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Artificial Neural-Network based model to forecast the electrical and thermal efficiencies of PVT air collector systems

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Abstract

In the recent decade, Machine Learning techniques have been widely deployed in solar systems due their high accuracy in predicting the performances without going through the physical modelling. In this work, the Artificial Neural Network (ANN) method is adopted to forecast the electrical and thermal efficiencies of a photovoltaic/thermal (PVT) air collector system. Indeed, two accurate modelling techniques have been used to generate the output results for training and validation. Both deployed electrical and thermal models have been validated experimentally and demonstrated high accuracy. Then, real climatic samples of one year with a 10 minute step of the Jordan valley location have been adopted to generate the electrical and thermal efficiencies. These latter are used in the training and validation of the developed ANN model under various combinations of the weather variables. The solar irradiance and the module temperature are the most important variables to consider as input in a NN-based model respectively. The developed ANN model shows MAE of 0.0078% and 3.3607% in predicting the electrical and thermal efficiency respectively. The electrical efficiency can be predicted with higher accuracy than the thermal efficiency. Further, the results demonstrate that the ANN outperforms the LS-SVM in forecasting the PVT air collector performances.

Keywords: Artificial neural network; PVT air collector; electrical model; thermal model; performance forecasting;

36 **1. Introduction**

37 Controlling global energy consumption over recent decades is becoming a central issue in
38 discussions on climate change and the global task to reduce carbon emissions (Yilmaz et al.,
39 2019). Today, renewable energy systems and energy efficiency are acclaimed by the
40 International Energy Agency (IEA) as a key driver of economic growth, reducing emissions
41 and boosting the energy security of countries (IEA PVPS, 2019). More specifically, solar-
42 based energy systems demonstrated a good compromise between the investment cost and
43 efficiency. According to the IEA, the electricity generation using solar energy systems
44 achieved a remarkable growth in the last decade (IEA PVPS, 2019).

45 One of the most effective solutions to reduce the consumption of electrical energy is the
46 development and implementation of hybrid solar systems that can generate two useful
47 products simultaneously. The PVT system is an interesting technology as it combines
48 photovoltaic and thermal systems, generating electrical and thermal energy simultaneously
49 (Rejeb et al., 2020). Most popular PVT systems are designed with a cooling fluid flowing in
50 an open-loop (usually air) (Yang and Athienitis, 2014) or a closed-loop (usually water) (Yu et
51 al., 2019), but there are also other PVT collectors using an hybrid cooling system of air and
52 water (Su et al., 2016). Water-based PVT systems are more efficient than air-based PVT
53 systems due to its high thermo-physical properties (Abdelrazik et al., 2018).

54 Over the last years, a significant number of research projects on PVT technology have been
55 carried-out and various synthesis papers on PVT systems have been published (Kumar et al.,
56 2015). Several authors have been interested in PVT air collectors due to their low-
57 manufacturing costs (Diwania et al., 2020). Air cooling system provides a simple and
58 economical solution for cooling the photovoltaic modules. Air can be heated to various
59 temperature levels and its circulation can be either forced (via a fan) or natural (Chaibi et al.,
60 2021). Forced circulation is required due to a better heat transfer by convection and
61 conduction, however, the fan power consumption decreases the net electricity gain (Ibrahim et
62 al., 2011).

63 The development of physical models is necessary to analyze and study the electrical and
64 thermal performances of PVT air systems (Kumar et al., 2015). In the literature, the electrical
65 behavior of PVT air systems has been imitated using equivalent-circuit models. Waliullah et
66 al. used the double-diode model to compute the output power of a PVT air system (Waliullah

67 et al., 2015). The results are compared to the experiments and shown a remarkable
68 disagreement, which is explained by the climatic data inaccuracy. Tarabsheh et al. adopted the
69 single-diode configuration to evaluate the PVT air system performances under different
70 ranges of temperature. The obtained results demonstrate the accuracy of this model by taking
71 into account the temperature gradient overall the PV module surface, and it was reported that
72 cooling PV cells enhances the electrical performances (Al Tarabsheh et al., 2016). Other
73 configurations of electrical models have been adopted in PVT air systems (Babu and
74 Ponnambalam, 2018) in order to forecast the electrical performances especially the electrical
75 efficiency.

76 A number of thermal models have been developed to study the thermal performance of PVT
77 air systems (Touafek et al., 2013). Most of the models are generic or based on electrical
78 analogy using thermal resistance to describe the heat transfers between the different layers
79 constituting the system (Agrawal and Tiwari, 2013). Tonui et al. developed a physical model
80 of an air PVT system using the analogy with the solar thermal collector model and
81 experimental results. The model allows the calculation of the thermal and electrical
82 efficiencies of the solar collector without requiring precise knowledge of its composition and
83 without involving thermodynamic modelling (Tonui and Tripanagnostopoulos, 2008, 2007).
84 In addition, the most of the physical models developed in the literature assume that the
85 temperature is uniform at each layer of the system and does not vary according to the airflow
86 direction (Barone et al., 2019). Such models are unable to predict the effects of the thermal
87 gradient along each layer on the thermal performance of the system.

88 In the last decades, predicting the performances of PVT systems by using artificial
89 intelligence becomes a key solution to avoid simulating the mathematical models and to
90 overcome their limitations. Accordingly, the advantages of reducing the computing time and
91 to get high prediction accuracy are the main reasons to adopt the use of machine learning
92 algorithms. In the literature, many studies have been conducted to forecast the electrical
93 (Maria and Yassine, 2020); and thermal efficiencies of PVT systems (Mojumder et al., 2017).
94 Caner et al. used 80 samples recorded of two solar air collectors to build an ANN-based
95 model in order to predict the thermal efficiency. The results were satisfactory comparing to
96 the experiments (Caner et al., 2011). In the same context, Varol et al. adopted the ANN, the
97 Adapted-Network-Based Fuzzy Interference System (ANFIS) and the Support Vector
98 Machine (SVM) methods to forecast the thermal performances of a phase change material in
99 solar collectors. The results demonstrated the high performance of the SVM technique (Varol

100 et al., 2010). Also, Ahmadi et al. proposed two models based on ANN and Least Squares
101 SVM methods to predict the electrical and thermal efficiencies of a PVT system. The results
102 shown that the LS-SVM represented the best performances (Ahmadi et al., 2019).

103 Most of reported studies about forecasting the electrical and thermal efficiencies adopted a
104 limited number of samples in the training and the validation processes, due to the
105 unavailability of experimental samples. The main contribution of this paper is the
106 implementing of an ANN based model to determine the electrical and thermal efficiencies of
107 air collector PVT systems. In this work the novelty is represented by the development of a
108 new and original accurate electrical model together with an original detailed transient thermal
109 model of PVT air system, by which it is possible to determine the temperature evolution in
110 each layer as a function of the system length. Further, the adopted data for the training and the
111 validation processes refer to 1 year of real climatic conditions of Jordan valley location with a
112 step of 30 minute. This overcome the limitation of previous studies, which used a limited
113 number of samples to train and test the neural network. Different combinations of the weather
114 variables were considered to assess the performance of the NN-based model to predict the
115 electrical and thermal efficiencies, demonstrating that the choice of the variables as input of
116 the neural network is very important to perform a model with low error. The developed ANN
117 model is also compared with the LS-SVM method in order to confirm the high accuracy in
118 predicting the electrical and thermal efficiencies of the PVT air systems.

