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Neuro-Fuzzy Digital Twin of a High Temperature Generator ⋆

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Abstract: Solar absorption plants are renewable energy systems with a special advantage: the cooling demand follows the solar energy source. The problem is that this plant presents solar intermittency, phenomenological complexity, and nonlinearities. That results in a challenge for control and energy management. In this context, this paper develops a Digital Twin of an absorption chiller High Temperature Generator (HTG) seeking accuracy and low computational effort for control and management purposes. A neuro-fuzzy technique is applied to describe HTG, internal Lithium-Bromide temperature, and water outlet temperature. Two Adaptative Neuro-Fuzzy Inference Systems (ANFIS) are trained considering real data of eight days of operation. Then, the obtained model is validated considering two days of real data. The validation shows a RMSE of $1.65e^{-2}$ for the internal normalized temperature, and $2.05e^{-2}$ for the outlet normalized temperature. Therefore, the obtained Digital Twin presents a good performance capturing the dynamics of the HTG with adaptive capabilities considering that each day can update the learning step.

Keywords: Solar Energy, Fresnel Solar Collector, ANFIS, High Pressure Generator, Absorption Chiller, Lithium-Bromide.

1. INTRODUCTION

Industrial development in the current era, immersed in digitalisation in all fields, means that, in the design, implementation, and start-up phase, replicas of the physical entities that make up the systems can be designed. These virtual replicas are now called Digital Twins (DT) and not only model a reality, but also interact with it. Besides, the growing technological development allows real-time data storage to be the main point in the monitoring process of physical entities and is used to a great extent for the interconnection between physical and virtual entities. The DT will compose intelligent manufacturing and Industry 4.0 as it stands out by the perfect integration between physical and virtual spaces, and its fundamental basis is modelling and simulation. The DT development of a physical entity gives high support to analyse its behaviour in different situations of operation, control, etc., without the need of doing it physically, avoiding experimental costs once it is possible to do virtually.

The term DT appears for the first time in a seminal paper by Grieves about Product Lifecycle Management (PLM). In this work, the author details the premise where each system consists of two systems, the physical system and the virtual system that contains all information of the physical system (Grieves (2016)). Several concepts were proposed for DT by (Grieves (2016); Haag and Anderl (2018); Boschert and Rosen (2016); Saracco (2019); Glaessgen et al. (2012)). The works have in common that the DT has three main parts: physical product, virtual product, and the connected data that indissolubly link and interconnect the physical and virtual products. Today, the DT concept is popular with several applications in industry and academy. The work published by Tao et al. (2019) presents a comprehensive view of the concept, types, development, and points the Prognostic and Health Management (PHM) area as the main application field. Moreover, (Rasheed et al. (2020)) presents methodologies and techniques for DT development from the modelling perspective.

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Obtaining DT maximum potential is possible because the Internet of Things (IoT), communication protocols, hardware advances like Graphical Processing Units (GPU), cloud data storage and processing, and high-performance computers. In addition, the creation of DT uses 3D and 2D virtual environment design and software tools focused on engineering (Rasheed et al. (2020); Ke et al. (2019); Havard et al. (2019)). In the industrial ambit, General Electric develops its DT focused on predicting the health and performance of its products throughout its life cycle, while Siemens' DT aims to improve the efficiency and quality of manufacturing (Lund et al. (2016); Wang and Canedo (2016)).

Besides, the human programming interface (HPI) developed by Siemens allows that a machine interacts with humans interpreting their behaviours. Nowadays, the automation systems are not aware of the critical role of humans in an automated system. Hence, the HPI can be used to create a DT of the human, whose behaviour is transformed into an autonomous system so that the automated system could become more intelligent.

Several Artificial Intelligence (AI) techniques are used to describe a system behaviour like Machine Learning (ML), Deep Learning (DP) that is capable of learning and modelling massive data sets, achieving success in various applications such as dynamic systems modelling, for example, artificial neural network (ANN) (Li et al., 2020), Genetic Algorithm (GA) (Shirazi et al. (2017)), Adaptive Neuro-Fuzzy Inference System (ANFIS) (Jang, 1993; Kharb et al., 2014; Yaïci and Entchev, 2014).

