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Sensors fusion for faults detection in plants: a case study of PEM electrolyser

Abiola, Abiodun O.*, Segura, Francisca*, Andújar, José Manuel, Barragán A. Javier
Centro de Investigación en Tecnología, Energía y Sostenibilidad (CITES), Universidad de Huelva, España

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Abstract

Control systems are often equipped with fault detection sub-systems which utilise signals from sensors to detect abnormalities in the plant. However, when the sensor itself fails, the fault may escape undetected, and failure will occur. To solve this problem, the concept of sensor data fusion can be utilised to fuse signals from one sensor with another one within the system and the resulting fusion can be used for fault detection. The fusion of different but correlated signals can give better information about a potential fault rather than relying on signal from only one sensor in the plant. This situation ensures that even when sensors fail, faults can be detected. The benefit of the proposed solution is demonstrated in a real case with a 1 Nm3/h-H2 PEM electrolyser.

*Keywords: S*ensor fusion, Faults detection, Fuzzy logic, PEM electrolyser.

Fusión de sensores para la detección de fallos en plantas: estudio de un electrolizador PEM

Resumen

Los sistemas de control suelen estar equipados con subsistemas de detección de fallos que utilizan las señales de los sensores para detectar anomalías en la planta. Sin embargo, cuando el propio sensor falla, el fallo puede pasar desapercibido y producirse la avería. Para resolver este problema, se puede utilizar el concepto de fusión de datos de sensores para fusionar las señales de un sensor con otro dentro del sistema y utilizar la fusión resultante para la detección de fallos. La fusión de señales diferentes pero correlacionadas puede dar mejor información sobre un posible fallo, que si utilizara la señal de un solo sensor de la planta. Esta situación garantiza la detección de fallos incluso cuando un sensor genera error. Las ventajas de la solución propuesta se demuestran en un caso real con un electrolizador de tipo PEM con ritmo de producción de 1 Nm3/h de H2.

Palabras clave: Fusión de sensores, Detección de fallos, lógica borrosa, Electrolizador PEM

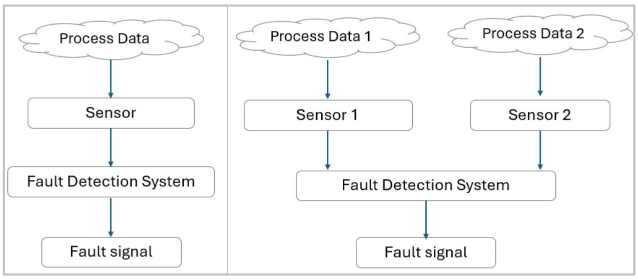
1. Introduction

1.1 Background study

In control systems there are fault detection sub-systems which use sensors to determine abnormal conditions within a process (Mouzakitis, 2013). In hydrogen-based control systems, various fault detection methods exist ranging from knowledge based, statistical, artificial intelligence, and physical methods (Kheirrouz et al., 2022). However, the reliability of such detection system is often affected by the accuracy of the sensors used as input signals. When sensors fail, then the detection system has a high possibility to allow some faults to go undetected. A promising solution for the detection of these sensor problems is the use of an approach called sensor data fusion (SDF) which is the process of using 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. In some

*Corresponding author: abiodun.abiola@alu.uhu.es; francisca.segura@diesia.uhu.es

other systems, two sensors measuring the same signal are used to create redundancy, but this increases cost unnecessarily. With the concept of sensors fusion, the second sensor can measure another process data within control system, but its signal can then be fused with the initial sensor to provide more information about a potential fault.



(a) (b)

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

Fusion of signals can be done using various methods based on physics, data and knowledge based. Fuzzy logic is one of the knowledge-based method which can be applied. Fuzzy logic is very useful in control systems for transforming human knowledge about a field into variables that can be combined together in a decision matrix made up of If-THEN rules to achieve control results in a simple manner. It provides a systematic procedure for transforming a knowledge base into a nonlinear mapping. Because of this transformation, we are able to use knowledge-based systems in engineering applications in the same manner as we use do in classical logic (Vélez et al., 2010).