119 This manuscript is arranged as follows: First, the followed methodology and the adopted data
120 are described in section 2. Then, the experimental results of both the electrical and thermal
121 models with the predicted efficiencies using the ANN are presented in section 3. Finally,
122 some conclusions are provided in section 4.

123 **2. Methodology and data**

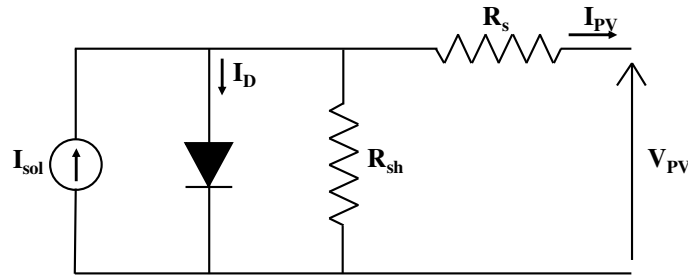
124 The main objective of this study is to present both thermal and electrical modeling process
125 and successively to implement an Artificial Neural Network model, which is able to forecast
126 the electrical and thermal efficiencies of air collector PVT systems. Then, real climatic data of
127 one year are used as an input of the electrical and thermal models to compute corresponding
128 efficiencies. These latter are adopted in the training and validation of the proposed ANN and
129 LS-SVM models.

130 **2.1. PVT air collector modeling**

131 The modeling procedure represents an important task to imitate the real electrical and
 132 thermal behaviors of PVT systems. Accordingly, two validated modelling techniques are
 133 developed to assess the electrical and thermal performances of the air collector PVT system.
 134

135 2.1.1. Electrical modeling

136 Photovoltaic module is a group of cells connected in series to provide important levels of
 137 voltage and current, which vary according to the fluctuations of solar irradiance G and cell
 138 temperature T_c (Chaibi et al., 2019a). The electrical behavior of PV modules is represented by
 139 the equivalent-circuit models. In **Fig.1**, one of the most adopted configurations is presented,
 140 noted as the single-diode presentation. Here, two resistances called the shunt R_{sh} and the
 141 series resistance R_s are added to take in account the PV cell losses (Chaibi et al., 2018).



142
 143 **Fig.1:** PV cell single-diode equivalent circuit model

144 The model in **Fig.1** is employed to plot the current-voltage characteristics (I-V). The PV
 145 module output current I_{pv} is defined as follows (Villalva et al., 2009):

$$146 \quad I_{PV} = I_{sol} - I_s \left\{ \exp \left[\frac{q}{a N_c K T} (V_{PV} + I_{PV} R_s) - 1 \right] \right\} - \frac{V_{PV} + R_s I_{PV}}{R_{sh}} \quad (1)$$

147 where:

- 148 a: diode ideality factor.
- 149 I_s : saturation current of the PV module.
- 150 I_{sol} : photo-generated current of the PV module.
- 151 K: Boltzmann constant.
- 152 N_c : number of cells in series.
- 153 q: electron charge.
- 154 V_{PV} : output voltage of the PV module.

155 From **Eq.(1)**, the I-V curves nonlinearity could be assessed using the manufacturer datasheet
 156 and a numerical process to determine the unknown electrical parameters. An iterative process
 157 to extract the equivalent-circuit physical parameters is adopted (Chaibi et al., 2020). This

158 method is based on the iteration of the shunt resistance until finding a good matching between
 159 computed and experimental power at the standard test conditions (STC).

160 In order to compute the corresponding powers for each value of solar irradiance and
 161 temperature, **Eq.(2)** is used together with **Eq.(1)** to find the maximum power point (MPP)
 162 coordinates.

$$163 \frac{\partial P_{PV}}{\partial V_{PV}} = I_{PV} + V_{PV} \frac{\partial I_{PV}}{\partial V_{PV}} = 0 \Rightarrow I_{PV} = (V_{PV} - R_s I_{PV}) \left\{ \frac{q}{a n_c k T} I_s \exp \left[\frac{q}{a n_c k T} (V_{PV} + R_s I_{PV}) \right] + \right.$$

$$164 \left. \frac{1}{R_{sh}} \right\} \quad (2)$$

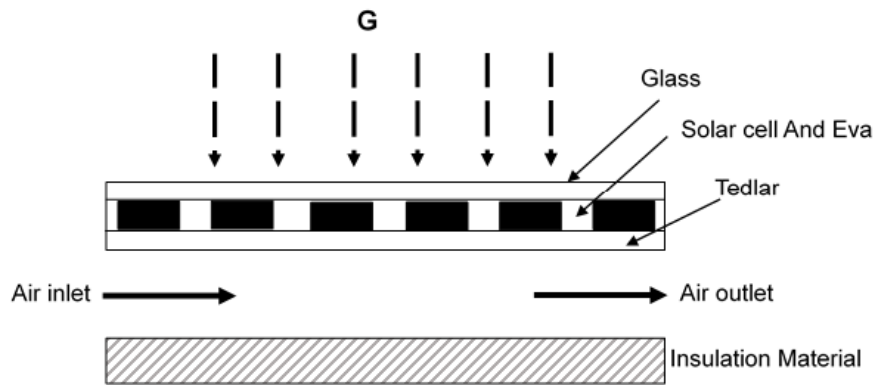
165 Computed powers at MPP are provided to calculate the electrical module efficiency using the
 166 following equation (Chaibi et al., 2019b):

$$167 \eta_{ele} = \frac{P_{pv}}{S_m G} \quad (3)$$

168 S_m is the module surface.

169 2.1.2. Thermal modeling

170 **Fig.2** depicts the PVT hybrid collector scheme considered in this work. It is constituted
 171 of a photovoltaic module with three layers: tempered glass, PV cells covered by two-ethylene
 172 vinyl acetate (EVA) layers and Tedlar (Sarhaddi et al., 2010a).



173

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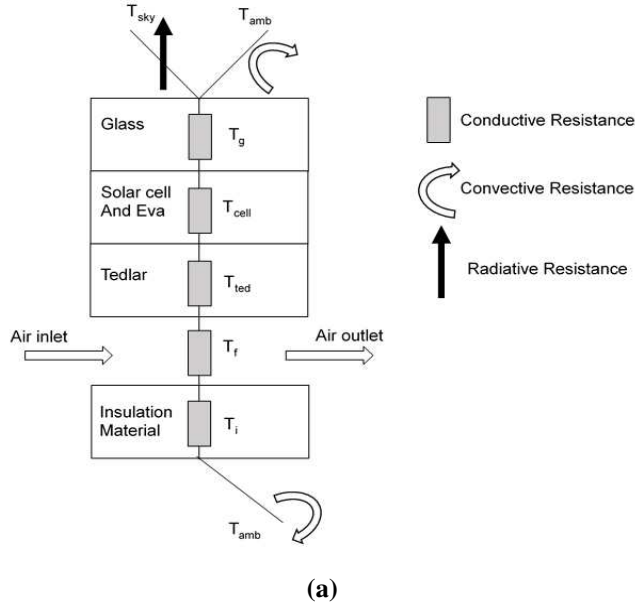
Fig.2: A cross-section picture of a PV/T air module

175 To perform the energy balance for each layer of the PVT module, various assumptions have
 176 been applied:

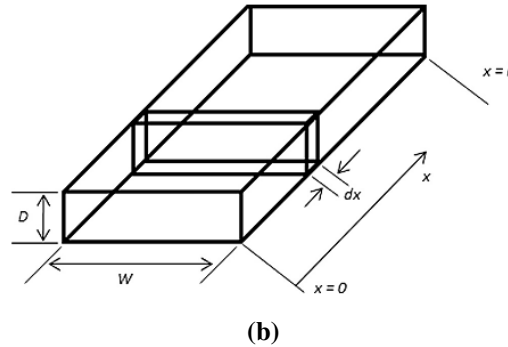
- 177 • unsteady state conditions;
- 178 • air is an incompressible fluid;
- 179 • EVA has a transmissivity of approximately 100%;
- 180 • temperature of glass, cell, tedlar and air depends only on the longitudinal dimension in
 181 the flow direction;

182 • heat loss is neglected as we consider the PV module to be well insulated.