Many works utilize AI techniques to model energy systems, such as (Papacharalampopoulos and Stavropoulos (2019)) which relies on the concept of data direction that exists between the physical entity and its DT to develop a nonlinear model of a thermal laser process. The work of (Elsheikh et al. (2019)) presents several methods based on ANN to optimize and predict the performance of different solar energy systems. A Neuro-Fuzzy estimator is developed in (Escaño et al. (2021)) to estimate the non-observable states in a parabolic trough solar field. In (Chicaiza et al. (2021)) a Neuro-Fuzzy model of a Fresnel solar field is developed, focusing on a rule-based model. In addition, neuro-fuzzy systems can use to manage and predict energy consumption (Gaber et al. (2021); González Perea et al. (2021); Jallal et al. (2020)).

Several works investigate the steady-state modeling of an absorption chiller for design and operation under steady-state conditions, although the dynamical modeling is quite limited ((Nielsen et al., 2015)). The available dynamic models are complex and time-consuming and not suitable for control and optimization purposes (Lazrak et al. (2016)). In the work of Lazrak et al. (2016), the authors build a dynamic and fast model of an absorption chiller using an ANN technique. The neural model validation is satisfactory, presenting absolute relative errors of the transferred energy within 0.1–6.6%. Another application of ANN was carried out in an absorption plant by (Nasruddin et al. (2018)). In the latter, the authors present a faster and simpler model compared to a physical-based model if input-output data is available. The lowest RMSE is 2.57. Lastly, (Tamiru (2009)) presents a neuro-fuzzy model that is capable of substituting the phenomenological model of a Cogeneration Cooling Plant operating with steam.

This work uses ANFIS to model the High Temperature Generator (HTG) for control and optimization purposes. The objective is to obtain two Fuzzy Inference Systems (FIS) capable of describing the dynamic behaviour of an absorption chiller subsystem in all operation ranges. The HTG subsystem is part of a solar absorption plant installed on the roof of the building of the Faculty of Engineering (ETSI) of the University of Seville, Spain. The plant is composed by Fresnel solar collectors and a two-stage absorption chiller. The solar collector uses mirrors to concentrate sun irradiation onto a concentrator composed of secondary mirrors and a receiver tube. Water flows into this receiver tube absorbing solar radiation and exiting at a higher temperature. The water carries thermal energy to the absorption chiller, which operates on a thermodynamic absorption cycle. This cycle is divided into two sides: a hot side that uses the solar-heated water as a high-temperature source and a cold side that chills a water stream through different Lithium-Bromide solution concentrations and evaporation/condensation heats. The chilled water of the cold side is employed to supplement the air conditioning system of ETSI. Finally, the cooled water of the hot side leaves the HTG and is fed back to the Fresnel solar collector in a hydraulic closed loop. For more information, refer to (Bermejo et al. (2010)).

This work main idea is to mathematically represent the absorption chiller performance considering solar intermittency, thus, the on-off operation throughout the day and night and off-design conditions. Besides, the HTG model must have a satisfactory response considering the disturbances of irradiation and chilled water demand due to clouds and users' actions in time. In addition, the internal processes of the absorption chiller have complex heat and mass transfer effects, internal controllers, and Lithium-Bromide stream recycles, resulting in a highly nonlinear system that the model must represent. This work objective is to obtain a Neuro-Fuzzy model that describes the dynamic behaviour of both the internal Lithium-Bromide temperature (T_5) and the outlet temperature (T_{16B}) of the HTG. The model considers various input variables that affect the process. Measured historical data from the SCP operation are used and compose the historical learning and validation data sets.

The article is organized as follows. Section 3 deals with the preparation of data for fuzzy inference systems. Section 2 presents literature contributions on neural and neuro-fuzzy modelling of absorption chillers and justifies the techniques used in this work. Section 4 discuss the design of Neuro-Fuzzy Model of HTG system. Section 5 shows evaluation results, and lastly, the article ends with a conclusion section.

