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JESÚS ENRIQUE SIERRA GARCÍA
MARIO PEÑACOBA YAGÜE
PEDRO J. CABRERA SANTANA

XIX SIMPOSIO CEA DE CONTROL INTELIGENTE

LIBRO DE ACTAS

UNIVERSIDAD
DE BURGOS

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ÍNDICE

PRÓLOGO 13

CONFERENCIAS 15

Hacia la optimización de trayectorias de robots colaborativos mediante algoritmos genéticos 17
Peñacoba, M.; Sierra-García, J. E.; Santos, M.

Control predictivo basado en modelo de red neuronal. Aplicación al control de procesos no lineales 21
J. Sendra; J. Sanchis; L. Iturbe; M. Larrea; E. Irigoyen

Selección de la tecnología de visión más adecuada para paletizado 27
Moreno-Román, G.; Sierra-García, J.E.

Fuzzy speed estimator for drives using optical encoders 33
Satué, M.G.; Escaño J.M.; Colodro, F.

Nuevo algoritmo de entrenamiento híbrido para modelos neuronales de sistemas dinámicos 39
Iturbe, Lucía; Irigoyen, Eloy; Larrea, Mikel; Sendra, Javier; Sanchis, Javier

Análisis del rendimiento de un sistema de control avanzado basado en el estándar IEC 61499 45
Guzmán González-Mateos, Miguel A. Prada, Antonio Morán, Raúl González-Herbón, José R. Rodríguez-Ossorio, Manuel Domínguez

Enfoque Centrado en el Humano para el Gemelo Digital de la Colaboración Humano-Máquina/Robot en una Línea Piloto de Industria 5.0 51
Alfaro, Diego.; Castaño, Fernando; Cruz, Yarens J.; Villalonga, Alberto; Haber, Rodolfo E.

La docencia en ingeniería de control frente a la inteligencia artificial generative 57
Barragán, A. Javier; Segura, Francisca; Martínez, Miguel A.; Andújar, José M.

Modelado de un Acumulador de Energía Dinámico Mediante Volante de Inercia en Simulink 63
Torres, Juan Carlos; Douairi, Hamza; González, Jaime; Carta, José Antonio; Cabrera, Pedro

Modelo lineal de pérdidas de un volante de inercia 69
Douairi, Hamza; Torres-Bordón, Juan Carlos; Carta, José Antonio; Cabrera, Pedro.

Modelos de predicción neuro-borrosos para un aerogenerador en una planta de fabricación industrial 75
Chicaiza, W.D.; Gómez, J.; Camacho, P.G.; Escaño, J.M.

Integration of artificial intelligence with automation for predictive maintenance in sustainable hydrogen production plants.. 81
Abiola, A O.; Segura, F M.; Andújar, J M.; Barragán, A. J.

Hacia la gestión de comunidades energéticas con Aprendizaje por Refuerzo 89
Arnay del Arco, R.; Riverón-Miranda, I.; Hamilton-Castro, A.; Torres-Álvarez, S.; González-Cava, J.M.; Castilla, I.; González Díaz, B.; Méndez-Pérez, J.A.

Ajuste multiobjetivo de PIDs robustos para el control de temperatura de una pila tipo PEM 92
Veyna, U.; Blasco, X.; Herrero, J.M.; Pajares, A.; Ramos, C.

XIX Simposio CEA de Control Inteligente
19-21 de junio de 2024, Burgos

Integration of artificial intelligence with automation for predictive maintenance in sustainable hydrogen production plants

Abiola, A O.*, Segura, F M.*, Andújar, J M., Barragán, A. J.

Research Centre on Technology, Energy and Sustainability (CITES), University of Huelva, 21071 Huelva, Spain.

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Abstract

Automation in modern industries is possible with the aid of sensors that measure signals needed for control, fault detection and decision making about a process. Such decisions include the time to perform predictive maintenance which is not possible when there is a failure in one of the sensors. Artificial intelligence techniques can be used to detect faults in a sensor and predict what its correct reading should be using signals from other sensors involved in the process. For accurate prediction, a signal from an alternative sensor, or a combination of signals from different sensors, should be selected that has a strong correlation with the signal to be predicted. In this study, to demonstrate the application of artificial intelligence in automation, an electrolyser operating in an automated process has been considered. A Deep Reinforcement Learning (DRL) algorithm was developed to select the best signal among others with the highest correlation coefficient of 0.99. The selected signal was then used in a long short-term memory (LSTM) to predict faulty temperature signals in the electrolyser. The root-mean-square error (RMSE) of the predicted signal was 0.1351.

