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Una propuesta basada en fusión de sensores y lógica borrosa para el mantenimiento de plantas de producción de hidrógeno

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Resumen

Los sensores utilizados en los sistemas de control de plantas de producción de hidrógeno son componentes críticos que están sometidos a diversas condiciones ambientales, que repercuten en su fiabilidad y en la precisión de las mediciones. El sistema de control depende de la precisión de las mediciones para tomar decisiones como la activación de la unidad de refrigeración o la optimización del proceso. Los sistemas también pueden equiparse con unidades de detección de fallos para detectar comportamientos fuera de rango. El problema surge cuando las mediciones del sensor se desvían del valor real. Este trabajo propone una solución práctica para detectar fallos de deriva en sensores de temperatura integrados en electrolizadores utilizando un concepto inteligente basado en la combinación de fusión de sensores y lógica difusa.
Palabras clave: fusión de sensores, detección de fallos, lógica borrosa, electrolizador PEM.

Sensor fusion and fuzzy logic-based approach for maintenance in hydrogen production plants

Abstract

Sensors used in control systems of hydrogen production plants are critical components which are subject to various environmental conditions that impact on their reliability and accuracy of measurements. The control system depends on accurate measurements to make decisions such as activation of the cooling unit or optimisation of the process. The systems can also be equipped with fault detection units to detect out-of-range performances. Problem arises when the sensor measurements drift from the actual value. This paper proposes a practical solution to detect drift faults in temperature sensors embedded in electrolysers using an intelligent concept based on the combination of sensor fusion and fuzzy logic. The proposed solution can be integrated into control systems to ensure that drifting sensors are detected, recalibrated or replaced early.
Key words: Sensor fusion, faults detection, fuzzy logic, PEM electrolyser.

1. Introduction

1.1 Background study

Hydrogen gas can be produced by electrolysers which are devices that convert electrical energy into hydrogen gas. The control system of electrolysers can be equipped with sensors which provide information for decision making.. This helps to avoid membrane drying or overheating. The challenge with such fault detection systems is that the sensors used can experience drift faults which are progressive loss of accuracy over time and can cause a misinterpretation of high or low temperature as normal and vice versa.

When drift fault occurs, the fault detection system has a high possibility to allow abnormal temperature faults to go undetected. A promising solution for the detection of these sensor problem is the use of an approach called sensor data fusion (SDF) which is the process of combining information from other sensors in a control system to estimate the state of a dynamic system. The resulting estimate is, in some senses, better than it would be if the sensors were used individually (Galar and Kumar, 2017). In Figure 1a the schematic representation of a conventional fault detection system is shown where a process data such as temperature is measured by a sensor and the signal is passed to a fault detection system to determine abnormal process data such as high temperature. In Figure 1b, the application of sensor fusion is shown where the same temperature sensor signal is fused with another sensor signal measuring a different but correlated process data such as voltage, current, pressure among others. The fusion of the two sensor signals provides better detection of faults than with a single sensor.

Limited studies exist in the use of SDF for detection of faults in hydrogen systems**.** Some of the available ones include the work by (Zhong et al., 2024) who used multi-sensor fusion

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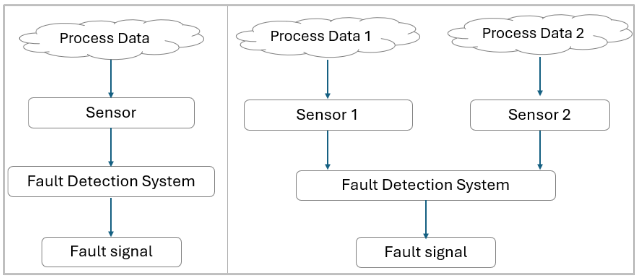
to detect internal water state in a proton exchange membrane (PEM) fuel cell based on particle filter using sensor signals from voltage and high frequency resistance measurements.



(a) (b)

Figure 1: (a) Schematic illustration of conventional fault detection system. (b) Application of sensor data fusion (SDF) to fault detection

The authors indicated that the detection with sensors fusion was more accurate than with either of voltage or high frequency alone.

In another study by Masali et al. (2024), sensor data fusion was used to detect hydrogen leakage by incorporating signals from electromagnetic, ultrasonic, and optical sensors.