2. ABSORPTION CHILLERS MODELLING

The subsystem referred to in this work is the High-Temperature Generator (HTG) depicted on Figure 1. The HTG is a chiller's subprocess between the hot and cold sides of the absorption chiller. The HTG is responsible for receiving solar thermal power from the Fresnel solar collector and exchanging the heat with the internal

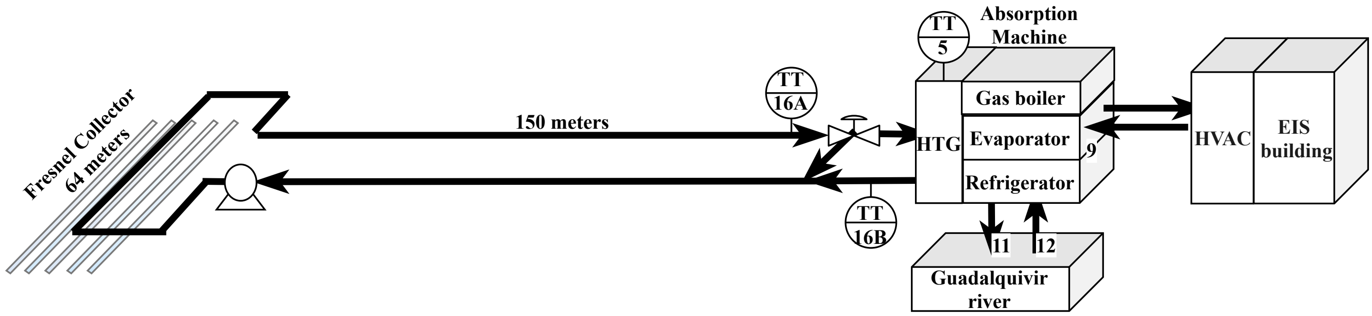


Fig. 1. ETSI absorption plant schematic.

Lithium-Bromide solution. Due to the HTG purpose, its temperature is the most sensitive to the absorption cycle coefficient of performance (COP), and Exergetic Efficiency (Karimi et al. (2018)). Therefore, the HTG is a subprocess directly coupled with both the Fresnel solar collector and chilling process, so its dynamics affect the whole plant. Due to the intermittent and variable nature of solar energy systems, the dynamic modelling of the HTG is critical for designing control systems with adequate safety, stability, and performance indexes. Moreover, to production planning and maintenance.

Two subsystems of neuro-fuzzy modelling represent the HTG. Subsystem 1 is related to the hot side of HTG with respect to the water flow that comes and goes to the Fresnel solar collector. Subsystem 2 is related to the cold side inside the chiller that will be used to evaporate/condensate the Lithium-Bromide solution to generate the chilling effect.

The contributions are a fast, simpler, dynamic model in comparison to phenomenological-based models, so a convenient tool for control. Furthermore, the neuro-fuzzy model can be considered a grey-box model (Lindskog (1997)), as the rules that define the behaviour of the system can be extracted from it. Leaving open the possibility of adding further information and offering more possibilities of optimization techniques. In addition, the training procedure can be directly linked to the real-time data, therefore the model can be updated each night, resulting in a DT of the HTG of the absorption plant.

3. PREPARATION OF OPERATIONAL DATA

The measured historical data from the SCP composes the learning set (training and checking) employed in the ANFIS learning process. In addition, a validation data set is used to evaluate if the model's learning is generalized. Table 1 presents the used variables to design the model of the DT.

The measured data were pretreated to prevent affecting the learning process with inconsistencies. The process consists of normalization to avoid the different nature and magnitude of the variables, noise filtering, and outlier interpolation, and not a number or blank filling.

Total data is composed by ten days of operation measurements sampled every 20 seconds. The the first five days data set starts at 05:02 am on 14^{th} August and ends at 05:22 am on 18^{th} August. The second five days data set is taken from 22^{th} September at 5:02 am, until 26^{th} September at 05:19 am, totalling 37641 samples. The total data is divided into 27737 samples for the learning process and 6934 samples for validation. Each variable is listed on Table 1.

$$DATA \begin{cases} (80\%)\ Learning & \begin{cases} (70\%)\ Training \\ (30\%)\ Checking \end{cases} \\ (20\%)\ Validation \end{cases}$$

4. HTG NEURO-FUZZY MODELLING

Fuzzy inference systems allow to obtain nonlinear models. ANFIS systems make it possible to obtain a structure based on rules, using the learning methods of ANNs. If one of the inputs of the system corresponds to previously sampled values of its output, we will have a type of autoregressive neural network, which manages to learn the dynamic behaviour of physical systems from the data.