183 **Fig.3** presents the corresponding equivalent thermal resistance circuit and the size of the
 184 control volume for airflow.



185
 186



187
 188

189 **Fig.3:** Layout of thermal resistance system of a PVT air module (a), and basic length "dx" of a
 190 control volume (b) (Sarhaddi et al., 2010b)

191 The thermal energy equations for various layers of the system are as follows:

192 • *Energy equation for glass*

$$193 \quad (\rho c \delta)_g \frac{\partial T_g}{\partial t} = \lambda_g \delta_g \frac{\partial^2 T_g}{\partial x^2} + \alpha_g G + \sigma \epsilon_g (T_{sky}^4 - T_g^4) + h_c (T_{am} - T_g) + \frac{\lambda_g}{\delta_g} (T_c - T_g)$$

194 (4)

195 where, ρ_g is the density of the glass, c_g is the heat capacity of the glass, δ_g is the thickness of
 196 the glass, λ_g is the thermal conductivity of the glass, G is the solar radiation received by the
 197 glass, α_g is the absorptivity of the glass, T_{am} is the ambient temperature, σ and ϵ_g are Stefan

198 Boltzmann constant and glass emissivity respectively. Swinbank (Sarhaddi et al., 2010a)
 199 expression is used to estimate the sky temperature T_{sky} :

$$200 \quad T_{sky} = 0.0552T_{am}^{1.5}$$

201 **(5)**

202 McAdams correlation is adopted to determine the heat transfer coefficient between air and
 203 glass (Swinbank, 1963):

$$204 \quad h_c = 5.7 + 3.8V_{wind}$$

205 **(6)**

206 where, V_{wind} is the wind speed.

207 • *Energy equation for PV cell*

$$208 \quad (\rho c \delta)_c \frac{\partial T_c}{\partial t} = \lambda_c \delta_c \frac{\partial^2 T_c}{\partial x^2} + \left[\frac{\delta_g}{\lambda_g} + \frac{\delta_c}{\lambda_c} \right]^{-1} (T_g - T_c) + \left[\frac{\delta_{ted}}{\lambda_{ted}} + \frac{\delta_c}{\lambda_c} \right]^{-1} (T_{ted} - T_c) + G\beta_c \tau_g \alpha_{pv} - P_{pv}$$

209 **(7)**

210 The electricity produced by PV cell P_{pv} can be calculated using the following expression
 211 (Sellami et al., 2019):

$$212 \quad P_{pv} = \tau_g \beta_c G \eta_o [1 - \beta (T_c - T_{ref})]$$

213 **(8)**

214 where, β is the cell temperature coefficient, β_c is the packing factor, τ_g is the glass
 215 transmittance, α_{pv} is the absorptivity of the PV cells and η_o is the reference electrical
 216 efficiency of PV panel for a reference temperature T_{ref} .

217 • *Energy equation for Tedlar*

$$218 \quad (\rho c \delta)_{ted} \frac{\partial T_{ted}}{\partial t} = \lambda_{ted} \delta_{ted} \frac{\partial^2 T_{ted}}{\partial x^2} + h_f (T_f - T_{ted}) + \left[\frac{\delta_{ted}}{\lambda_{ted}} + \frac{\delta_c}{\lambda_c} \right]^{-1} (T_c - T_{ted}) \quad (9)$$

219 • *Energy equation for air*

$$220 \quad (\rho c A)_f \frac{\partial T_f}{\partial t} + c_f \dot{m}_f \frac{\partial T_f}{\partial x} = \lambda_f A_f \frac{\partial^2 T_f}{\partial x^2} + h_f \cdot W (T_{ted} - T_f) \quad (10)$$

221 where, \dot{m}_f is the mass flow rate of air and A_f is the cross-sectional area of the fluid and W is
 222 the PVT width.

223 The thermal (η_{th}) and electrical efficiency (η_{ele}) are calculated as (Evans, 1981):

$$224 \quad \eta_{th} = \frac{\dot{m}_f c_f (\bar{T}_f - T_{f,in})}{G.A_{pv}} \quad (11)$$

$$225 \quad \eta_{ele} = \eta_{ref} \beta_c (1 - 0.0045(\bar{T}_c - 298.15)) \quad (12)$$

226 where, \bar{T}_c is the average temperature of the PV cell and \bar{T}_f is the average temperature of the

227 fluid (Rejeb et al., 2020). In this work the reference efficiency η_{ref} is assumed to be 12%,

228 which is in the range of the efficiency of common PV modules (Hazami et al., 2016).

229 The overall energy efficiency of the PVT module is calculated using the following expression

230 (Good, 2016):

$$231 \quad \eta_g = \eta_{th} + \frac{\eta_{ele}}{C_F} \quad (13)$$

232 The electrical energy conversion factor C_F ranges from 0.35 to 0.40 and is generally used for

233 PVT systems (Patankar, 1980).

234 A fully implicit finite volume method was used to solve the energy equations system. The

235 first-order upwind scheme was applied to address convective terms, and diffusion terms are

236 discretized using the second order of the central differential scheme. In this paper, the

237 discretized equations were solved iteratively by using a Tridiagonal Matrix Algorithm

238 (TDMA) method (Patankar, 1980). The computation procedure was carried out using Fortran

239 90. The specified iteration in each time interval was considered convergent when the

240 maximum relative residual of T_g , T_c , T_{ted} and T_f was less than 10^{-4} .

241 2.2. Machine learning based methods

242 This section introduces the supervisor machine learning techniques as the Artificial

243 Neural Network and the Least Squares Support Vector Machines adopted to predict both

244 electrical and thermal performance of a photovoltaic-thermal air collector system.

245 2.2.1. Artificial Neural Network

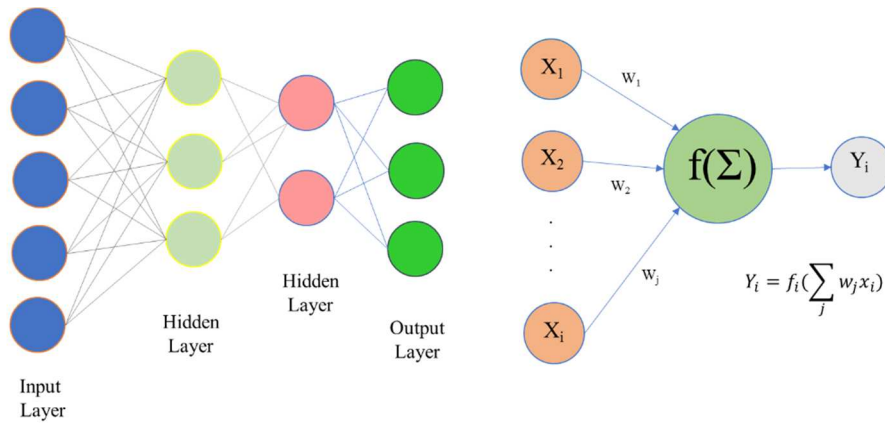
246 Artificial neural network includes an input layer, an output layer and one or more hidden

247 layers. Each layer consists of neurons connected between them. The outputs of each layer are

248 the input for the next layer, get by a transfer (activation) function f as follows:

$$249 \quad Y_i = f(\sum_j w_j X_j + b) \quad (14)$$

250 where, Y_i represents the output for the i -th layer based on the input X_i the connection weights
 251 w_j and b is the bias (Haykin, 2007). A common scheme of a multi-layer NN is shown in
 252 **Fig.4.**



253
 254

Fig.4: Common multi-layer neural network

255 The neural networks can be classified into feed-forward and feed-back networks. A feed-
 256 forward network is a non-recurrent network where the output is determined by the activation
 257 of the neurons starting from input through all the layers in one direction. Unlike a feed-back
 258 network can adopt a loop, so the neuron connections can be in more directions (Schmidhuber,
 259 2015).