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 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. This is to avoid the problem of inadequate water management which can undermine the reliability and durability. The authors indicated that the detection with sensor 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.

A review paper by Ross et al. (2023) suggested the use of SDF in electrochemical applications for electro chlorination monitoring. However, the study has limited references on the technology of SDF as regards electrochemical processes based on hydrogen. 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.

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 which will be based on fuzzy system (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.

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 according to the paper by Abiola et al (2023). The paper also shows that temperature also has a good correlation with voltage in the sense that if the hydrogen temperature sensor TT121 gives wrong measurement due to drift fault, the cooling unit will not activate and the cell membrane will be degraded, provoking loss of efficiency and unsafe operation. Hence both signals will be fused for use in fault detection.

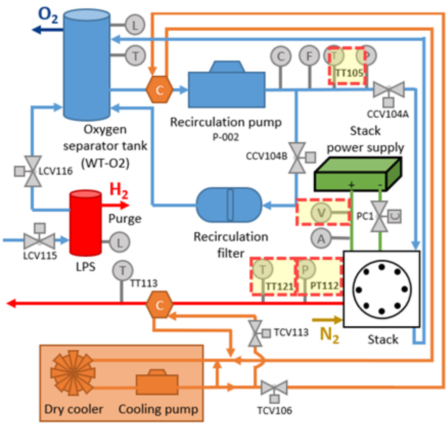


Figure 2: Layout of PEM electrolyser used in this research.

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 system whose output provides a means to characterise the health status of the temperature sensor in terms of the presence of drift fault. The proposed solution can serve as a useful fault detection subsystem in control systems to detect drift faults in sensors.

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).

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

Where:
$\dot{m}_{\mathrm{H_2}}$ is the stack hydrogen mass flow (g/s)
$c_{\mathrm{H_2}}$ is the specific heat capacity of hydrogen (14.30 J/g K)
$\dot{m}_{\mathrm{O_2}}$ is the stack oxygen mass flow (g/s)
$c_{\mathrm{O_2}}$ is the specific heat capacity of oxygen (0.92 J/g K)
$\dot{m}_{\mathrm{H_2O}}$ is the water mass flow (g/s)
$c_{\mathrm{H_2O}}$ 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 $\dot{m}_{\mathrm{H_2}}$, oxygen $\dot{m}_{\mathrm{O_2}}$ and water $\dot{m}_{\mathrm{H_2O}}$ mass flows can be obtained from (3).

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

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

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

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

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:

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

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}. The derivation of equation (7) arises from the principle of the law of conservation of energy which indicates that energy cannot be lost but can be converted from one form to another. In general, the physical assumptions behind equation (7) are applicable to other electrolyser systems and include the following:

- Energy is conserved within an electrolyser unit in the sense that a loss of efficiency is proportional to an increase in heat energy.
- Heat energy generated in the electrolyser is mainly dissipated through the flow of the fluids (water, oxygen and hydrogen) out of the system
- The specific heat capacities of the exiting fluids are assumed constant for the operating temperature range.
- Energy consumed by the auxiliary within the control system are assumed negligible compared to what is required to produce hydrogen.

Once the expression that relates temperature change and efficiency has been obtained, 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 inference system which is capable of detecting drift-type faults in TT121 hydrogen temperature sensor. Indeed, if the fuzzy system detects a correlation between temperature change and efficiency different to (7), it means that an abnormality is happening.

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 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.

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

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

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

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.