Keywords: Automation, hydrogen technology; PEM electrolyser; predictive maintenance; artificial intelligence; reinforcement learning; neural network; long short-term memory (LSTM).

1. Introduction

Automation was first described in 1947 by Ford Motor Company as the enhanced usage of electromechanical, hydraulic, and pneumatic machinery in an attempt to reduce labour in the manufacturing sector (Noble, 1984).

In the paper by Sundari et al., (2021) it was concluded that automation is made possible through sensors, controllers, data storage and communications. The quality, production rate and customer satisfaction are enhanced through the realization of such automation process. These benefits of automation can further be enhanced by integration with artificial intelligence (AI), which is a form of digital technology that gives machines the ability to do what humans were normally doing such as making predictions and decisions (Spencer et al., 2021). In the paper, the author indicated that AI-enabled digital automation is growing to such a degree that data-based intelligent systems are re-organising and coordinating the whole sectors of the economy. Integration of automation with AI can be applied to various sectors of the economy such as manufacturing industries, agriculture, energy generation, healthcare, and many more. However, such integration is still new as indicated in a paper by (Zheng, 2023) who studied the application of AI in electrical automation and control engineering. In this present study, the integration of automation and AI is further investigated within the field of renewable energy (RE) systems with a focus on proton exchange membrane (PEM) electrolyser. We conducted a search through selected databases namely ScienceDirect, MDPI and IEEE from 2001 to 2023. Keywords used were automation, control, sensors, AI and RE. Logical operators such as “OR”, “AND” as well as wildcard operator (*) were used to narrow the search and the results shown in Figure 1.

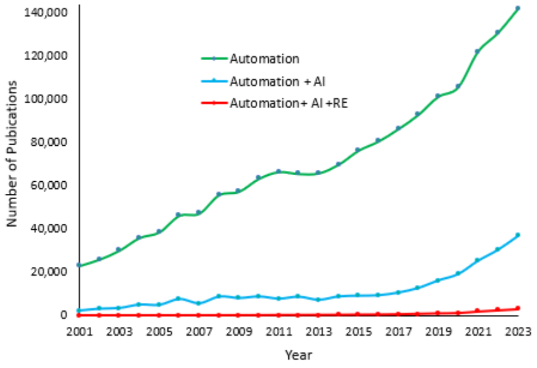

Figure 1: Analysis of publications on automation, artificial intelligence and application to renewable energy from 2001 to 2023 in the present work.

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

The results of the database investigated, show that studies on the topic of automation have progressively increased over the years reaching as much as 141,982 publications in 2023, while those on the integration of automation with AI were initially slow in progression until 2017 when a spike occurred in number of academic works. However, when the application of these integrated technologies (automation and AI) was considered within the field of RE, it was observed that there is very limited number of studies done. Therefore, this study seeks to contribute to the body of knowledge on the integration of AI with automation and its application in the field of RE considering a PEM electrolyser as study case.

1.1 Application of artificial intelligence to electrolysers

In a paper by (Vasseur and Dunkels, 2010) one of the benefits of automation is for condition monitoring. This concept can be applied together with AI for the maintenance of electrolysers which are used within the field of RE technology to produce hydrogen. Rey et al. (2023) indicated that operation and maintenance cost is repeated along the lifespan of hydrogen-based microgrids and affect the replacement costs. Electrolysers used in such system can only function effectively to produce hydrogen at the desired parameters if its components do not fail during the period of operation. Failures can be avoided if they are detected early and resolved. To achieve this, there is a need to define an appropriate maintenance strategy. Predictive maintenance is one of such solution, but it often relies on data from sensors embedded in electrolysers which can also become faulty, resulting into false prediction of potential faults. Consequently, maintenance will not be performed at the right time and failure will occur. To address this problem, AI concept can be applied to make predictions on sensor readings based on data obtained from another instrument within the process. In this paper, authors develop a novel algorithm using Deep Reinforcement Learning (DRL) to select best feature(s) among measured data of the electrolyser, which can best predict on the target sensor data for predictive maintenance. The features are used as input into a type of deep neural network called long short-term memory (LSTM) to make prediction. This is depicted in Figure 2.

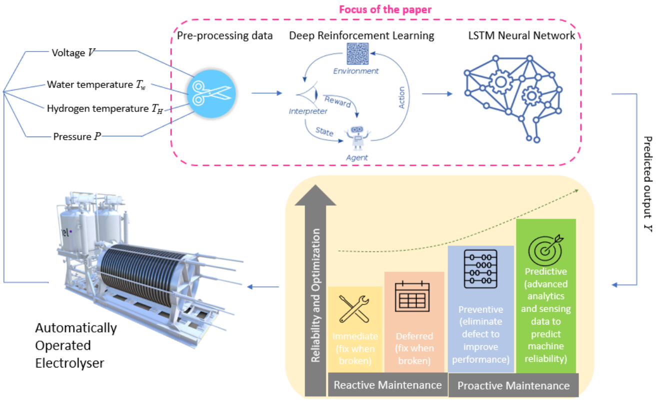


Figure 2: Illustration of problem statement and focus of the paper.