260 In common applications, fit a neural network means use a training dataset to set the
 261 connection between the neurons (weights) in order to map the inputs and the outputs in the
 262 best way possible. So, the training of a feedforward neural network phase consists of an
 263 optimization algorithm based on the back-propagation learning algorithm. It includes forward
 264 phase and backward phase (De Giorgi et al., 2013). In the Forward phase, the error is obtained
 265 as the difference between the target and the actual output with parameters of the network
 266 fixed. the Backward phase the weights are adjusted to minimize the error.

267 The Levenberg–Marquardt algorithm is one of the most popular training algorithm for neural
 268 network that adopts the gradient descent approach, by which the training can be considered as
 269 completed when the performance is minimized to the goal. A description of the Levenberg-
 270 Marquardt algorithm for neural network application can be found (Rojas, 1996).

271 2.2.2. Least Squares Support Vector Machines

272 The Least Squares Support Vector Machines represents a noteworthy learning technique
 273 with several applications to overcome the overfitting problem successfully. The LS-SVM
 274 maps the outputs y_i by using a regression function φ , applied to the inputs x_i as follows:

275 $y_i = w\varphi(x_i) + b \quad i = 1 \dots N$ (15)

276 where, w is the weight vector, b is the bias and N is the size of the training dataset. The
277 Lagrange function given by:

278 $L(w, b, e, \alpha) = \mathcal{J}(w, e) - \sum_{i=1}^N \alpha_i \{y_i [w\varphi(x_i) + b] - 1 + e_i\} \quad i = 1 \dots N$ (16)

279 It is introduced to solve the optimization problem and to minimize the cost function.

280 $\min_{w,e} \mathcal{J}(w, e) = \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^N e_i^2 \quad i = 1 \dots N$ (17)

281 With e_i and α_i are unknown variables and γ is the regularization factor. The Mercer's
282 theorem introduces a kernel function K and claims that:

283 $\varphi^T(x_i)\varphi(x_j) = K(x_i, x_j) \quad i, j = 1 \dots N$ (18)

284 It assumes the Radial Basis Function (RBF) as the kernel function given by:

285 $K(x_k, x_j) = \exp\left(-\frac{\|x_k - x_j\|_2^2}{\sigma^2}\right)$ (19)

286 with σ the tuning parameter. So, an approximation of y is given by:

287 $y(x) = \sum_{i=1}^N \alpha_i K(x, x_i) + b$ (20)

288 2.3.3 Accuracy assessment

289 The performance of the prediction models is evaluated by:

- 290 • *Pearson correlation coefficient (R)*

291 $R = \frac{n \sum_1^n (x_i * \hat{x}_i) - (\sum_1^n x_i) * (\sum_1^n \hat{x}_i)}{\sqrt{(n \sum_1^n x_i^2 - (\sum_1^n x_i)^2) * (n \sum_1^n \hat{x}_i^2 - (\sum_1^n \hat{x}_i)^2)}}$ (21)

- 292 • *Root Mean Square Error (RMSE)*

293 $RMSE = \sqrt{\frac{1}{n} \cdot \sum_1^n (x_i - \hat{x}_i)^2}$ (22)

- 294 • *Mean absolute Error (MAE)*

295 $MAE = \frac{1}{n} \cdot \sum_1^n (x_i - \hat{x}_i)$ (23)

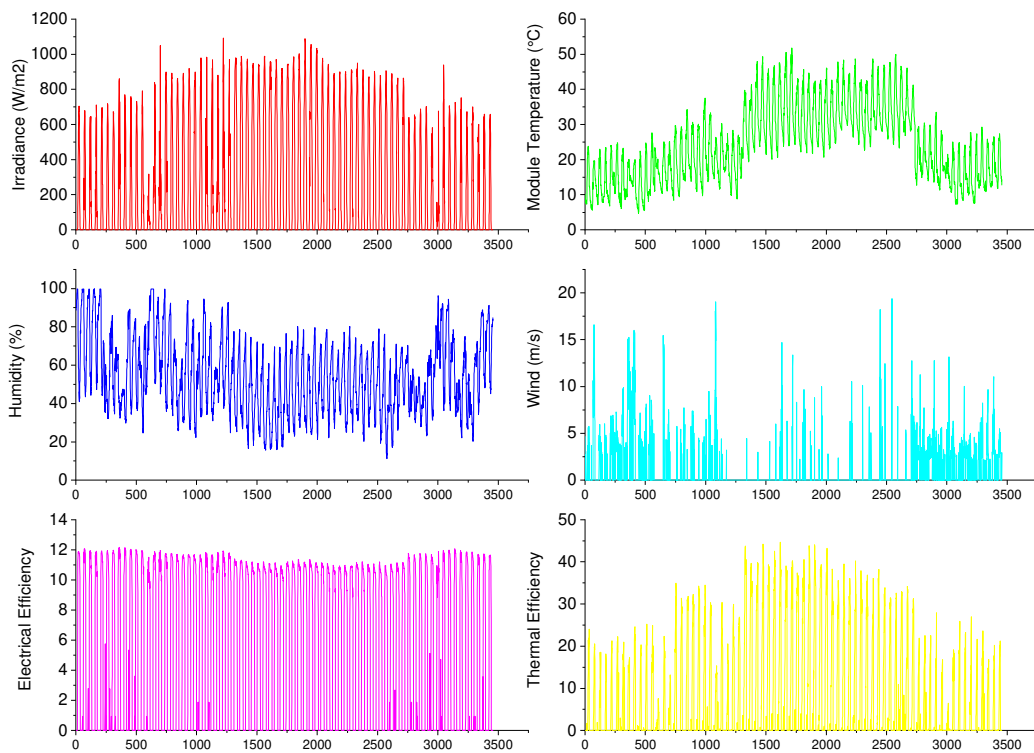
296 with \hat{x}_i outputs, x_i targets and n is the size of the testing dataset. Low MAE implies good
297 fitting between actual outputs and targets. R value is closed to 1 mean a good relationship
298 among actual data and predicted one.

299 **3. Results and discussion**

300 In this section, the experimental validation of both electrical and thermal models is
301 assessed. Then, the obtained results of the ANN-based model are presented and compared to
302 the
303 LS-SVM model.

304 **3.1. Data description**

305 In this study, the input climatic data (Dalala et al., 2020) are the real measurements of
306 solar irradiance, module temperature, humidity and wind recorded in a weather station located
307 at Jordan valley site (Hashemite Kingdome of Jordan) for the 2017 year. More details are
308 reported in (Dalala et al., 2020). The monitored data every 30 minutes, for 12.238 samples
309 overall, are used as input of the developed electrical and thermal models. The test dataset of
310 3456 samples are plotted in **Fig.5**.



