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Predicting the Thermal Performance of a Flat Plate Solar Collector Network by Programming a Neural Network

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Collector networks have various operational variables, including irradiance, ambient temperature, wind speed, flow rates, pressure drop, flow distribution, and pumping performance. Since a solar collector network is hydraulically interconnected, a non-uniform thermal behaviour can be observed. A neural network is a computational model inspired by the structure and function of the human brain, designed to process information and learn patterns from data. It comprises artificial neurons arranged in interconnected layers that transform and transmit signals using mathematical functions. A hybrid layer in neural networks is a layer that combines elements of physical or mathematical models with components of neural networks. This work presents a hybrid neural network model to improve and predict the thermal performance of a flat plate solar collector network. This work consists of two analytical sections. In the first stage, a hybrid neural layer was designed to predict the performance of a solar collector. Each solar collector has an area of 2.31 m², an inlet temperature of 25 ºC, and an inlet flow rate of 4 L/min. The input radiation data originated from a dataset concerning one day of operation at a Solar Plant in Mexico. Based on the behaviour of the hybrid neural layer, the second stage involved utilising these neurons to analyse the thermal performance of a line consisting of 10 collectors. The maximum predicted temperature was 79 ºC versus 72 ºC (solar plant value). The Artificial Neural Network model calculated an R^2 score of 0.9884 for the temperature profile. It is feasible to develop specialised neural modules for solar collector networks.

1. Introduction

An artificial neural network is a mathematical and computational model based on a connected data structure that models, predicts, and analyses processes (Hu et al.,2018). The data comprises artificial neuron processing units (Petersen et al., 2018). They are organised in layers, and their main task is to transform input vectors into output vectors by applying non-linear activation functions and weighted linear operations (Jürgen et al., 2015). Artificial neural networks (ANNs) are versatile tools for numerous applications, including natural language processing (Petersen et al., 2018), image analysis (such as facial recognition) (Qamar et al., 2023), science, technology, engineering, and even social media (Goodfellow et al., 2016). Additionally, an ANN can be designed for engineering applications, such as solar energy (Elsheikh et al., 2019), dryers, water/air heaters, heat exchangers, and other similar applications (Shahrukh et al., 2024). This paper presents the development and application of a neural network to predict the thermal performance of a flat-plate solar collector network. It also describes a special hybrid layer for solar collectors, incorporating the typical parameters of solar collectors and combining machine learning with energy balance, heat transfer, and profile temperature.

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2. Methodology

This work was validated using data from the solar plant located in Calera Zacatecas, Mexico (García et al., 2019). These 40 flat-plate solar collectors are used to heat water.

The network configuration consists of four lines, with 10 units installed in each line. The total water flow is 80 L/min. In the first line, 20 L/min of water is fed in parallel into five collectors (Lugo et al., 2024). Subsequently, this flow is fed in series to another five collectors. Figure 1 shows a schematic representation of a single branch (branch 1) (Ortiz et al., 2020). These measurements were taken at 14:00 h, representing only an intermediate operation to gain a closer insight into the temperature profile of the network.

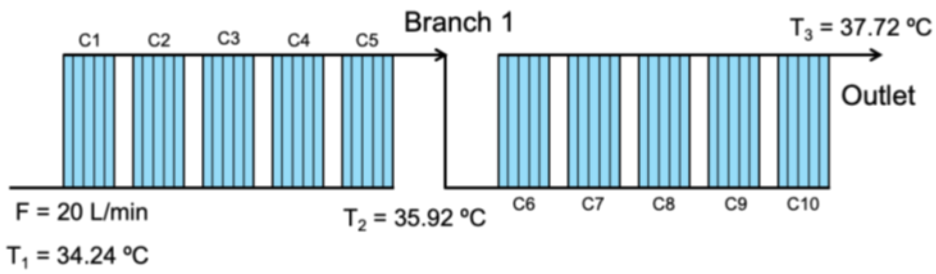

Figure 1: Solar collector configuration

A water flow of 20 L/min was fed to five collectors in parallel at a temperature of 34.24 ºC. After heating, the water reached 35.92 ºC. Subsequently, with these output conditions, it was fed in series to another five collectors, which were configured in parallel. The outflow reached 37.72 ºC. The target temperature should reach 70 ºC throughout the day. The solar energy received during this time was measured in terms of direct solar irradiance, ranging from 488 to 675.1 W/m², and global solar irradiance, from 493.2 to 628.5 W/m². Tmix determines the maximum temperature reached at the outlet of the network. At these operating conditions, the solar plant reported a maximum temperature of 39.67 ºC. The temperature profile of this intermediate operation is presented in Table 1.