Overall, various scientific literatures have shown that there are limited studies on the use of SDF for fault detection in hydrogen-based systems. This paper aims to fill this research gap and demonstrate the application of SDF in a PEM electrolyser. The remaining part of this paper is structured as follows. Section 2 identifies a proposed solution to implement the concept of sensor fusion which is subsequently used to solve the problem of drift faults in temperature sensors. In section 3, results are presented and discussed while in section 4 conclusions and future work are identified.

2. Methodology

The methodology proposed seeks to detect drift faults within sensors used in control systems and involves the incorporation of the technique of sensor data fusion along with fuzzy logic (Vélez et al., 2010). This is all together applied to a real case of a 1 Nm^3/h H_2-PEM electrolyser (Caparrós et al., 2021), Figure 2. In this layout, de-ionized water in a tank (WT-02) flows through a cooling unit to bring the water to the optimum operating temperature after which it passes through a recirculating pump (P002). The outlet of the pump has two pathways. One path is through is a filtration unit to remove ions before returning to back to the tank. The other path feeds the electrolyser. The electrolyser is energised by a power supply unit providing direct current. The water is split into oxygen and hydrogen at the anode and cathode respectively. The hydrogen produced passes through a cooling unit to reduce the temperature. The oxygen produced contains a significant amount of moisture both of which passes into a separator tank where oxygen is separated from water. The entire process is controlled by a programmable logic controller (Siemens® S7-1200). Various input sensors are incorporated for measuring process data such as conductivity, temperature, pressure, flow, voltage and current. The controller uses these input signals to determine when to operate output devices such as valves and pumps.

As the interest of the authors is to demonstrate the use of the proposed solution in electrolysers, hydrogen temperature sensor, TT121 (see Figure. 2), has been chosen for this research because it is a critical variable in the hydrogen production process (Abiola et al., 2023). If the hydrogen temperature sensor TT121 gives wrong measurement due to drift fault, the cell membrane (interface where the separation between oxygen and hydrogen occurs) will be degraded, provoking loss of efficiency and unsafe operation. To address drift fault in the temperature sensor, authors proposed solution involves the fusion of signals related to temperature and electrolyser voltage efficiency. These two signals will be used as input to a fuzzy logic system whose output provides a means to characterise the health status of the temperature sensor in terms of the presence of drift fault.

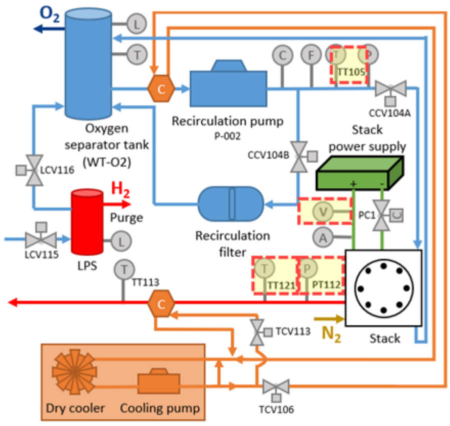


Figure 2: Layout of PEM electrolyser used in this research.

The proposed solution can serve as a useful fault detection subsystem in control systems to detect drift faults.

2.1. Development of the fault detection system.

To find the relation between efficiency and temperature, expression (1a) is considered (Bessarabov and Millet, 2018). This relates the heat dissipated and the electrical power consumed by the electrolytic cell. To scale up from single cell to multi-cell stack, it is possible to obtain (1b).

$$\eta_{cell} = 1 - \frac{Q_{cell}}{P_{cell}} \tag{1a}$$

$$\eta_{stack} = 1 - \frac{Q_{stack}}{P_{stack}} = 1 - \frac{N_{cell}Q_{cell}}{N_{cell}P_{cell}} \tag{1b}$$

Where:
η_{cell} is the cell efficiency
Q_{cell} is the heat dissipated in the cell (W)
P_{cell} is the electrical power consumed by the cell (W)
η_{stack} is the stack efficiency
Q_{stack} is the heat dissipated in the stack (W)
P_{stack} is the electrical power consumed by the stack (W)
N_{cell} is the number of cells in the stack