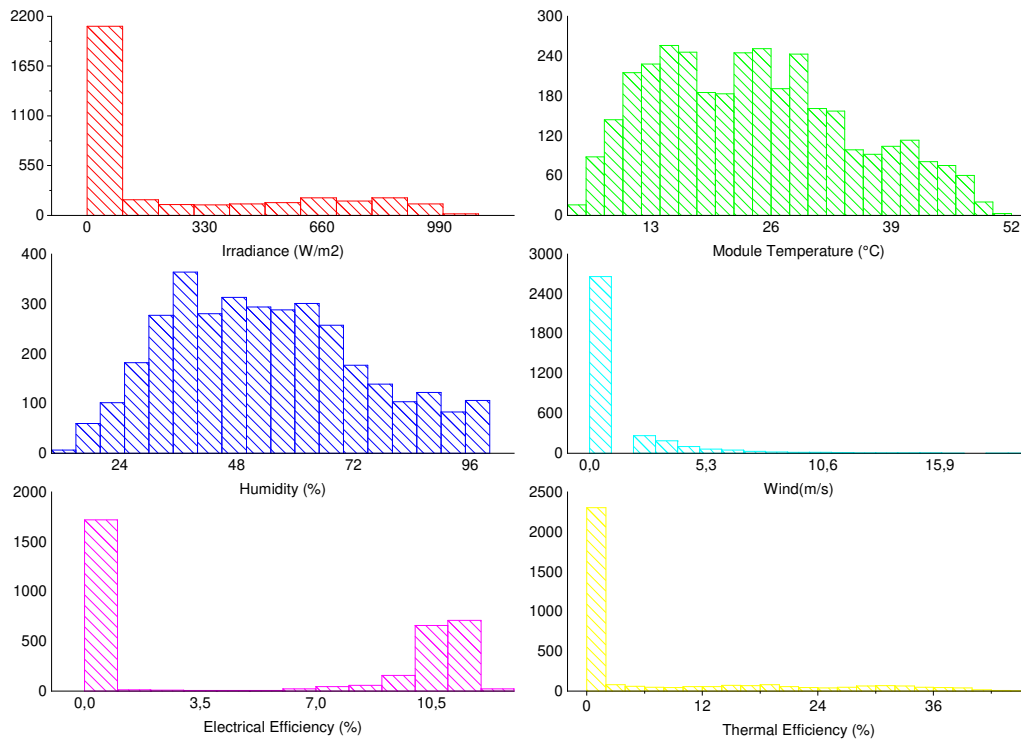
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312

Fig.5: Test weather data and efficiency related to 2017 year.

313 The horizontal solar irradiance varies between 0 and 1093.06 W/m² with the mean value is
314 229.52 W/m². The module temperature is in the range 4.72 °C ÷ 51.82 °C with the lowest
315 value in January, the highest value in June and a mean value of 24.13°C. The humidity is
316 11.33% in September, 99.81% in March and 54.12% on annual average. The highest wind
317 value is recorded of 19.4 m/s with a mean of 1.1 m/s. The highest electrical and thermal

318 efficiencies are 12.7% in January and 44.66% in June with a mean of 5.27% and 6.98%
319 respectively.



320

321 **Fig.6:** Variables Distribution Histograms

322 The distribution histograms of the used data are plotted in **Fig.6**. The solar irradiance and the
323 wind show a distribution that “leans” to the left (positive skewness) that means the lack of
324 symmetry with respect to the mean, unlike by the module temperature and humidity which
325 present a distribution similar to the uniform one. It is noted that the electrical and thermal
326 efficiencies show the same distribution as the solar irradiance and wind.

327

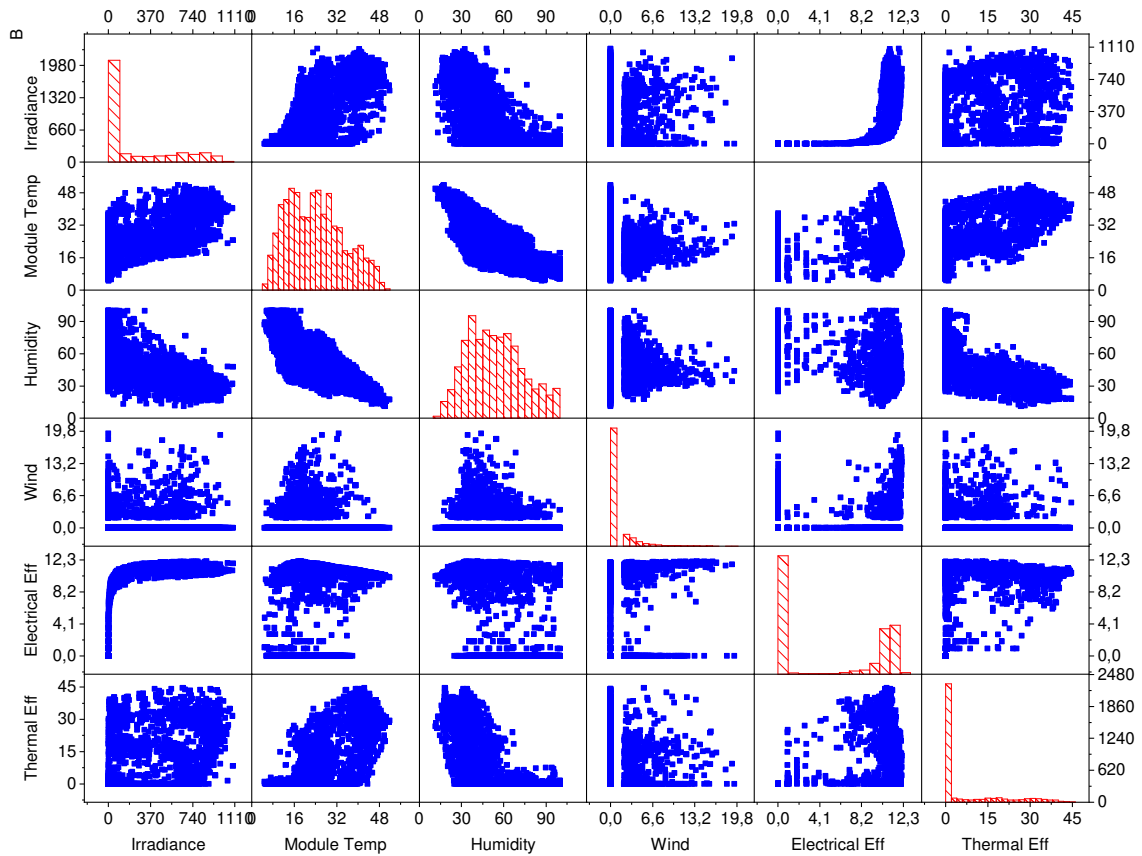


Fig.7: Scatter matrix of the variables

328
329

330 The **Fig.7** shows the correlation between the input climatic data and the efficiencies (electrical
331 and thermal). In very few cases it is possible to see a correlation between the variables. An
332 increase/decrease pattern exists between irradiance, module temperature, electrical and
333 thermal efficiency.