Unlike simple neural networks, ANFIS systems allow the addition of knowledge through the later inclusion of rules, which makes them very flexible to reflect further changes in the physical system in the DTs.

The models based on ANFIS are of type TS (Takagi and Sugeno (1985)) composed of j type rules:

$$\texttt{IF}\ x_1\ \texttt{is}\ F_{1j}\ \texttt{and}\ x_2\ \texttt{is}\ F_{2j}\ \texttt{and}\ x_i\ \texttt{is}\ F_{ij}\ ,$$
$$\texttt{THEN}: f_j(x) = g_{0j} + g_{1j}x_1 + \cdots + g_{ij}x_i$$

where $g_{ij} \in \Re$ are parameters, x_i are the inputs, f_j the output respectively for each rule and F_{ij} represents the fuzzy sets defined by Gaussian membership functions (MF) of the type:

Table 1. Variables

Symbol	Description	Units
T_{16B}	Waste heat outlet temp sensor	$^\circ C$
T_{16A}	Waste heat inlet temp sensor	$^\circ C$
T_6	Exhaust temperature sensor	$^\circ C$
T_{amb}	Local ambient temp	$^\circ C$
T_3	Cooling water inlet temp sensor	$^\circ C$
T_4	Cooling water outlet temp sensor	$^\circ C$
T_5	HTG Lithium-Bromide internal temp	$^\circ C$
V_1	Chilled/heating water flow.	m^3/h
V_2	Cooling water flow	m^3/h
V_3	Gas flow	m^3/h
V_6	Heat source water flow	m^3/h
V_4	Hot water flow	m^3/h
F_1	Evaporator inlet valve aperture	%
P_3	Pressure related to the absorber water flow	Bar
INV_6	Cooling water pump inverter	%

$$\mu_{F_{ij}}(x_i) = \frac{1}{1 + \left[\left(\frac{x_i - c_{ij}}{a_{ij}}\right)^2\right]^{b_{ij}}} \quad (1)$$

where a_{ij}, b_{ij}, c_{ij} is the set of parameters used to vary the MFs. The value of the function $\mu_{F_{ij}}$ for a given x_i is known as the degree of membership of x_i for the fuzzy set F_{ij}.

The models that capture the dynamic behaviour of the HTG are modelled employing ANFIS, using several correlated variables as inputs and T_5 and T_{16B} as output. Each ANFIS training is executed by firstly applying a subtractive clustering method (Chiu (1994)) that initially estimates the number of clusters to determine the number of rules and Membership Functions (MF). Then, the parameters of each ANFIS layer are updated using a hybrid learning method that combines gradient descent to optimize the antecedent parameters and least squares to determine the consequent linear parameters. The parameters of ANFIS architecture are similar in both cases, but for each input, they have a different number of rules which are obtained once the learning process of each NF model is finished as shown in Table 2.

Table 2. ANFIS parameters for HTG

Description	**ANFIS**	
MF type:	*Gaussian*	
Optimization method:	*hybrid*	
Output MF type:	*linear*	
FIS	$\mathbf{HTG}^{SUB_1}$	$\mathbf{HTG}^{SUB_2}$
Number MFs:	2	3
Number rules:	2	3
Influence range	0.7	0.70
Epoch number:	250	250

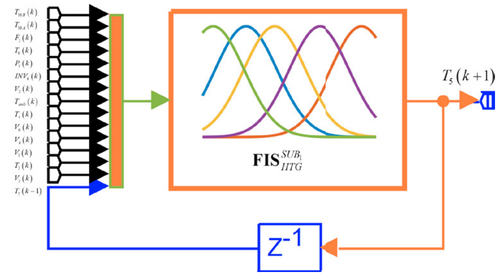
The learning process of each ANFIS uses a few epoch numbers, and the training and checking sets present small errors, indicating that the learning was general. The error indexes obtained in the learning process for each model are shown in Table 3.