From the physicochemical point of view, the heat dissipated in the stack, Q_{stack}, can be expressed in terms of the heat due to the hydrogen, oxygen and water flows in the electrolytic reaction, (2).

$$Q_{stack} = (\dot{m}_{H_2}c_{H_2} + \dot{m}_{O_2}c_{O_2} + \dot{m}_{H_2O}c_{H_2O})\Delta T \tag{2}$$

Where:
$\dot{m}_{H_2}$ is the stack hydrogen mass flow (g/s)
c_{H_2} is the specific heat capacity of hydrogen (14.30 J/g K)
$\dot{m}_{O_2}$ is the stack oxygen mass flow (g/s)
c_{O_2} is the specific heat capacity of oxygen (0.92 J/g K)
$\dot{m}_{H_2O}$ is the water mass flow (g/s)
c_{H_2O} is the specific heat capacity of water (4.18 J/g K)
ΔT is the change in temperature from initial to new state (K)

The hydrogen $\dot{m}_{H_2}$, oxygen $\dot{m}_{O_2}$ and water $\dot{m}_{H_2O}$ mass flows can be obtained from (3).

$$\dot{m}_i = \dot{mol}_i M_i \tag{3}$$

Where:
i is H_2, O_2 or H_2O respectively
$\dot{mol}_{H_2}$ is the stack hydrogen molar flow (mol/s)
M_{H_2} is the hydrogen molar mass (2 g/mol)
$\dot{mol}_{O_2}$ is the stack oxygen molar flow (mol/s); in electrolysis, molar relation between H_2, and O_2 is: $\dot{mol}_{O2} = \dot{mol}_{H2}/2$
M_{O_2} is the oxygen molar mass (32 g/mol)
$\dot{mol}_{H_2O}$ is the water molar flow (mol/s)
M_{H_2O} is the water molar mass (18 g/mol)

From (3), (2) can be written as (4).

$$Q_{stack} = (\dot{mol}_{H_2}M_{H_2}c_{H_2} + \dot{mol}_{O_2}M_{O_2}c_{O_2} + \dot{mol}_{H_2O}M_{H_2O}c_{H_2O})\Delta T \tag{4}$$

Regarding the molar flow, according to Faraday law, the hydrogen molar flow of an electrolytic stack powered by an electrical current I_{stack}, can be obtained from (5):

$$\dot{mol}_{H2} = \frac{N_{cell}I_{stack}}{2\mathrm{F}} \tag{5}$$

Where:
I_{stack} is the current consumed by the stack (A)
F is the Faraday constant (96 485.33 As/mol)

On the other hand, the electrical power consumed by the stack can be written as (6).

$$P_{stack} = I_{stack}V_{stack} \tag{6}$$

Where:
V_{stack} is the voltage required by the stack (V).

Then, replacing (2), (4), (5) and (6) in (1b), it is possible to obtain (7) that relates temperature and stack efficiency:

$$\Delta T = \left(\frac{1 - \eta_{stack}}{\frac{\left(M_{H_2}\, c_{H2} + \frac{1}{2}M_{O_2}c_{O2}\right)}{2F} + \frac{\dot{m}_{H2O}c_{H2O}}{P_{stack}}} \right) \tag{7}$$

Equation (7) shows that the greater the temperature change, the lower the efficiency. Then, when the temperature change is maximum, ΔT_{max}, the stack operates at minimum efficiency, $\eta_{stack,min}$. Consequently, maximum efficiency, $\eta_{stack,max}$, will correspond to minimum temperature change, ΔT_{min}. Once it has been obtained the expression that relates temperature change and efficiency, we will consider developments from Bessarabov at al. (Bessarabov and Millet, 2018) to obtain the expression that allows us to determine the efficiency (8a) for single-cell and (8b) for multi-cell stack.

$$\eta_{cell} = \frac{V_{th}}{V_{cell}} \tag{8a}$$

$$\eta_{stack} = \frac{V_{thstack}}{V_{stack}} = \frac{N_{cell}V_{th}}{N_{cell}V_{cell}} \tag{8b}$$

Where:
V_{th} is the theoretical potential of the reversible redox reaction in the water decomposition (1.23 V)
V_{cell} is the experimental cell voltage (V)

Then, expression (8b) allows us to calculate the stack efficiency at any operation point, and expression (7) computes the temperature change, taking into account the calculated value of the efficiency.