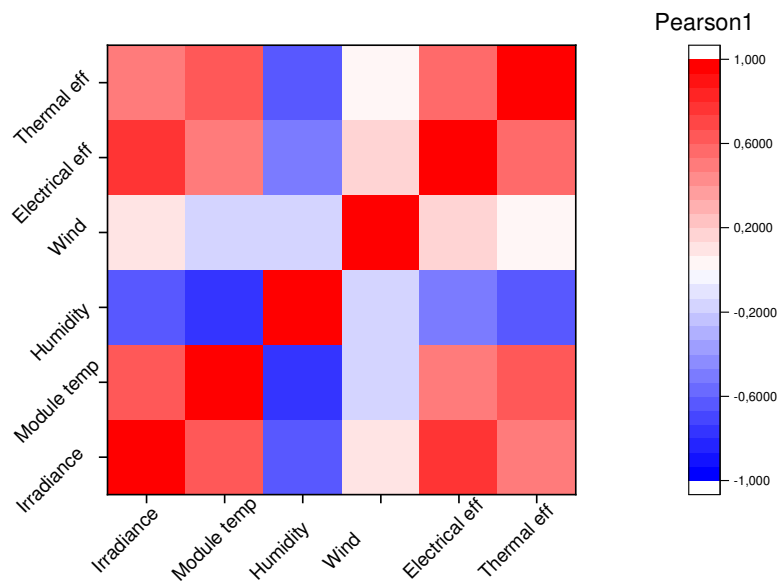


Fig.8: Pearson Correlation Coefficients

334
335

336 In fact, as shown in **Fig. 8**, the Pearson correlation coefficient is close to 1, or however higher
 337 than 0.6 in very few cases. Sometimes we can see also negative correlations. The electrical
 338 and thermal efficiencies present a correlation of 0.78 and 0.53 with irradiance respectively; of
 339 0.49 and 0.62 with the module temperature. The remain variables such as humidity and wind
 340 show a correlation very closed to 0 or even negative correlation.

341 Such analysis will be considered in the development of the ANN model. In particular, the
 342 correlations will represent the criteria by which the variables will be chosen as input for the
 343 ANN.

344 3.2.Validation of the electrical and thermal models

345 3.2.1. Electrical model

346 To assess the accuracy of the electrical PV modeling, datasheet values of the SP75 PV
 347 module (See **Table 1**) are used to compute the electrical parameters using the iterative process
 348 reported in (Chaibi et al., 2020). The founded parameters are summarized in **Table 2**.

349 **Table 1:** Specifications of the used PVT air collector system (Sarhaddi et al., 2010a)

Solar PVT air module parameters	Value
PV module type	Siemens SP75, monocrystalline silicon
The number of cells in series, N_c	36
The maximum power of PV module at STC, $P_{pv,MPP}$	75 W
The maximum voltage of PV module at STC, $V_{pv,MPP}$	17 V
The maximum current of PV module at STC, $I_{pv,MPP}$	4.4 A
The short-circuit current of PV module at STC, I_{sc}	4.8 A
The open-circuit voltage of PV module at STC, V_{oc}	21.7 V
The temperature coefficient of I_{sc} , K_i	2.06 mA/°C
The length of PV module, L	1.2 m
The width of PV module, W	0.527 m
The area of PV module, S_m	0.632 m ²
The electrical efficiency at the reference conditions, $\eta_{ele,ref}$	0.12
The density of glass cover, ρ_g	2450 kg.m ⁻³
The specific heat capacity of glass cover, C_g	500 J.kg ⁻¹ .K ⁻¹
The thickness of glass cover, δ_g	0.003 m
The conductivity of glass cover, λ_g	1 W.m ⁻¹ .K ⁻¹
The transmissivity of glass cover, τ_g	0.95
The conductivity of solar cell, λ_c	130 W.m ⁻¹ .K ⁻¹
The specific heat capacity of solar cell, c_c	677 J.kg ⁻¹ .K ⁻¹
The density of solar cell, ρ_c	2330 kg.m ⁻³
The absorptivity of solar cell, α_c	0.85
The thickness of solar cell, δ_c	0.0003 m

The conductivity of solar cell, λ_c	0.036 W. m ⁻¹ .K ⁻¹
The thickness of tedlar, δ_{ted}	0.0005 m
The conductivity of tedlar, λ_{ted}	0.033 W. m ⁻¹ .K ⁻¹
The specific heat capacity of tedlar, c_{ted}	1250 J.kg ⁻¹ .K ⁻¹
The density of tedlar, ρ_{ted}	1200 kg.m ⁻³

350

351 **Table. 2:** Extracted parameters of the Siemens SP75 PV module at the STC (Chaibi et al., 2020)

Parameters	Value
Photo-generated current	4.8 A
Saturation current	1.1e-06 A
Ideality factor	1.5352
Series resistance	0.2616 Ω
Shunt resistance	2670 Ω

352 The parameters in **Table 2** are adopted to generate the I-V curves of the SP75 PV module.

353 Then, these characteristics are compared to the experimental curves for various level of solar

354 irradiance and temperature. These I-V curves are presented in **Fig.9**, with a variation of solar

355 irradiance and fixed temperature at 25 °C (**Fig.9-a**), and variation of temperature with a fixed

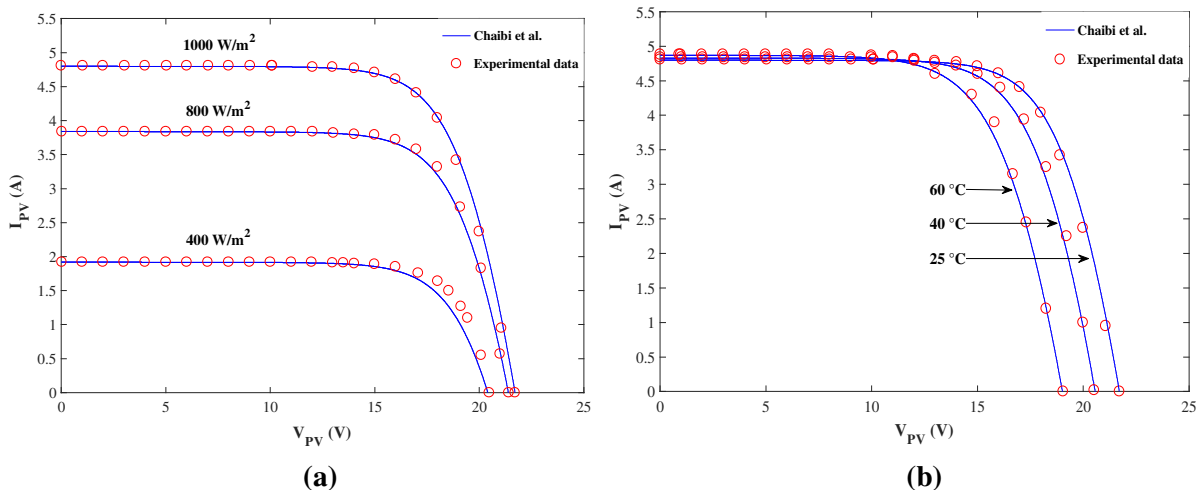
356 irradiance at 1000 W/m² (**Fig.9-b**). It is clear from these curves that the adopted modeling

357 method exhibits high accuracy for different variations of solar irradiance and temperature.

358 Besides, a little disagreement is remarked for irradiances below 400 W/m², but it will not

359 affect the performances of the electrical model since it does not exceed 2% of difference

360 compared to experimental data.