1.2 Previous works on intelligent condition monitoring

Regarding the scientific literature, very few authors focus their work on addressing the problem of maintenance in PEM electrolysers using AI. For example, Kumar et al. (2021) propose an artificial neural network based on LSTM capable of detecting and localizing faults at every time step without any pre-processing. But the artificial intelligence-based faults detection system is only applied to the power electronics of the electrolyser. Mohamed et al. (2022) used machine learning to predict up to eleven different parameters of the electrolytic cell using only four input parameters. Lee et al. (2023) presents a prognostics and health management (PHM) model based on machine learning to predict the load voltage of the electrolyser for the state of health information. The voltage is used as a state of health indicator which increases according to the time elapsed, and it is caused by the degradation of the electrolyser.

2. Materials and Method

In this paper, an intelligent predictive maintenance model is developed to predict sensor data in an PEM electrolyser for condition monitoring of the process and fault prediction. The model takes input data from other sensor(s) to be used for predicting a desired output. Hydrogen temperature is one of such desired data based on its importance in PEM electrolysers as discussed in (Chandesris et al., 2015). In the experimental study, results show that membrane degradation is strongly influenced by temperature.

Hence, considering the importance of temperature in the degradation of an electrolyser, this work uses hydrogen temperature as the sensor data to be predicted. With the predicted data, an intelligent predictive model allows monitoring and detection of any worsening condition.

2.1. Study case of a PEM electrolyser within an automated process

Experimental data from a previous work (Mancera et al., 2020), is used for the demonstration of the integration of AI with automation, focusing on a PEM electrolyser operating within a process. Layout of a section of the process is shown in Figure 3.

From Figure 3, the sensor data used for the current study are from the hydrogen pressure transmitter (PT112), hydrogen temperature transmitter (TT121), stack voltage (V) and cooling water temperature transmitter (TT105). Other resource needed is a computer equipped with an Intel(R) Core (TM) i5-8250U CPU @ 1.60GHz 1.80 GHz, 8.00 GB memory, 64-bit, x64-based processor. The operating system is Windows 11 Enterprise while software considered is MATLAB®.

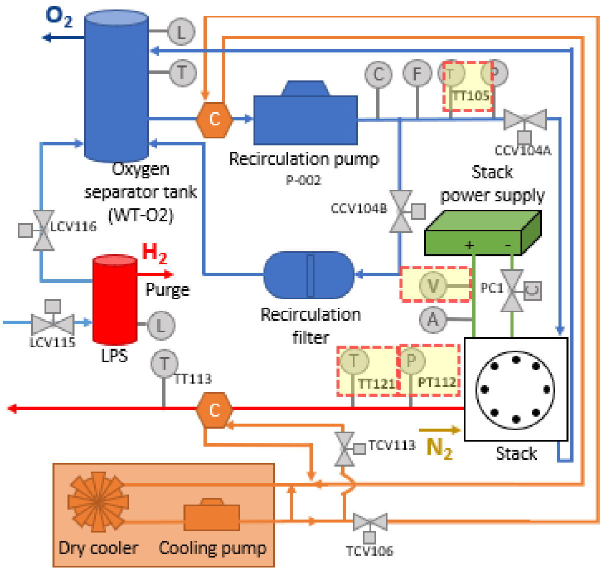


Figure 3: Layout of the automated process involving a PEM electrolyser. (Sensor data used for this study are highlighted as dashed squares).

2.2. Method. Phase 1. Pre-processing of input data

Sensor data is pre-processed by normalizing the experimental dataset to ensure that one feature does not affect the contribution of the other in the artificial intelligent models to be developed (Hudson et al., 2023).