2.2. The fuzzy variables.

From the previous section, the two variables of interest (η_{stack} and ΔT) can be used to design the fuzzy logic system which is capable of detecting drift-type faults in hydrogen temperature sensor (TT121). To determine the universe of discourse of the fuzzy sets representing the input variables, the manufacturer's data obtained from (Caparrós et al., 2021) are used, together with expressions (7) and (8b) to calculate maximum and minimum values of temperature change ΔT and efficiency η_{stack}, respectively, as shown Table 1.

Expression (7) indicates that, when the temperature changes from an initial state, t_o, to a new state, *t*, this involves a change in efficiency, that now is η_{stack}.

To handle the variables in the fuzzy logic system, they are going to be normalised as show in equations (9) and (10).

$$\overline{\eta_{stack}} = \frac{\eta_{stack_t} - \eta_{stack,min}}{\eta_{stack,max} - \eta_{stack,min}} \tag{9}$$

Where $\overline{\eta_{stack}}$ is the normalised stack efficiency.

Table 1: Numerical calculation of η_e and ΔT

Parameter	Numerical data and calculations
Electrolyser data from (Caparrós et al., 2021)	Number of cells, $N_{cell} = 6$ Minimum cell voltage $V_{cell,min} = 1.6$ VDC (begin of life, BoL) Maximum cell voltage $V_{cell,max} = 2.4$ VDC (end of life, EoL) Maximum H_2 operating pressure = 40 bar Minimum stack current $I_{stack,min} = 100$ A Maximum stack current $I_{stack,max} = 900$ A Water flow rate 16.97 l/min (Caparrós et al., 2021); this corresponds to $\dot{m}_{H2O} = 0.2778$ kg/s
Stack efficiency, η_{stack}	$\eta_{stack,min} = \frac{V_{th}}{V_{cell,max}} = \frac{1.23\ \text{VDC}}{2.4\ \text{VDC}} = 0.51$ $\eta_{stack,max} = \frac{V_{th}}{V_{cell,min}} = \frac{1.23\ \text{VDC}}{1.6\ \text{VDC}} = 0.77$
Temperature change, ΔT	Room temperature 22.2 ˚C $\Delta T_{min} = \left(\frac{1-\eta_{stack,max}}{\frac{\left(M_{H_2}\, c_{H2} + \frac{1}{2} M_{O_2} c_{O2}\right)}{2F} + \frac{\dot{m}_{H2O} c_{H2O}}{P_{stack,min}}} \right)$ $\Delta T_{max} = \left(\frac{1-\eta_{stack,min}}{\frac{\left(M_{H_2}\, c_{H2} + \frac{1}{2} M_{O_2} c_{O2}\right)}{2F} + \frac{\dot{m}_{H2O} c_{H2O}}{P_{stack,max}}} \right)$ Solving the above equations yields the following: $\Delta T_{min} = 0.19$ ˚C $\Delta T_{max} = 5.43$ ˚C

$$\overline{\Delta T} = \frac{\Delta T_t - \Delta T_{min}}{\Delta T_{max} - \Delta T_{min}} \tag{10}$$

Where:
$\overline{\Delta T}$ is the normalised temperature change.
ΔT_t is the change in electrolyser temperature in t (ºC).

Also, considering the data from Table 1, Figure 3a shows efficiency dependency with changes in temperature, while a similar plot with normalised values is displayed in Figure 3b. This plot is then used along with (7) to define the various fuzzy variables shown in Table 2 and Figure 4.