361

362

363 **Fig.9:** Experimental and simulated I-V characteristics of the SP75 PV module: irradiance varies and

364 fixed temperature (T=25°C) (a), temperature varies and fixed irradiance (G=1000 W/m²) (b)

365 **3.2.2.** Thermal model

366 Numerical results obtained by the thermal model are compared to the experimental results
 367 reported by Joshi et al. (Joshi et al., 2009). Solar irradiance, ambient temperature, air
 368 temperature at the inlet and outlet of the PVT, and PV cell temperature are some of the
 369 parameters that Joshi et al. (Joshi et al., 2009) have measured. The design parameters and
 370 thermophysical properties of the PVT air collector are presented in **Table 1** (Sarhaddi et al.,
 371 2010a). **Fig.10** indicates the experimental day's variations in solar radiation intensity, ambient
 372 temperature and inlet air temperature. **Fig.11** illustrates the variation versus time of the air
 373 temperature at the output of the PVT module, the average PV cell temperature and the related
 374 experimental data. Based on this figure, there is generally a good correspondence between
 375 experimental and numerical results. The thermal and electrical efficiencies of the PVT air
 376 system are illustrated in **Fig.12**. Here, it can be seen that there is a reasonable agreement
 377 between experimental and calculated values of these efficiencies. The slight difference
 378 between the experimental and calculated efficiencies can be explained as follows:

- 379 • Wind speed is considered constant. However, in practice this velocity is not constant and
 380 has a direct effect on the heat loss through the system;
- 381 • The absorption and transmission coefficients were considered constant while they vary
 382 over the day as solar incidence angle on the PVT system surface changes.

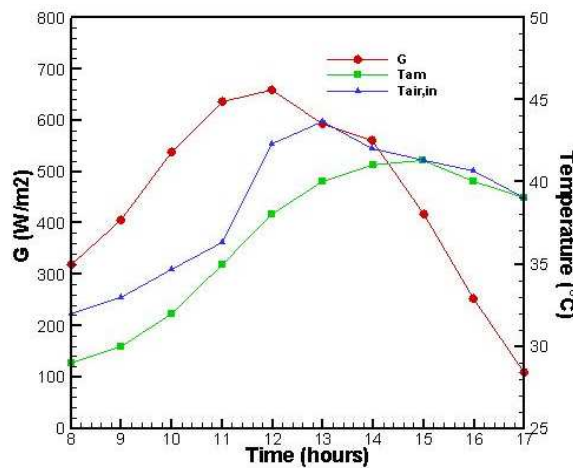


Fig.10: The hourly variation of G, T_{amb} and T_{air,inlet}

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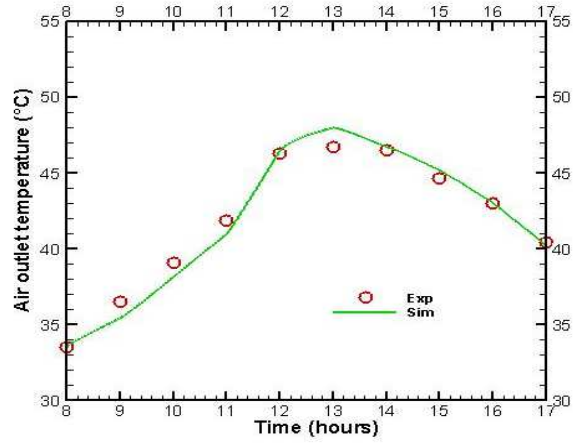
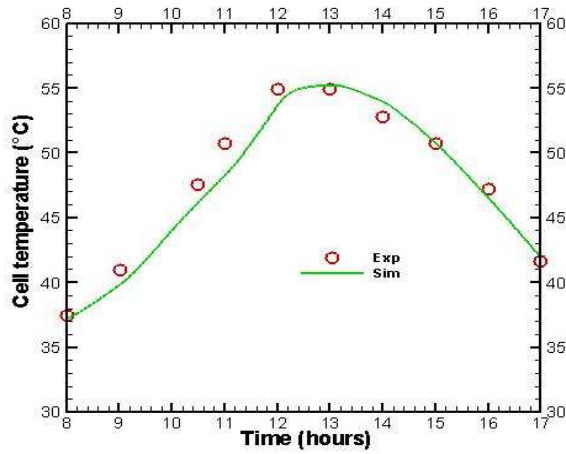


Fig.11: Numerical and experimental results: Outlet air temperature (a), and average cell temperature (b)

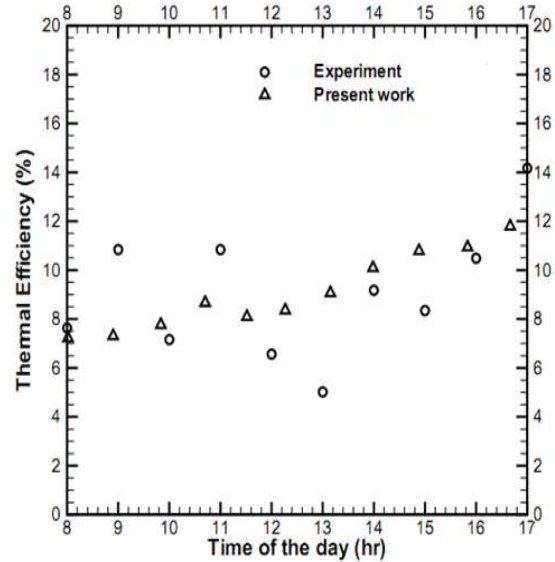
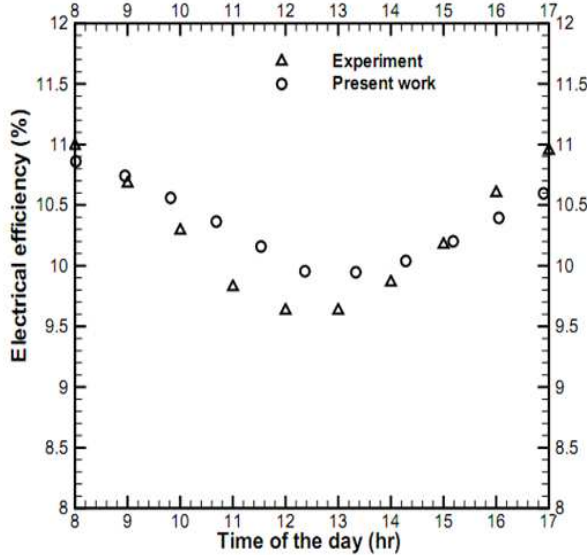


Fig.12: Efficiencies of the PV/T air versus time: Electrical efficiency (a), and thermal efficiency (b)

3.3. ANN-based model results

In the present work a Multilayer Perceptron (MLP) feedforward neural network of 4 layers is design with 1 input node and 1 output neuron, 1 hidden layers 10 nodes and 1 output layer. The two-layer feedforward network consists of sigmoid hidden neurons and linear output neurons as shown in **Fig.13**.

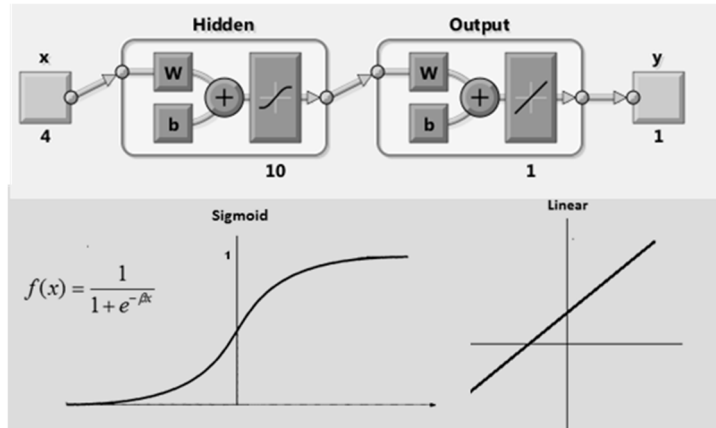


Fig.13: Network Architecture

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402 The sigmoid function used in the ANN hidden layer is defined as (Kang, 2017):

403
$$f(x) = \frac{1}{1 + e^{-\beta x}} \quad (24)$$

404 The linear function is given by:

405
$$g(x) = ax + b \quad (25)$$

406 They are shown in **Fig.13**. The MLP feedforward neural network implements the Back-
407 Propagation (BP) learning in Batch mode during the BP training, in which the weights are
408 adjusted through epoch-by-epoch that means, the whole dataset is use to training.