Table 3. RMSE index obtained of learning process for each ANFIS

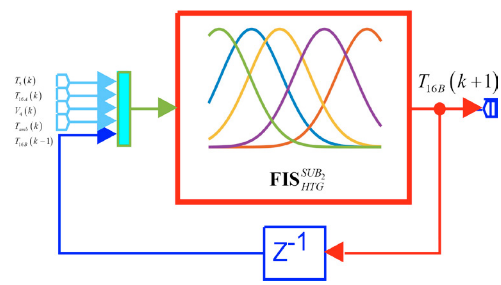
RMSE min of Training & Checking	**ANFIS obtained**	
	$\mathbf{FIS}_{HTG}^{SUB_1}$	$\mathbf{FIS}_{HTG}^{SUB_2}$
$RMSE_{Train}$	$2.461e^{-3}$	$1.1774e^{-3}$
$RMSE_{Check}$	$2.517e^{-3}$	$1.880e^{-3}$

This paper develops two models based on ANFIS (see Fig.2). The $\mathbf{FIS}_{HTG}^{SUB_1}$ and $\mathbf{FIS}_{HTG}^{SUB_2}$ describes the dynamics of HTG and are shown on Fig.2(a) and Fig.2(b), respectively. The FIS that describes the dynamic behaviour of subsystem $\mathbf{HTG_{SUB-1}}$ is modelled through an ANFIS, it utilizes as inputs the variables mentioned in Table 1, with exception of (T_5) that is chosen as the model output and, therefore, the variable that the neuro-fuzzy model must learn.

In this way, it is obtained a first-order recursive $\mathbf{FIS}_{HTG}^{SUB_1}$, that once trained, gives the estimation of T_5 as output based on the input data. Similarly, this paper obtains the FIS that describes the dynamic of subsystem $\mathbf{HTG_{SUB-2}}$, it uses as inputs $[T_5, T_{16A}, V_4, T_{amb}, T_{16B}]$, and as output



(a) Neuro-Fuzzy Model HTG-1 - Lithium-Bromide internal temperature. The chosen input variables in historical data have a correlation coefficient greater than 0.5.



(b) Neuro-Fuzzy Model HTG-2 - Outlet water temperature. The chosen input variables in historical data have a correlation coefficient greater than 0.7.

Fig. 2. Neuro-Fuzzy models obtained

the outlet temperature (T_{16B}), resulting in a first-order recursive $\mathbf{HTG_{SUB-2}}$.

5. VALIDATION OF THE NEURO-FUZZY MODELS

Four error indexes were used to compare the models: mean error, standard deviation (Std), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) shown in Eqs. 2 and 3.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(x_t - x_t')^2}{n}} \quad (2)$$

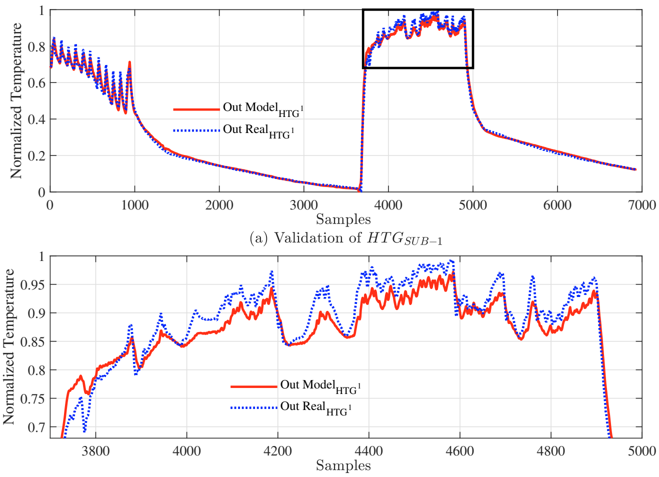
$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{x_t - x_t'}{x_t}\right|}{n} \quad (3)$$

This section simulates the $\mathbf{FIS}_{HTG}^{SUB_1}$ model and contrast its results with real data. Figure 3 shows that $\mathbf{FIS}_{HTG}^{SUB_1}$ model is capable to follow the internal Lithium-Bromide measured temperature trend with an error of $4.9379e^{-4} \pm 3.30e^{-2}$ as shown in Table 4, with an interval estimate of 95% considering a normal distribution of measurements. Note that the temperature decrease between samples 1000 and 4000 is related to the night period. Thus, the model can capture the dynamics of HTG in all temperature ranges of HTG operation.