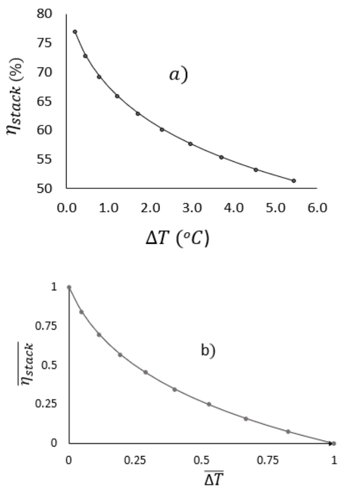
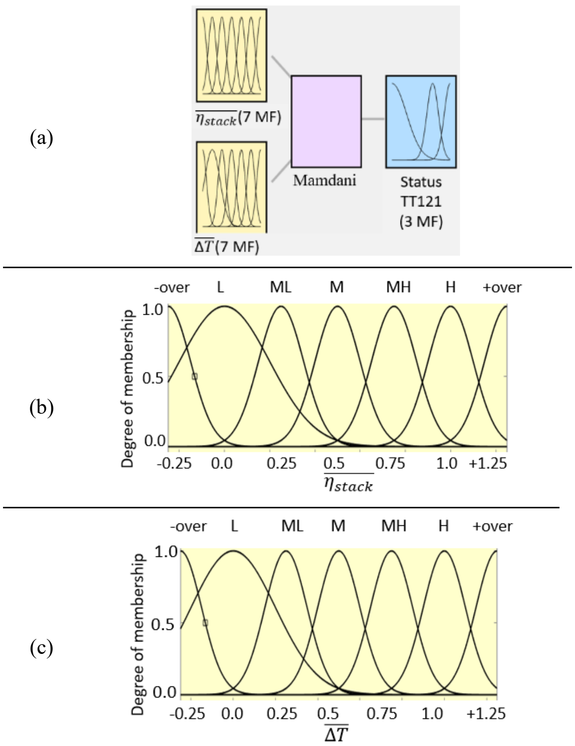


Figure 3: (a) Plot of efficiency ($\boldsymbol{\eta_{stack}}$) with changes in temperature (ΔT). (b) Normalised values of efficiency ($\overline{\eta_{stack}}$) and temperature change ($\overline{\Delta T}$).

Table 2: Fuzzy variables

Fuzzy Variables	Linguistic Variable	Gaussian Parameters [σ , c]
Input 1 $\overline{\eta_{stack}}$	-Over (below range)	[0.1 , -0.25]
	L (Low)	[0.2 , 0]
	ML (Medium Low)	[0.1, 0.25]
	M (Medium)	[0.1 , 0.5]
	MH (Medium High)	[0.1 , 0.75]
	H (High)	[0.1 , 1]
	+Over (above range)	[0.1 , +1.25]
Input 2 $\overline{\Delta T}$	-Over (below range)	[0.1 , -0.25]
	L (Low)	[0.2 , -0]
	ML (Medium Low)	[0.1, 0.25]
	M (Medium)	[0.1 , 0.5]
	MH (Medium High)	[0.1 , 0.75]
	H (High)	[0.1 , 1]
	+Over (above range)	[0.1 , +1.25]
Output (Sensor health)	Healthy	[0.2 , 0]
	Warning	[0.1 , 0.75]
	Faulty	[0.2 , 1]

According to Figure 3b, the range of values is expected to be within 0 to 1. Hence the fuzzy set is divided into sets at intervals of 0.25 with out-of-range sensor values defined as -0.25 and +1.25. This is shown in Table 2Figure 4 is built from two inputs which are the normalised efficiency, $\overline{\eta_{stack}}$, and normalised temperature change, $\overline{\Delta T}$**,** while the output is the hydrogen temperature TT121 sensor health condition.
The x-axis in Figure 4b and 4c is enlarged from -0.25 to +1.25. The membership L for both inputs ($\overline{\eta_{stack}}$ and $\overline{\Delta T}$) have the Gaussian parameter (σ = 0.2) which makes it wider compared to others with σ = 0.1. Regarding the sensor health condition, the memberships are classified into three fuzzy sets namely: "healthy", "warning" and "faulty", Figure 4d.



(d)

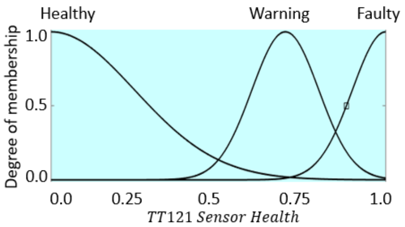


Figure 4: (a) Conceptual scheme of the fuzzy logic system; (b) $\overline{\eta_{stack}}$ input membership plot; (c) $\overline{\Delta T}$ input membership plot; (d) Hydrogen sensor (TT121) health condition output with membership plot.