Normalizing can be done in several ways. One alternative consists of ensuring that the range of all the features (data) are within 0 to 1. In another form called z-scoring, the input data are pre-processed using (1) where the data have a mean of 0 and standard a deviation of 1. For this study, z-scoring is used as shown in Figure 4, considering that it helps to stabilize and speed up network training (Hudson et al., 2023).

$$zScoring = \frac{Sensor\ Data(feature) - Mean}{Standard\ deviation} \qquad (1)$$

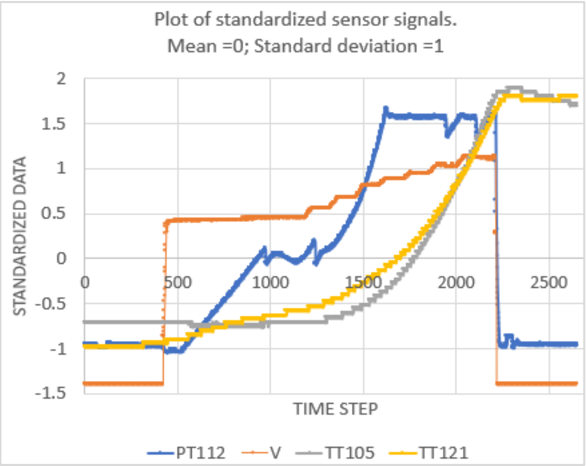


Figure 4: Normalised sensor data

2.3. Method. Phase 2: DRL for selecting features.

After pre-processing the data, a novel algorithm is developed based on DRL to select among the various sensor data, the one that has the greatest correlation to hydrogen temperature sensor (TT121) which is to be predicted with minimum root-mean-squared-error (RMSE).

DRL is a subcategory of reinforcement learning within the parent body of AI (MathWorks®, 2019). The structure of the DRL algorithm is shown in Figure 5.

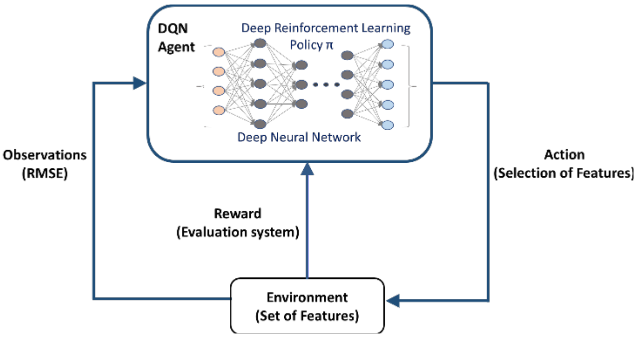


Figure 5: The concept of Deep Reinforcement Learning (DRL)

In the DRL model, an intelligent agent takes actions among several options to achieve an intended objective which is defined within the memory of the agent. The objective in this case is to determine which sensor data has the highest correlation to the hydrogen temperature.

The actions available to the agent are the selection of various sensor data called features, while the reward is a defined scalar amount added each time the agent chooses a feature that is more correlated to the hydrogen temperature compared to a previous selection. If a new action taken (selection) has less correlation compared to the previous, then the agent loses the reward. Before the agent begins the process of taking actions, it is first trained to identify increased or reduced correlation. An RMSE is the feedback to the agent, and it is calculated for each iteration using an internal neural network within the agent to determine the correlation values of each feature. The feedback of observations is used by the reinforcement learning policy within the agent to adjust the action and get the desired objective.

For the DRL agent, the entire feature set that can be selected to measure the correlation to the hydrogen temperature includes individual sensor data or a combination of two or more as follows: [PT112], [TT105], [V], [PT112 TT105], [PT112 V], [TT105 V] and [PT112 TT105 V]. When the agent finally determines which sensor data has the highest correlation to the hydrogen temperature, the data from the sensor will then be used as input to another AI model called long short-term memory (LSTM) neural network, which will eventually be used for predicting the hydrogen temperature in case its sensor fails during electrolyser operation; the concept of LSTM is discussed in section 2.5. Hence two AI models (DRL and LSTM) are developed and used together to predict the hydrogen temperature in the event of failure of its sensor.

Without the DRL it will be tedious and time-consuming to take each sensor data (feature), feed into the LSTM model and check the root-mean-square error (RMSE). This manual approach can be further complicated with features that number in the tens, hundreds or more from the dataset of electrolysers.

2.4. Method. Phase 3. Authors approach: DRL-based algorithm for feature selection

A novel DRL algorithm has been developed and implemented in MATLAB for feature selection as follows:

Step 1 *Input data consisting of features: Pressure* [PT112], *Cooling water temperature* [TT105], *stack Voltage* [V] *and Hydrogen temperature* [TT121].
Step 2 *Normalize each feature using: z-scoring.*
Step 3 *Create the system of observation: RMSE*
Step 4 *Obtain the matrix consisting of the subset of features. Subset 1= [PT112]; Subset 2 = [TT105], Subset 3 = [V]; Subset 4 = [PT112, TT105], Subset 5 = [PT112, V]; Subset 6 = [TT105, V]; Subset 7 = [PT112, V, TT105].*
Step 5 *For feature subset having two or more sensor data, obtain a single representation by computing the average.*
Step 6 *Create DRL environment with observations and actions*
Step 7 *Create a policy for the DRL agent to decide actions*
Step 8 *Define discrete actions for the DRL agent. Each action is denoted by a scalar value (1 to 7) and represents the selection of each feature from the set of 7.*
Step 9 *Define the reward for the agent for correct actions. Reward = 2 for correct; and -1 for incorrect actions*
Step 10 *Train the DRL agent*
Step 11 *For each stochastic action, RMSE is calculated as observations for each action.*

```
If ($RMSE_{new}$ <$RMSE_{old}$) and (Reward>0), then
    Store feature selected by the agent.
    Else
    Take action to select another feature from the subset.
    Endif
```

