; Elleithy, K., Ed.; Springer: Dordrecht, The Netherlands; pp. 127-136, 2007.
21. Chao, H., Cao, Y., and Chen, Y., "Autopilots for Small Unmanned Aerial Vehicles: A Survey," Int. J. Control Autom. Syst. 8(1), 36–44, 2010.
22. Gutiμerrez-Zea, L., An Architecture for Adaptive Mode Transition Control of Unmanned Aerial Vehicles. PhD thesis, Georgia Institute of Technology, School of Electrical and Computer Engineering, Atlanta, GA 30332, 2004.
23. "Aircraft Control and Simulation," 2nd Edition, B.L. Stevens & F.L. Lewis, John Wiley and Sons Inc., 2003.
24. Beard, R.W., and McLain, T.W., "Navigation and Control Technologies for Autonomous Micro Vehicles," Brigham Young University Technical Report, http://hdl.lib.byu.edu/1877/65, 25 Aug., 2005.
25. M. R. Napolitano, G. Silvestri, D. A. Windon, II, J. L. Casanova, and M. Innocent,"Sensor validation using hardware-based on-line learning neural networks,"Aerospace and Electronic Systems, IEEE Transactions on, vol. 34, pp. 456-468, 1998.
26. F. E. Nasuti and M. R. Napolitano, "A learning approach to the SFDIA problem using radial basis function networks," presented at Intelligent Control, 2000. Proceedings of the 2000 IEEE International Symposium on, 2000.
27. A. Alessandri, M. Baglietto, and T. Parisini, "Robust model-based fault diagnosisUsing neural nonlinear estimators," presented at Decision and Control, 1998.Proceedings of the 37th IEEE Conference on, 1998.
28. A. Alessandri and T. Parisini, "Neural state estimators for direct model-based faultDiagnosis," presented at American Control Conference, 1998. Proceedings of the1998, 1998.
29. Li. Yan, N. Sundararajan, P. Saratchandran, Dynamically Structured Radial basis Function NeuralNetworks for robust aircraft flight control, Proc. American Control Conference, pp. 3501-3505, Chicago, 2000.
30. Junge, T.F. and Unbehauen, H., "Off-Line Identification of Nonlinear Systems Using Structurally Adaptive Radial Basis Function Networks "Proceedings of the 35th Conference on Decision and Control, pp. 943-948, Kobe, Japan, Dec.1996
31. Junge, T.F. and Unbehauen, H., "On-Line Identification of Nonlinear Time-Variant Systems Using Structurally Adaptive Radial Basis Function Networks", American Control Conference, pp. 1037-1041, Albuquerque, New Mexico, 1997.