The healthy condition indicates that the sensor measurement is good (sensor at healthy condition), "warning" indicates that the measurement is going out of expected range and faulty indicates that sensor measurement has drifted. See Table 3 for a section of the fuzzy rules out of a total of 49.

Table 3: A section of the fuzzy rules

Rule	Details
rule1	If $\overline{\eta_{stack}}$ is -over and $\overline{\Delta T}$ is -over then TT121 is Faulty
rule2	If $\overline{\eta_{stack}}$ is L and $\overline{\Delta T}$ is -over then TT121 is Faulty
rule3	If $\overline{\eta_{stack}}$ is ML and $\overline{\Delta T}$ is -over then TT121 is Faulty
rule4	If $\overline{\eta_{stack}}$ is M and $\overline{\Delta T}$ is -over then TT121 is Faulty
rule5	If $\overline{\eta_{stack}}$ is MH and $\overline{\Delta T}$ is -over then TT121 is Faulty
rule6	If $\overline{\eta_{stack}}$ is H and $\overline{\Delta T}$ is -over then TT121 is Faulty
rule7	If $\overline{\eta_{stack}}$ is +over and $\overline{\Delta T}$ is -over then TT121 is Faulty
rule8	If $\overline{\eta_{stack}}$ is -over and $\overline{\Delta T}$ is L then TT121 is Faulty
rule9	If $\overline{\eta_{stack}}$ is MH and $\overline{\Delta T}$ is M then TT121 is in Warning
rule10	If $\overline{\eta_{stack}}$ is M and $\overline{\Delta T}$ is M then TT121 is Healthy

2.3. Model development.

In the development of the proposed solution as shown in Figure 5, a model is developed in MATLAB Simulink®, version 2024. The fuzzy logic unit was developed using the fuzzy logic toolbox in MATLAB. The electrolyser cell voltage values, V_{cell}, are used to calculate the efficiency, η_{stack_t} using equation (8) for each time step.

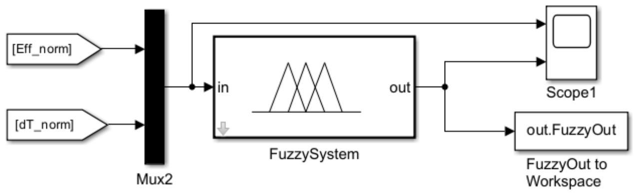


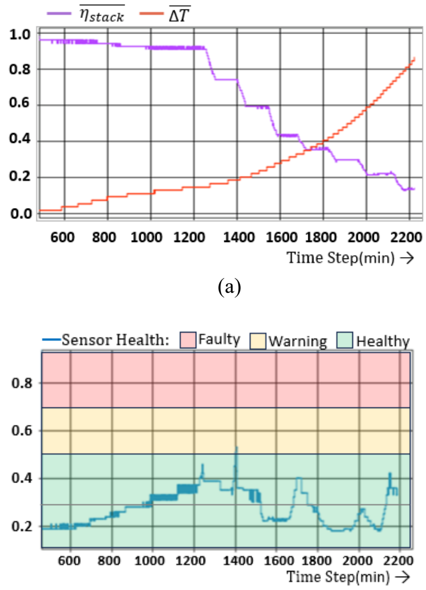
Figure 5: Fault detection model in MATLAB Simulink® environment.

In addition, changes in hydrogen temperature measurements from an initial state, t_o, to a new state t, are obtained corresponding to the same instance of the efficiency calculated. The stack efficiency values, and temperature measurements computed from (9) and (10) are fused together in the fuzzy logic system, to compute normalised efficiencies, $\overline{\eta_{stack}}$, and normalised temperature changes, $\overline{\Delta T}$. These data are then used for evaluation of the hydrogen sensor TT121 health.