The parameters used to train the DRL agent are listed in the Table 1. These were the optimal values that enabled the agent to be trained for recognizing its environment and take actions.

Table 1: Parameters used to train the DRL agent.

DRL Model Component	Type	Training Parameter	Value
DRL Agent policy	Deep Q-Network (MathWorks Inc, 2019)	Learning Rate	0.01
		Number of hidden layers	128
		Discount factor	0.99
		Batch size	64
		Initial epsilon	1
		Epsilon decay	0.005
		Epsilon min	0.01
		Number of Training episodes	50
Environment		Observation type	Continuous
		Observation dimension	[3,1]
		Action Type	Discrete
		Actions	[1,2,3,4,5,6,7]
		Observation Lower Limit	[-inf, -inf, 0]
		Observation Upper Limit	[inf, inf, inf]

The DRL algorithm has been developed using Simulink programming interface in MATLAB and shown in Figure 6. The training parameters were input into the DRL agent as well. After iterations, the feature with least RMSE was selected by the agent; which is the feature with highest correlation with TT121.

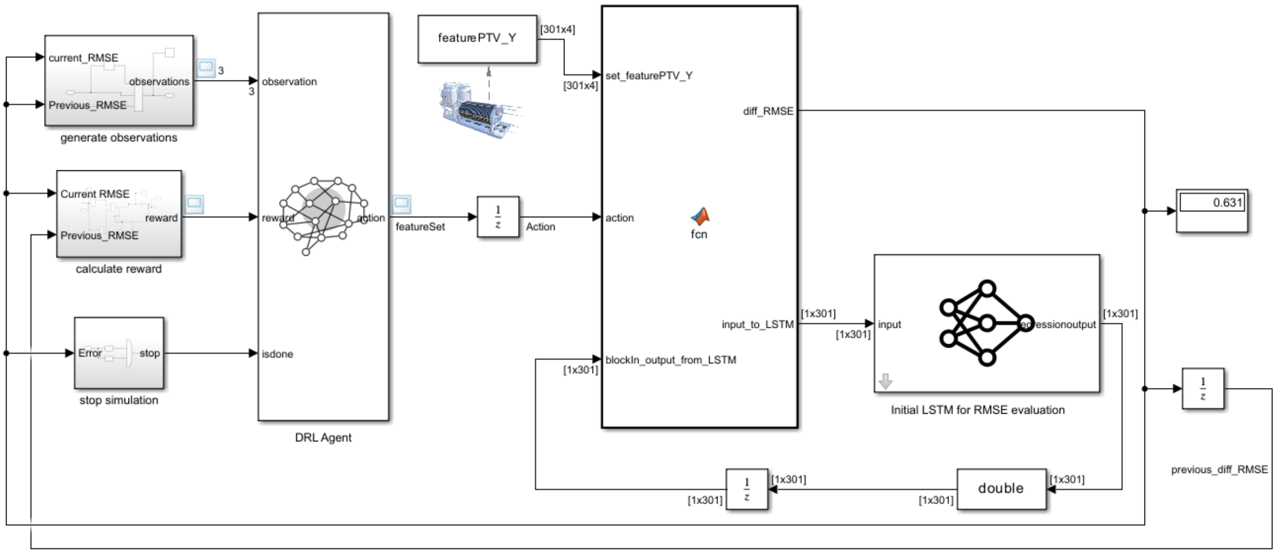


Figure 6: MATLAB programming environment for the developed DRL algorithm

2.5. Method Phase 4. Development of an intelligent predictive model for maintenance of the PEM electrolyser

After the DRL model has selected the feature with the highest correlation to the hydrogen temperature (TT121), the dataset of this feature is used to train another deep neural network called long-short-term-memory (LSTM) in Figure 7. After training the LSTM model, it can be used to predict the hydrogen temperature for maintenance in the event of failure of the existing sensor.