Table 1: Solar collector network branch temperature profile

Temperature sensor	Time	Time	Time	Unit
	14:00	14:10	14:15	h
T_1	34.24	35.11	35.75	ºC
T_2	35.92	36.72	37.85	ºC
T_3	37.72	38.37	39.89	ºC
Tmix	37.54	38.24	39.67	ºC
I_d	488	523.7	675.1	W/m^2
I_g	493.2	508.9	628.5	W/m^2

A hybrid layer in a neural network is a layer that combines different types of operations, architectures, or representations within a single functional unit. Unlike a dense or convolutional layer, this layer performs multiple tasks and can even combine several forms of processing simultaneously. For example, it can perform a convolution, then an activation, and finally a normalisation, all within the same layer. It can also incorporate ideas from various types of networks, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) and utilise them simultaneously. The hybrid layer enables the integration of physical models or empirical equations related to the system being examined. The mathematical constraints of these physical models provide structure and ensure that predictions adhere to known laws. Additionally, they prevent the network from generating physically impossible values (e.g., breaking the conservation of) energy). This work developed a custom hybrid layer in Python 3.11.9 using the Tensorflow library. It contains the activation function and operation parameters of the solar collector network. Figure 2 presents a hybrid layer configuration. Within the programming of the layer, mathematical equations specific to the analysis case can be added. This layer comprises a dense layer and a physical model, aiming to integrate pattern learning with physical knowledge of the system.

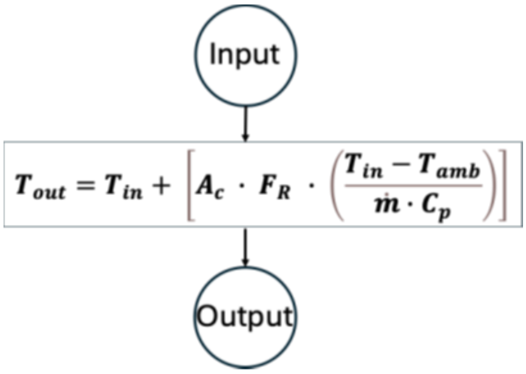

Figure 2: Hybrid layer description

The hybrid layer learned from the data by adjusting the weights and biases during training. The physical model represents known and well-defined relationships, such as energy conservation laws and empirical equations. In this work, Eq(1) was used to calculate the output temperature. Figure 3 illustrates a graphical representation of the hybrid layer, known as Water_Flat_Solar_Collector. Tw_1 represents the inlet temperature, Tw_2 is related to a mid-temperature, Tw_4 is the outlet temperature, and Tw_6 is the maximum temperature reached by the solar collector network. The physical model used in the programming of the hybrid neuron is presented in Eq(1). Where Tout and Tin are the output and input temperatures respectively, both in ºC. Ac is the collector area in m2, Fr is the removal factor, Tamb is the ambient temperature, in ºC, m is the mass flow in kg/s and Cp is the heat capacity in J/kg K.

$$T_{out} = T_{in} + \left[A_c F_R \left(\frac{T_{in} - T_{amb}}{mC_p}\right)\right] \quad (1)$$