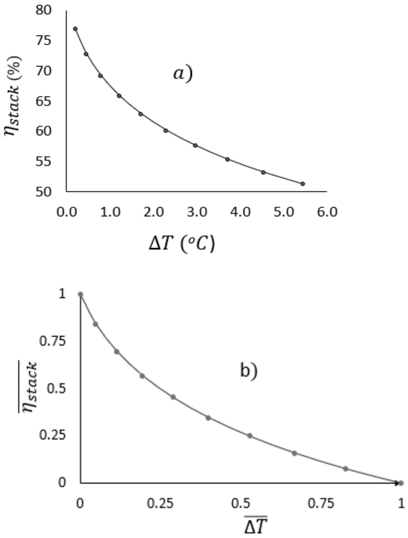


Figure 3: (a) Plot of efficiency ($\boldsymbol{\eta_{stack}}$) with changes in temperature (ΔT). (b) Normalised values of efficiency ($\overline{\eta_{stack}}$) and temperature change ($\overline{\Delta T}$).

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 2

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]

Figure 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 ($\sigma = 0.2$) which makes it wider compared to others with $\sigma = 0.1$. Regarding the sensor health condition, the memberships are classified into three fuzzy sets namely: "healthy", "warning" and "faulty", Figure 4d. 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 the appendix for a full list of the 49 fuzzy rules designed.

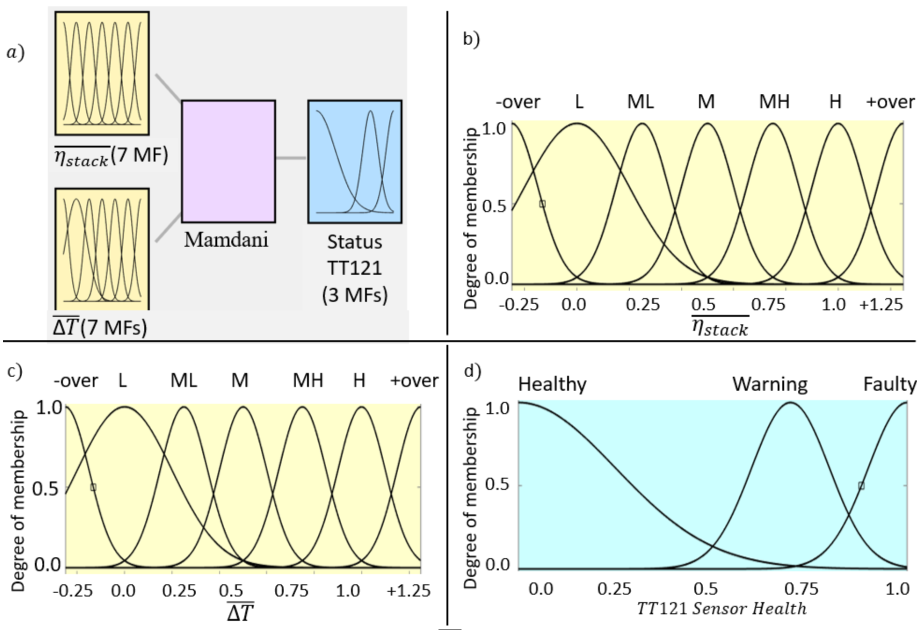


Figure 4: (a) Scheme of the fuzzy system; (b) $\overline{\eta_{stack}}$ input plot; (c) $\overline{\Delta T}$ input plot; (d) Hydrogen sensor (TT121) health condition output plot.

2.3. Model development and physical implementation

In the development of the proposed solution, a model is created in MATLAB Simulink® as shown in Figure 5a and interfaced with an actual programmable logic controller (PLC) hardware in Figure 5b through ethernet communication to exchange required data ($\overline{\eta_{stack}}$, and $\overline{\Delta T}$) with the MATLAB environment running on a PC. The voltage signals logged within the PLC are used to calculate the efficiency, η_{stack_t} using equation (8) for each time step.

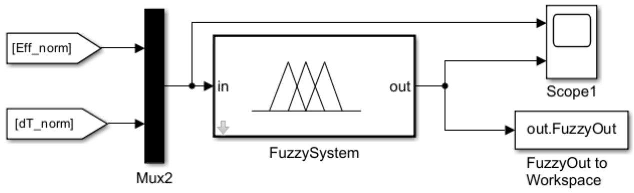


Figure 5a: Fault detection model in MATLAB Simulink® environment.