The concept of LSTM was introduced by (Hochreiter and Schmidhuber, 1997). LSTM neural networks belong to a type of recurrent neural network (RNN) which itself is a subcategory under deep neural network (DNN). The DNN is a type of supervised learning under machine learning and artificial intelligence concepts.

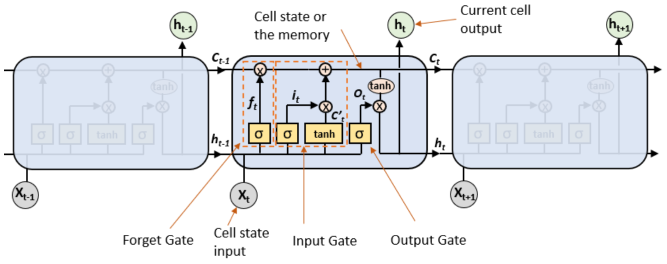


Figure 7: Conceptual design of LSTM neural network

LSTM neural network is configured from three gates where it can store both present and historical information after it has been trained with input data. The governing equations are:

$$Forget\ Gate: f_t = \sigma\left(W_f.\left[h_{t-1},x_t\right] + b_f\right) \quad (2)$$

$$Input\ Gate: i_t = \sigma\left(W_i.\left[h_{t-1},x_t\right] + b_i\right) \quad (3)$$

$$Output\ Gate: O_t = \sigma\left(W_o.\left[h_{t-1},x_t\right] + b_o\right) \quad (4)$$

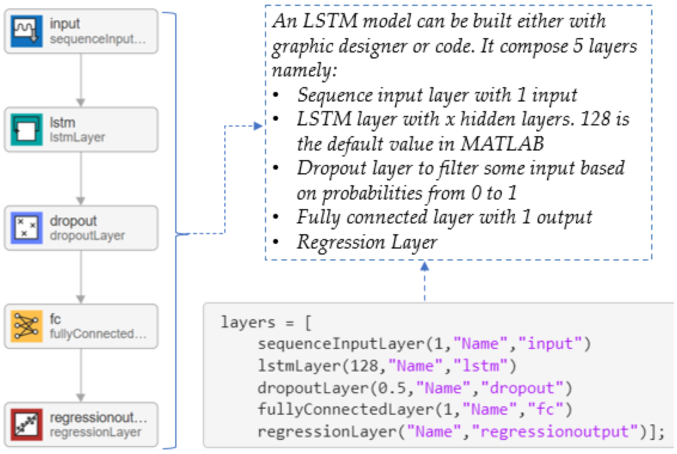
$$Candidate\ valve\ C'_t = \tanh\left(W_c.\left[h_{t-1},x_t\right] + b_c\right) \quad (5)$$

$$Cell\ State: C_t = f_t * C_{t-1} + i_t * C'_t \quad (6)$$

$$Hidden\ State: h_t = \sigma_t * \tanh(C_t) \quad (7)$$

Where *t* is the time step, *b* is a bias added for each gate. W_f , W_i *and* W_o are the weight of each gate. h_t and $h_{t\text{-}1}$, *are* the output for the hidden layers in time steps t and t-1 respectively. x_t, is the input at time *t* and *σ* is the sigmoid activation function.

Based on these equations, an LSTM neural network was designed in MATLAB as shown in Figure 8.



An LSTM model can be built either with graphic designer or code. It compose 5 layers namely:

- *Sequence input layer with 1 input*
- *LSTM layer with x hidden layers. 128 is the default value in MATLAB*
- *Dropout layer to filter some input based on probabilities from 0 to 1*
- *Fully connected layer with 1 output*
- *Regression Layer*

```
layers = [
    sequenceInputLayer(1,"Name","input")
    lstmLayer(128,"Name","lstm")
    dropoutLayer(0.5,"Name","dropout")
    fullyConnectedLayer(1,"Name","fc")
    regressionLayer("Name","regressionoutput")];
```

Figure 8: Conceptual design of LSTM neural network.

The flow chart of the entire process to deploy AI technique for the electrolyser is shown in Figure 9.

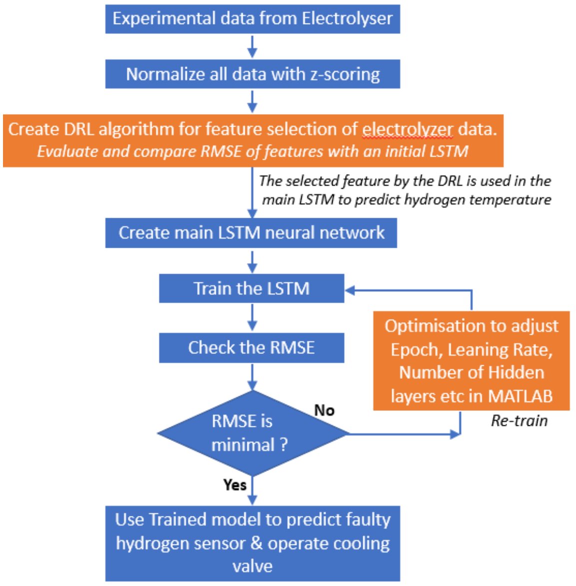


Figure 9: Flow chart for implementing intelligent maintenance in PEM electrolyser.