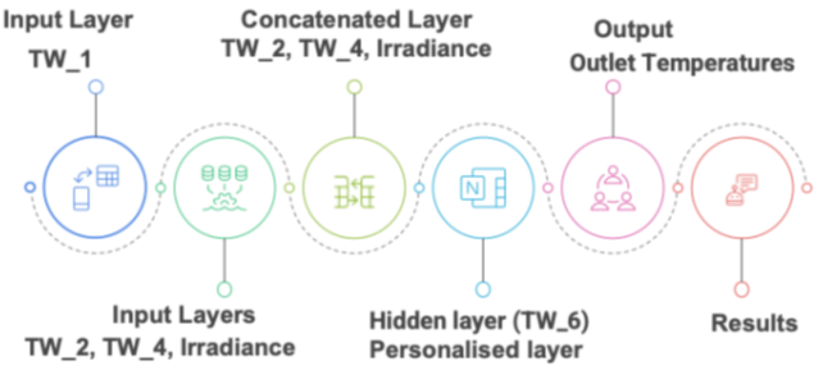

Figure 3: TS-1 neural topology

The hybrid model combines sequential and functional networks. Figure 3 shows the input layers, Input_Tw_1 and solar energy (irradiance). The first input layer is connected to TW_2 and TW_4, two different sequential models developed using the hybrid layer but with varying hyperparameter settings to optimise them. The predicted temperature values in TW_2 and TW_4 are concatenated into a functional model called TW_6. The final output temperature value is then predicted. Real data from the solar thermal plant located in Morelos, Zacatecas, Mexico, was used (García et al., 2019). The dataset was stored in different Excel files. The following libraries were imported: TensorFlow (is an open-source library developed by Google for numerical computation and machine learning), NumPy (a fundamental package for scientific computing in Python. It provides support for arrays, matrices, and a wide range of mathematical functions to operate on these data structures), Pandas (is a powerful data manipulation and analysis library that provides data structures like Data Frames and Series), Matplotlib (is a plotting library for Python that enables users to create static, animated, and interactive visualisations), Keras (It simplifies the process of building and training deep learning models by providing an intuitive interface), Sklearn (it offers simple and efficient tools for data mining and data analysis, including classification, regression, clustering, and dimensionality reduction), Viznet (it provides tools for creating interactive visualizations of neural network architectures, helping users understand the structure and flow of data within their models) y Random (It is commonly used in data science and machine learning for tasks such as shuffling datasets, creating random samples, and initializing weights in neural networks). The hybrid layers were trained and tested using Skealrn on training and test sets with a 60 % training and 25 % testing ratio. The model converged after 40 iterations. Table 2 presents the configuration of the hyperparameters that controlled the learning process. The learning rate for TW-2 and TW-4 was 0.01 and 0.2, respectively, as well as the number of epochs, 15 and 1, respectively.

Table 2: TS-1 hipper parameters

Variable	Model	Hidden layers	Neurons number	Activation function	Optimizer	Lost function
TW-2	Sequential	1	149	ReLu	Adam	Huber (1.0)
TW-4	Sequential	1	15	ReLu	Adam	Huber (1.0)
TW-6	Functional					

3. Results

The case study consisted of a row of 10 solar collectors (Figure 1). Each collector has a net solar absorption area of 2.31 m^2. The total flow in the line was 20 L/min. A uniform water flow distribution of 4 L/min per collector was considered. Wind speed and ambient temperature were kept at constant levels. Radiation was considered variable over time, depending on the operation of the solar plant (García-Valladares et al., 2019). The heating operation begins by feeding 20 L/min of water at ambient temperature into the first five collectors (an area of 11.55 m^2). Then, that amount of water is fed in series to another five solar collectors to increase its temperature (Figure 1). The actual plant operation involves a continuous heating cycle, starting from an initial temperature of 25 ºC and progressing until the water reaches a temperature of 70-90 ºC. The solar plant operational period was from 06:00 to 16:00 hours. However, in the actual operation of the solar plant, from 09:00 h onwards, thermal energy starts to be produced with an initial water temperature of 25 ºC. At approximately 14:00 h, the heating of the water ends, as the maximum temperature has been reached. After that time, energy is allowed to be recovered in the storage tank.
From the operational data above, the Ts_1 network predicted 974 temperature values, calculating a new temperature value every 2 s. The prediction time was set from 6:22 to 15:51 h. Figure 4 illustrates the numerical prediction profile of the outlet temperatures. At 15:00 h of operation and simulation, the solar plant and the neural network, respectively, present the maximum temperature reached in the solar collectors. After that time, in actual operation, the collector plate temperature begins to drop due to a decrease in solar irradiance. The neural network was also able to predict the reduction in water temperature after 15:00 h.

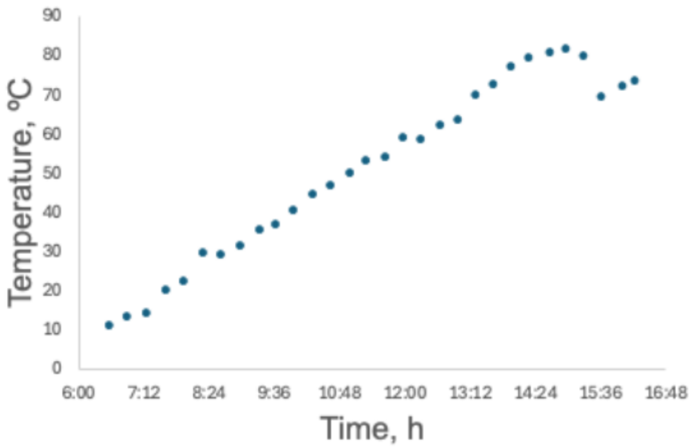

Figure 4: Predicted outlet temperatures by ANN Ts-1

Figure 5 illustrates the linear regression of the neural network temperature profile. An R^2 of 0.97 was achieved. The value of R was obtained by considering the temperature profile calculated up to 15:00 h of the solar plant operation. The maximum thermal energy production was reached at that time. The temperature profile presented in Figure 5 does not account for variations in wind speed. It also assumes that the ambient temperature and the heat transfer coefficient to the environment are constant. However, the same solar irradiance values reported by the solar plant during its operation were used (García et al., 2019).