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 are used in (9) and (10) to compute normalised efficiencies, $\overline{\eta_{stack}}$, and normalised temperature changes, $\overline{\Delta T}$. These data are then fused together with the aid of the fuzzy model to evaluate the health status of the hydrogen sensor (TT121).

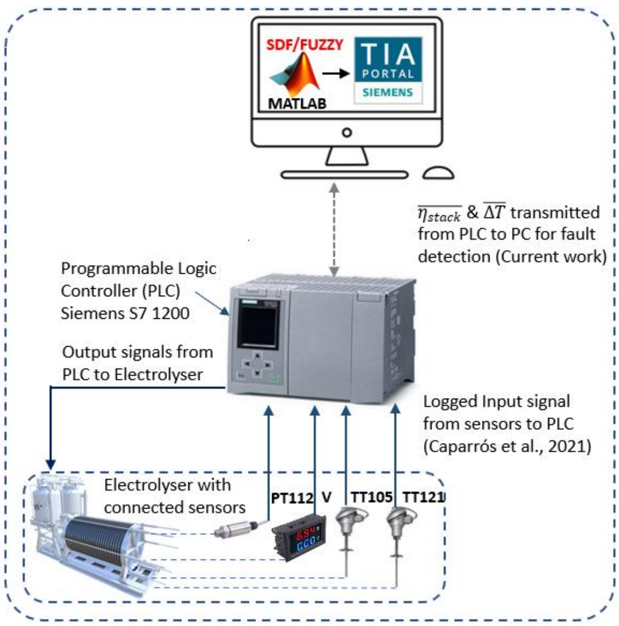
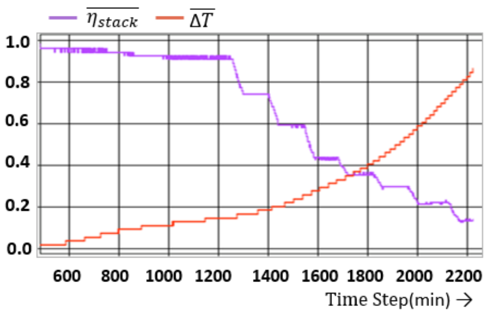


Figure 5b: Implementation of developed solution for an electrolyser

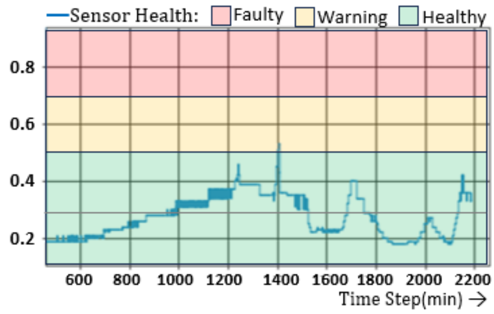
3. Result and discussion

3.1. Testing of the proposed solution.

An initial test for normal electrolyser operation (no failures) was performed and the signals from the fuzzy 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 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.



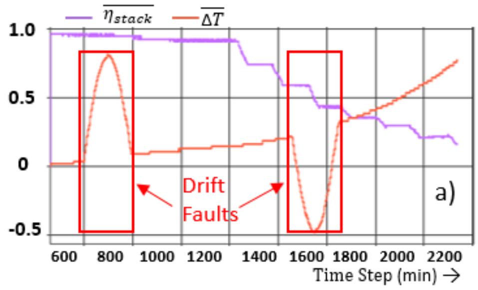
(a)



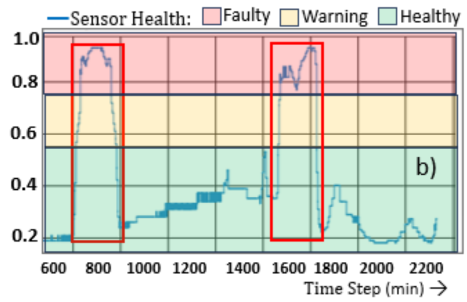
(b)

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

In points t = 1400 min, t = 1700 min, t = 2000 min and t = 2150 min, it is observed that the fuzzy system output notifies of a potential problem with the sensor health condition, Figure 6b. 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. Once the faults disappear, as demonstrated at t = 800 min and t = 1580 min, the fuzzy system indicates that the temperature sensor reading has return to healthy operation.