The physical implementation of the AI model designed for the electrolyser is shown Figure 10.

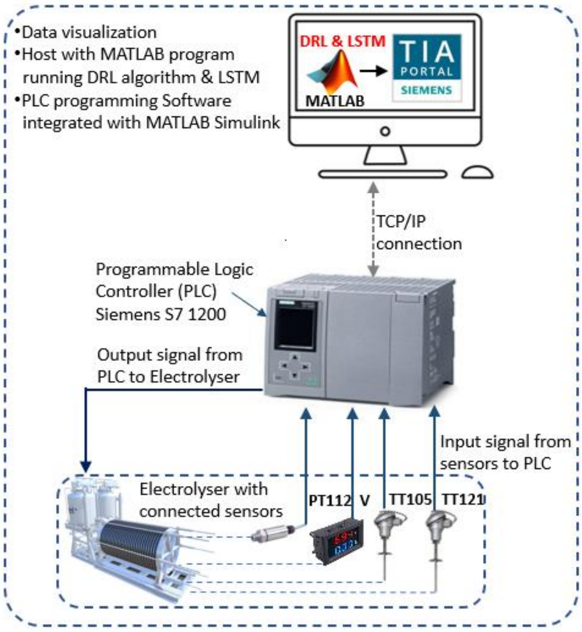


Figure 10: Overview for the entire system for the intelligent maintenance

3. Results

3.1. Results of feature selection by the novel DRL algorithm.

Figure 11 shows a plot of the agent's action to select features, observations (RMSE) and reward received for each action. It is important to note that there is a time-step difference between the instant when the agent takes actions and when observations are made. The feature with highest correlation to TT121 is feature 2(TT105).

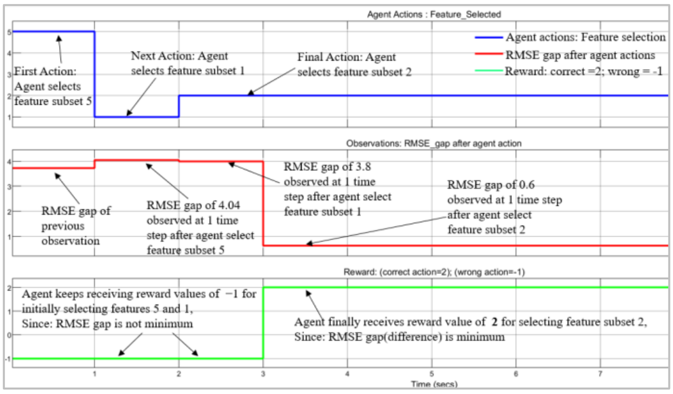


Figure 11: Plot of DRL model showing agent actions, RMSE and rewards.

Validation of the selection by the DRL is done using a correlation plot (Guyon and Elisseeff, 2003) between the various sensor data as shown in Figure 12 which confirms that TT105 has the highest correlation to TT121 with value of 0.99.

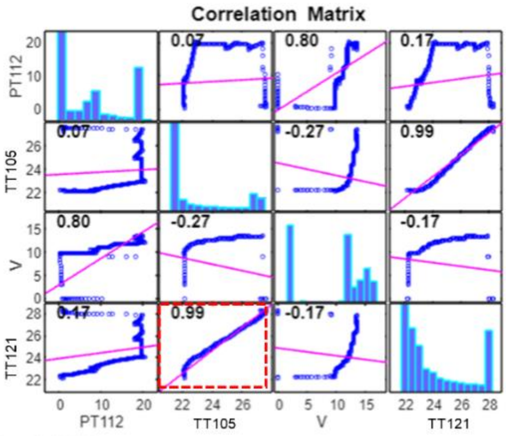
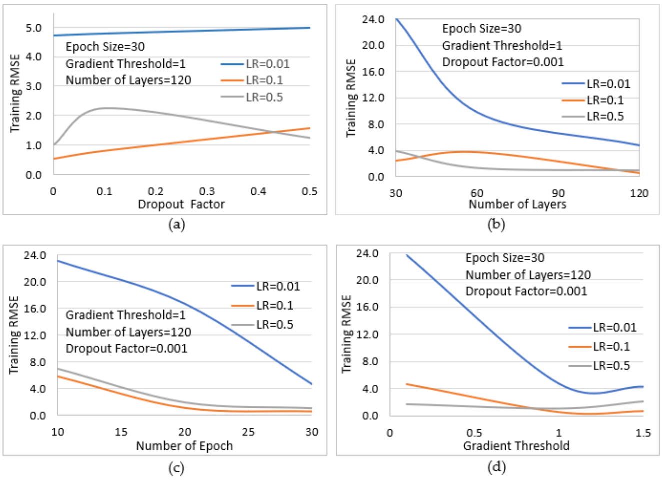


Figure 12: Correlation coefficient between various electrolyser data.