Figure 4 shows that $\mathbf{FIS}_{HTG}^{SUB_2}$ model is capable to follow the measured outlet temperature trend with an error of $20e^{-4} \pm 4.08e^{-2}$ as shown in Table 4, with a interval estimate of 95%. It is observed that the temperature decrease between samples 1000 and 4000 is related to the night, when the flow rate is zero. Thus, the model can

Table 4. Error indexes obtained for Neuro-Fuzzy Model.

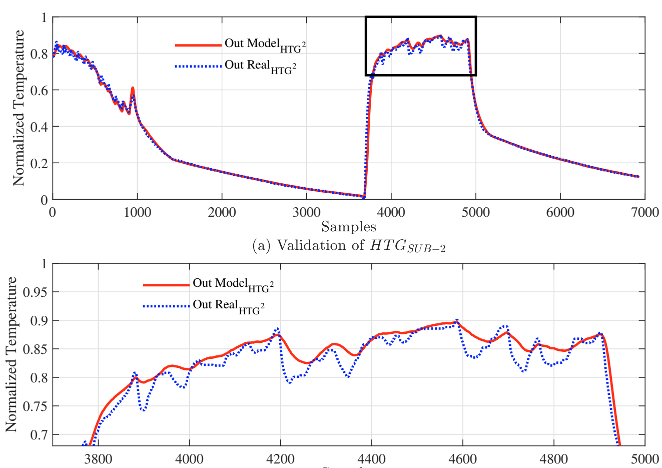
Error indexes	$\mathbf{FIS}_{HTG}^{SUB_1}$ **model**	$\mathbf{FIS}_{HTG}^{SUB_2}$ **model**
Mean	$0.05e^{-2}$	$0.20e^{-2}$
Std	$\pm 3.30e^{-2}$	$\pm 4.08e^{-2}$
RMSE	$1.65e^{-2}$	$2.05e^{-2}$
MAPE	0.0407%	0.0272%



(a) Validation of HTG_{SUB-1}

(b) Detail of HTG_{SUB-1} validation

Fig. 3. (a) $\mathbf{FIS}_{HTG}^{SUB_1}$ model evaluation, model data vs real data. (b) Zoom of model during operation



(a) Validation of HTG_{SUB-2}

(b) Detail of HTG_{SUB-2} validation

Fig. 4. $\mathbf{FIS}_{HTG}^{SUB_2}$ model evaluation, model data vs real data. (b) Zoom of model during operation

capture the dynamics of the HTG outlet temperature over all HTG operating ranges.

To compare the results of both models ($\mathbf{FIS}_{HTG}^{SUB_1}$ and $\mathbf{FIS}_{HTG}^{SUB_2}$), a set of simulations results are shown in Table 4 where the RMSE and MAPE indexes are shown for the different test days. It can be observed that models 1 and 2 present low errors: RMSE of $1.65e^{-2}$ and $2.05e^{-2}$, while a MAPE of 0.0407% and 0.0272%, respectively.

6. CONCLUSION

In this work, ANFIS with feedback were applied to capture the dynamics of the Lithium-Bromide internal temperature and water outlet temperature in HTG. First-order recurrent fuzzy inference systems are attained, specifically, two models with a different number of rules. The ANFIS was trained with real measured data of 8 days and validated on 2 days considering Root Mean Square Error and Mean Absolute Percentage Error indexes. The range of influence of clustering and the number of epoches were varied, obtaining fast models with low error indexes for each model. This model can be used to design control and optimization strategies in future works.

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