(a)



(b)

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.

3.2. Fuzzy rules base validation.

Finally, the fuzzy rules defined previously are also validated with experimental electrolyser data under stationary conditions. Figure 8 shows that the numerical data obtained from the developed fuzzy system which corresponds closely with the experimental data obtained from (Caparrós et al., 2021). The plots also confirm that the relationship between changes in efficiency and temperature are inversely proportional to each other. 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 fault detection system with conventional systems as shown in Table 3. The signal from the fuzzy 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). Additionally, in authors' proposal, response time is shortened by a factor of 120, and accuracy is four times better.

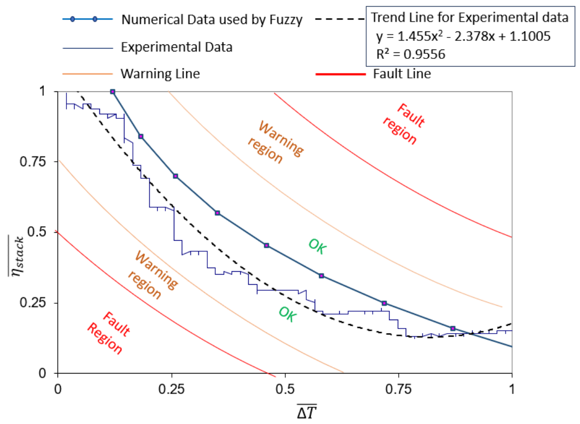


Figure 8: Plot of relation between normalised efficiency $\overline{\eta_{stack}}$ and normalised temperature $\overline{\Delta T}$ comparing the profile used to tune the fuzzy system and the profile obtained from experimental data.

Table 3: 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

The use of the developed fault detection system could be expanded for use in other critical sensors used in modern control systems

4. Conclusion and future work

This paper demonstrates the application of sensor data fusion to detect drift faults in sensors used within control systems. 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 any abnormal sensor readings due to drift. Such information will help maintenance personnel to plan when to replace or re-calibrate the faulty sensor. The system is also better than conventional fault detection systems, which mainly detect faults when the sensor has failed. The risk of having to reach the failure is that a previous undetected erroneous measurement can prevent the cooling system of the electrolyser from responding at the right time and cause severe damage to the plant. Future work involves demonstrating the proposed solution in other types of clean energy systems such as wind turbines coupled with electrolysers. An interesting area of focus is in tracking health status of wind speed sensors. This can be achieved by fusing signals from the sensor with signals from voltage output of turbines to determine when signals from speed sensor begins to drift.