3.2. Training and testing of the LSTM neural network.

TT105 is used as input data and is divided into training (90%) and testing (10%) sets. There are several parameters that can influence the accuracy of the LSTM during training; to study them, a parametric analysis is performed as shown in Figure 13.



(a) (b)

(c) (d)

Figure 13: Optimisation of parameters to reduce RMSE during training of the LSTM. The effect of variation in (a) Dropout factor; (b) Number of layers; (c) Number of Epoch and (d) Gradient Threshold on the RMSE, are shown.

An optimum parameter set which gave an RMSE of 0.09 during training and 0.1351 during test is shown in Table 2.

Table 2: Parameters used to train the LSTM.

Training Parameter	Value	Training RMSE (LSTM)	Testing RMSE (Predicted variable TT121).
Learning Rate	0.1		
Number of layers	40		
Epoch	400	0.09	0.1351
Gradient Threshold	1		
Dropout	None (0)		

The trained LSTM network was tested by using it to predict the electrolyser hydrogen temperature (TT121). Figure 14 shows a plot of the actual and predicted sensor data.

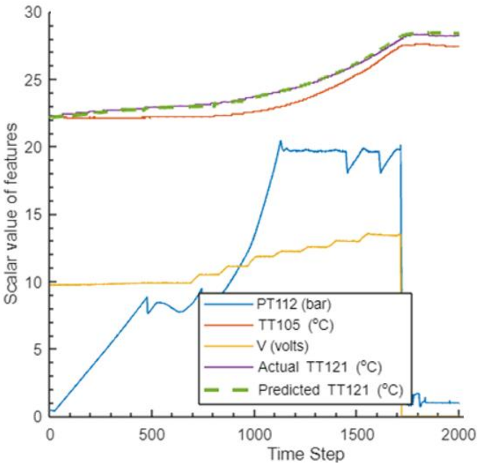


Figure 14: Plot showing actual and predicted hydrogen temperature (TT121).

3.3. Accuracy validation and comparison with related papers.

Table 3 compares the authors' proposal with other proposals found in the literature in terms of RMSE.

Table 3: Comparison of testing RMSE with other papers

Study	Method Used	Testing RMSE
Authors' proposal	Hybrid of deep reinforcement learning (DRL) and long-short-term memory (LSTM)	0.1351
(Siraskar et al., 2023)	Reinforcement Learning hybridised with LSTM	0.5196*
Duhirwe et al., 2023	Hybrid of DRL with extreme gradient boosting	4.008
Pannakkong et al., 2023	Reinforcement Learning based on Double DQN	0.3956*

*RMSE is obtained from: $\sqrt{mean\ squared\ error(MSE)}$

4. Discussion

The developed AI model (novel DRL algorithm and LSTM) have been able to select the cooling water temperature sensor (TT105) as the best feature with the highest correlation (0.99) to the hydrogen temperature sensor (TT121). This is shown in Figures 11 and 12. The DRL algorithm saves computation time since it uses a small sample of data for feature selection and also a single representation of features having multiple sensor data as indicated in step 5 of section 2.4. Hence it can be extended for cases with tens or hundreds of sensor data. Furthermore, the LSTM was able to use the cooling water temperature of the PEM electrolyser to predict the hydrogen temperature with an RMSE value of 0.1351 which is good compared to other papers shown in Table 5.

A limitation of the AI model is that it needs to be re-trained to adapt to a different hydrogen system, such as an alkaline electrolyser or fuel cell with different physical phenomena.

5. Conclusions

This proposal shows that integration of AI with automation can indeed be beneficial in various fields such as in RE technologies. A case study was demonstrated with a PEM electrolyser in which a hybridized AI model (DRL & LSTM) was integrated within an automated process for condition monitoring and forecasting critical process data (hydrogen temperature) for use in predictive maintenance of the system.

Due to the limitation discussed in the previous section as regards the need to retrain the AI model for a different hydrogen system, further work is needed to develop models that can be adapted to these changes.

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