3. **Result and discussion**

3.1. Testing of the proposed solution.

An initial test for normal electrolyser operation (no failures) was performed and the signals from the fuzzy logic system were observed. In normal operation, normalised input information represented in terms of $\overline{\eta_{stack}}$, and operating temperature, represented in terms of $\overline{\Delta T}$ are plotted as shown in Figure 6. The time step is measured in minutes of which values from 0 to 500 are not plotted since this represent period of initialisation and purging of the electrolyser. The stack current is from 100A until 900A with a corresponding increase in voltage. Initial temperature is 22 ºC and peaks around 28 ºC. Efficiency values at the beginning of electrolyser operation was 77% ($\overline{\eta_{stack}} \sim 1$) and gradually decreases as temperature increases ($\overline{\Delta T} > 0$). Based on the developed fuzzy system, it is noted from Figure 6b that during the beginning of operation up to the time step, 1200 min, the signals generated by the fuzzy logic system are tending towards the warning zone. Figure 6a shows the normalised changes in temperature $\overline{\Delta T}$ is increasing at a faster rate compared to the drop in normalised efficiency $\overline{\eta_{stack}}$ which is often experienced when the system is starting to operate. At time step $t > 1200$ min, $\overline{\eta_{stack}}$ starts to decrease at a rate comparable with $\overline{\Delta T}$, meaning that the electrolyser temperature is ramping up. This performance matches with normal operation. The fuzzy system output advises that the sensor reading is healthy. In points $t = 1400$ min, $t = 1700$ min, $t = 2000$ min and $t = 2150$ min, it is observed that the fuzzy logic system output notifies of a potential problem with the sensor health condition, Figure 6b.



(b)

Figure 6: a) Evolution of $\overline{\eta_{stack}}$ and $\overline{\Delta T}$ during normal operation. b) Response of the fuzzy system during normal operation.

This is explained because at these points, the efficiency remains almost constant. If the efficiency doesn't change, neither should the temperature; otherwise, this is an indicator of the sensor health is being harmed.

In the second test, Figure 7a, drift fault signals, δ, with a half-wave sine profile between $t = [600$ min, 800 min$]$ and $t = [1400$ min, 1600 min$]$ are introduced into the hydrogen temperature measurement TT121. Failure signals cause $(\overline{\Delta T} + \delta_1)$ to rise to 0.7 in the first case, and $(\overline{\Delta T} - \delta_2)$ drop to -0.5 in the second one. These deviations (drift-type faults) over the normal operation of the electrolyser plant, are detected early so that it can produces warnings and alarms for each case, as indicated in 7b.

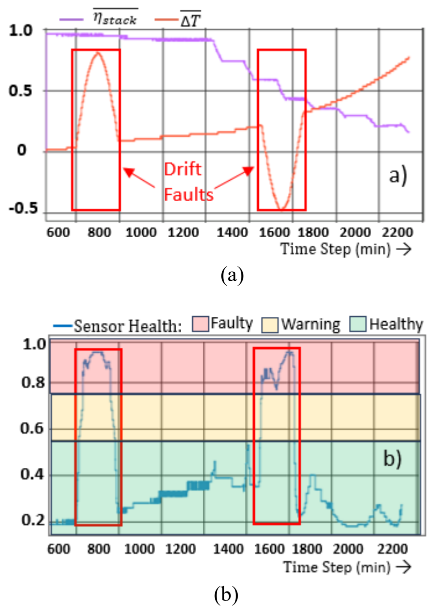


Figure 7: a) Evolution of $\overline{\eta_{stack}}$ and $\overline{\Delta T}$ during drift-type fault at two different samples. b) Response of the fuzzy output to the drift-type sensor faults.

Once the faults disappear, as demonstrated at $t = 800$ min and $t = 1580$ min, the fuzzy logic system indicates that the temperature sensor reading has return to healthy operation.

3.2. Fuzzy rules base validation.

Finally, the fuzzy rules defined previously are also validated with experimental electrolyser data. Figure 8 shows that the numerical data obtained from the developed fuzzy system corresponds closely with the experimental data obtained from (Caparrós et al., 2021). The plots also confirm inverse relationship between changes in efficiency and temperature. The figure shows that the rules defined for fault detection are within the ± 0.25 accuracy, as indicated by the region marked OK. Any sensor signal measurement outside the normal zone will trigger a warning or fault.

3.3. Comparison with conventional fault detection.

Comparing the developed solution with conventional fault detection systems as shown in Table 4, the output signal from the fuzzy logic system is particularly useful to determine when the sensor accuracy begins to deviate, rather than the conventional system which indicates faults only when the sensor has failed in form of Boolean logic (1 or 0).