Appendix

Table 4: A complete list 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 L and $\overline{\Delta T}$ is L then TT121 is Faulty
rule10	If $\overline{\eta_{stack}}$ is ML and $\overline{\Delta T}$ is L then TT121 is Faulty
rule11	If $\overline{\eta_{stack}}$ is M and $\overline{\Delta T}$ is L then TT121 is Faulty
rule12	If $\overline{\eta_{stack}}$ is MH and $\overline{\Delta T}$ is L then TT121 is Warning
rule13	If $\overline{\eta_{stack}}$ is H and $\overline{\Delta T}$ is L then TT121 is Healthy
rule14	If $\overline{\eta_{stack}}$ is +over and $\overline{\Delta T}$ is L then TT121 is Faulty
rule15	If $\overline{\eta_{stack}}$ is -over and $\overline{\Delta T}$ is ML then TT121 is Faulty
rule16	If $\overline{\eta_{stack}}$ is L and $\overline{\Delta T}$ is ML then TT121 is Faulty
rule17	If $\overline{\eta_{stack}}$ is ML and $\overline{\Delta T}$ is ML then TT121 is Faulty
rule18	If $\overline{\eta_{stack}}$ is M and $\overline{\Delta T}$ is ML then TT121 is Healthy
rule19	If $\overline{\eta_{stack}}$ is MH and $\overline{\Delta T}$ is ML then TT121 is Healthy
rule20	If $\overline{\eta_{stack}}$ is H and $\overline{\Delta T}$ is ML then TT121 is Warning
rule21	If $\overline{\eta_{stack}}$ is +over and $\overline{\Delta T}$ is ML then TT121 is Faulty
rule22	If $\overline{\eta_{stack}}$ is -over and $\overline{\Delta T}$ is M then TT121 is Faulty
rule23	If $\overline{\eta_{stack}}$ is L and $\overline{\Delta T}$ is M then TT121 is Faulty
rule24	If $\overline{\eta_{stack}}$ is ML and $\overline{\Delta T}$ is M then TT121 is Healthy
rule25	If $\overline{\eta_{stack}}$ is M and $\overline{\Delta T}$ is M then TT121 is Healthy
rule26	If $\overline{\eta_{stack}}$ is MH and $\overline{\Delta T}$ is M then TT121 is Warning
rule27	If $\overline{\eta_{stack}}$ is H and $\overline{\Delta T}$ is M then TT121 is Faulty
rule28	If $\overline{\eta_{stack}}$ is +over and $\overline{\Delta T}$ is M then TT121 is Faulty
rule29	If $\overline{\eta_{stack}}$ is -over and $\overline{\Delta T}$ is MH then TT121 is Faulty
rule30	If $\overline{\eta_{stack}}$ is L and $\overline{\Delta T}$ is MH then TT121 is Warning
rule31	If $\overline{\eta_{stack}}$ is ML and $\overline{\Delta T}$ is MH then TT121 is Healthy
rule32	If $\overline{\eta_{stack}}$ is M and $\overline{\Delta T}$ is MH then TT121 is Warning
rule33	If $\overline{\eta_{stack}}$ is MH and $\overline{\Delta T}$ is MH then TT121 is Faulty
rule34	If $\overline{\eta_{stack}}$ is H and $\overline{\Delta T}$ is MH then TT121 is Faulty
rule35	If $\overline{\eta_{stack}}$ is +over and $\overline{\Delta T}$ is MH then TT121 is Faulty
rule36	If $\overline{\eta_{stack}}$ is -over and $\overline{\Delta T}$ is H then TT121 is Faulty
rule37	If $\overline{\eta_{stack}}$ is L and $\overline{\Delta T}$ is H then TT121 is Healthy
rule38	If $\overline{\eta_{stack}}$ is ML and $\overline{\Delta T}$ is H then TT121 is Warning
rule39	If $\overline{\eta_{stack}}$ is M and $\overline{\Delta T}$ is H then TT121 is Faulty
rule40	If $\overline{\eta_{stack}}$ is MH and $\overline{\Delta T}$ is H then TT121 is Faulty
rule41	If $\overline{\eta_{stack}}$ is H and $\overline{\Delta T}$ is H then TT121 Faulty
rule42	If $\overline{\eta_{stack}}$ is +over and $\overline{\Delta T}$ is H then TT121 is Faulty
rule43	If $\overline{\eta_{stack}}$ is -over and $\overline{\Delta T}$ is +over then TT121 is Faulty
rule44	If $\overline{\eta_{stack}}$ is L and $\overline{\Delta T}$ is +over then TT121 is Faulty
rule45	If $\overline{\eta_{stack}}$ is ML and $\overline{\Delta T}$ is +over then TT121 is Faulty
rule46	If $\overline{\eta_{stack}}$ is M and $\overline{\Delta T}$ is +over then TT121 is Faulty
rule47	If $\overline{\eta_{stack}}$ is MH and $\overline{\Delta T}$ is +over then TT121 is Faulty
rule48	If $\overline{\eta_{stack}}$ is H and $\overline{\Delta T}$ is +over then TT121 is Faulty
rule49	If $\overline{\eta_{stack}}$ is +over and $\overline{\Delta T}$ is +over then TT121 is Faulty

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