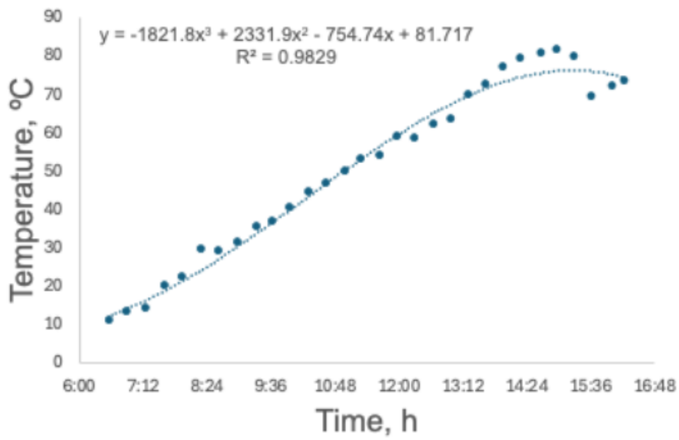

Figure 5: Linear regression of the neural network prediction

Figure 6 illustrates the temperature profile reported by the solar plant (represented by the orange line). The actual temperature profile of the solar plant exhibits a polynomial behaviour. Figure 6 compares the solar plant temperature profile with the ANN-predicted temperature. Both processes report a temperature of approximately 82 °C. Environmental variations, including solar irradiance, wind speed, ambient temperature, and dynamic loss heat transfer coefficient, influence the thermal performance of a solar plant. The neural network is related to solar irradiance while holding ambient temperature and wind speed constant. The objective of this work was to propose a customised hybrid neuron designed to predict the thermal performance of a solar collector network. This represents an opportunity to develop a general neural model that enables the modelling of solar collector network performance under various environmental conditions.

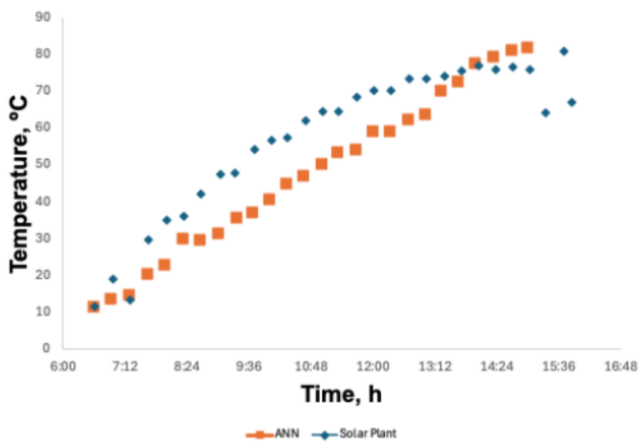

Figure 6: Temperature comparison between the solar plant and an artificial neural network (ANN)

The solar plant contains four branches. These results were calculated for the first branch, as that line is equipped with the suitable instrumentation to measure both inlet and outlet flows, as well as inlet temperatures at the midpoint of the line and the branch outlet. For these reasons, only the first branch was considered, as these results allowed predictions of the Ts-1 neural network to be validated numerically. To perform a complete prediction of the solar plant, it is necessary to assume that the water flow through the 4 branches is uniform, as well as to consider that the feed temperature is the same in all four lines, and that the outlet temperatures of each branch are the same. However, it is possible to balance the hydraulic resistances that make up the network to predict the distribution of the water flow in each branch and thus calculate the useful energy in each collector line. Therefore, it is possible to calculate the mixing temperature (T_mix) among the four lines and to determine the total heat load.

4. Conclusions

It is possible to simulate a flat-plate solar collector network using an artificial neural network (ANN). Incorporating a hybrid layer into the modelling of engineering problems enables more accurate predictions of system behaviour. This approach enhances the ability to generalise using a smaller amount of data, reduces the presence of non-physical errors and provides higher interpretability to the process by integrating physical insights with machine learning. This represents an opportunity to analyse outlet temperature, improve the thermal and hydraulic performance of solar collector networks, and design a solar collector network. The use of neural networks will enable engineers to size, integrate, and control solar collector networks more precisely. They will also facilitate more accurate predictions of heat recovery, leading to better utilisation of renewable energy and a reduction in fossil fuel consumption to lower the carbon footprint. The empirical equations provide structure, physics, and interpretability, while the ANN adds flexibility, adaptability, and data-driven corrections. This work demonstrates that it is possible to develop customised ANN models for specific applications, particularly for solar collector networks. There is also a need to improve the structure or architecture of these models to optimise the convergence for predicting and training neural networks for more complex chemical processes, such as distillation, chemical reactors, heat exchanger networks and bioprocess.

Nomenclature

A_c – collector area, m^2
C_p – heat capacity, J/kg ºC
F_r – removal factor
m – mass flow rate, kg/s
T_{amb} – ambient temperature, ºC
T_{in} – inlet temperature, ºC
T_{out} – outlet temperature, ºC

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