Table 4: Comparison with conventional fault detection systems

Parameter	**Authors´ Proposal**	**Conventional Systems** (Wang et al., 2017)
Accuracy	± 0.25	± 1
Detection range of fault	Continuous values 0 to 1	Discrete values 0 and 1
Response time	0.2 - 0.5 s	60 s

Additionally, in authors' proposal, response time is shortened by a factor of 120, and accuracy is four times better.

4. Conclusion and future work

This paper demonstrates the application of sensor data fusion to detect drift faults in temperature sensors used within control systems of hydrogen plant. The developed system does not depend on training data before it can be used to detect drift faults in sensors. Once the electrolyser plant starts operation, the proposed solution allows an immediate detection of abnormal sensor readings due to drift. Such information will help maintenance personnel to plan when to replace or re-calibrate the faulty sensor. This situation is better than conventional fault detection systems, which mainly detect faults when the sensor has failed. The solution developed can be used in other types of systems such as fuel cells.

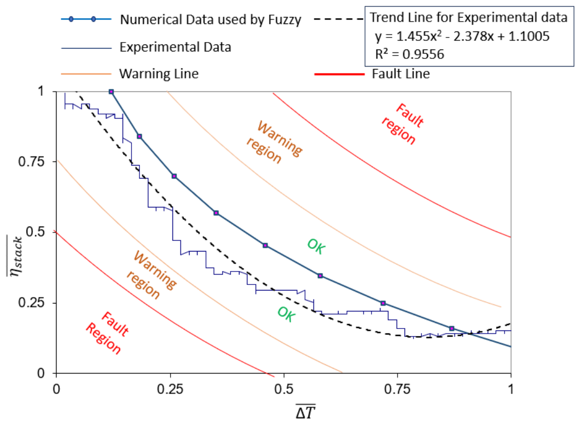


Figure 8: Plot of relation between normalised efficiency $\overline{\eta_{stack}}$ and normalised temperature $\overline{\Delta T}$; comparing the profile used to tune the fuzzy system and the profile obtained from experimental data.

Acknowledgement

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References

Abiola, A., Manzano, F.S., Andújar, J.M., 2023. A Novel Deep Reinforcement Learning (DRL) Algorithm to Apply Artificial Intelligence-Based Maintenance in Electrolysers. Algorithms 16. https://doi.org/10.3390/a16120541

Bessarabov, D., Millet, P., 2018. Fundamentals of Water Electrolysis. PEM Water Electrolysis. Elsevier, 43–73. https://doi.org/10.1016/b978-0-12-811145-1.00003-4

Caparrós, J.J., Vivas, F.J., Segura, F., Andújar, J.M., 2021. Optimized Balance of Plant for a Medium-size PEM Electrolyzer. SNE Simulation Notes Europe 31, 133–141. https://doi.org/10.11128/sne.31.tn.10574

Galar, D., Kumar, U., 2017. Sensors and Data Acquisition. EMaintenance. Elsevier, 1–72. https://doi.org/10.1016/b978-0-12-811153-6.00001-4

Masali, M.H., I, R.B., Zargarzadeh, H., 2024. Sensor Fusion for Incipient Hydrogen Detection Using Deep Learning. International Journal of Research Publication and Reviews 5. https://doi.org/10.55248/gengpi.5.0924.2419

Vélez, M.Á., Sánchez, O., Romero, S., Andújar, J.M., 2010. A new methodology to improve interpretability in neuro-fuzzy TSK models. Applied Soft Computing Journal 10, 578–591. https://doi.org/10.1016/j.asoc.2009.08.027

Wang, J., Yang, Z., Chen, K., Zhou, D., 2017. Practices of detecting and removing nuisance alarms for alarm overloading in thermal power plants. Control Engineering Practice 67, 21–30. https://doi.org/10.1016/j.conengprac.2017.07.003

Zhong, Y., Yang, Y., Diao, L., Song, K., Li, R., Yao, N., Ma, T., Lin, W., 2024. Design of multi-sensor fusion water state observer for proton exchange membrane fuel cell based on particle filter. Energy Conversion and Management 320. https://doi.org/10.1016/j.enconman.2024.118978