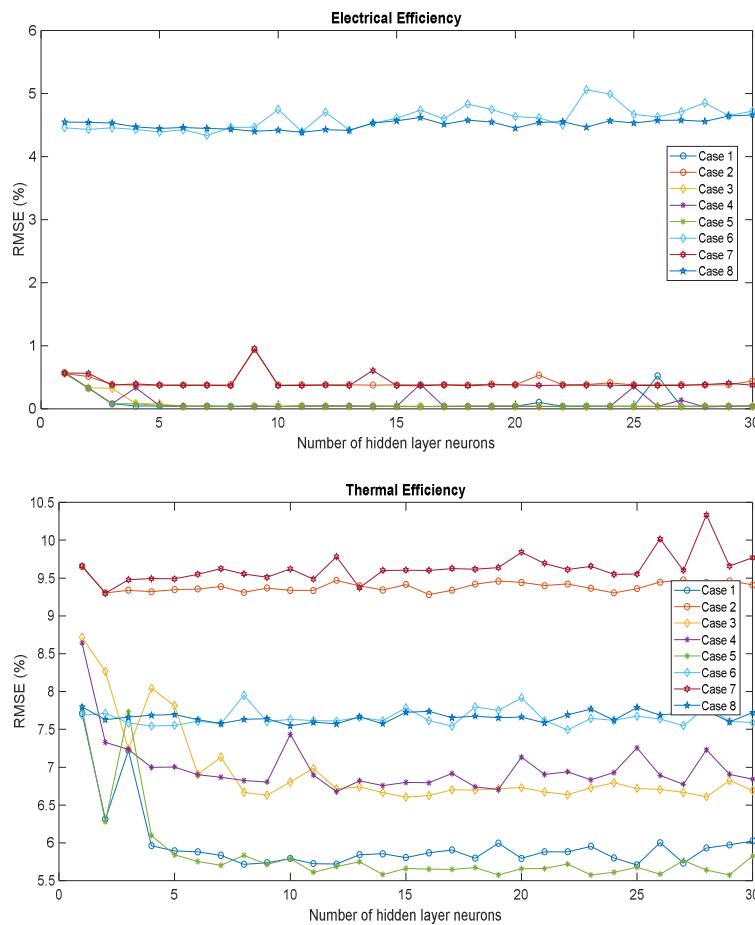
409 The **Table. 3** includes several combinations of the weather variables as the potential input of
410 the neural network. They were chosen on the base of the results regarding the Pearson
411 Correlation Coefficients. So, the variables which exhibited high correlations with the output
412 variables (electrical and thermal efficiencies) were considered to define the cases as presented
413 in the **Table 3**. Further, 2 combinations (case 6 and case 8) of the input variables with low
414 correlations were also considered to analyze their impact on the neural network performance.

415 **Table. 3:** Several combinations of the weather variables as the potential input of the neural network

	Solar Irradiance	Module Temperature	Humidity	Wind
Case 1	√	√	√	√
Case 2	√			
Case 3	√	√		
Case 4	√	√		√
Case 5	√	√	√	
Case 6		√	√	√
Case 7	√			√

Case 8		√	√	
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416 For each case, different neural networks were trained and tested by varying the number of
 417 hidden layer neurons. The RMSE as defined by Eq.(22) is used to assess the performance of
 418 the network. The number of hidden layer neurons with lower RMSE was chosen to get the
 419 network with higher performance. Fig. 14 shows the performance in term of RMSEs related
 420 to neural networks implemented to predict the electrical and thermal efficiencies respectively
 421 for each case. Steady RMSEs were observed within 30 as number of hidden layer neurons.
 422 This was established as the maximum number of hidden layer neurons to apply in the
 423 performance assessment.



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426 **Fig.14:** Performance of different neural networks by varying the number of hidden layer neurons

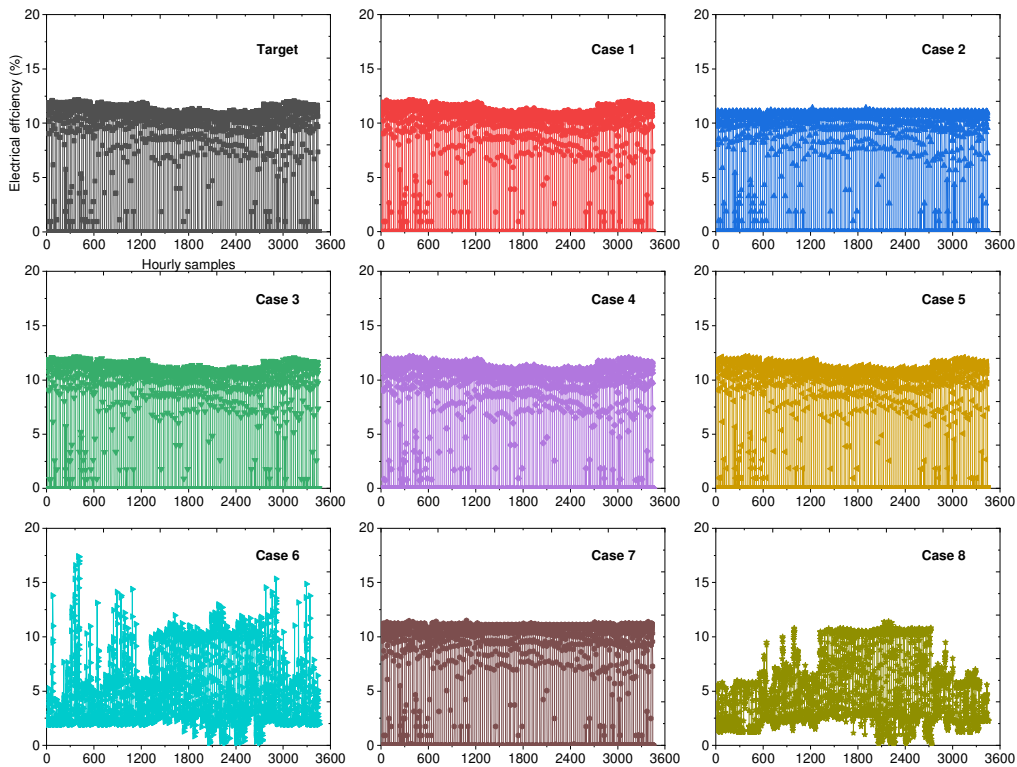
427 In Fig 14, it is clear that the RMSE related to the electric efficiency is lower than 1%
 428 excepted for case 6 and 8 in which it varies between 4% and 5%. The case 3 and 5 result more
 429 performing with a number of hidden layer neurons starting from 6. The RMSEs of the thermal
 430 efficiency are in the range [5.5%, 10.5%]. The best and the worst perform were for the case 5
 431 and the case 7 respectively.

432

Table 4: Summary of number of hidden layer neurons and R for 8 cases

	Electrical Efficiency		Thermal Efficiency	
	Number of hidden layer neurons	R	Number of hidden layer neurons	R
Case 1	6	0.99998	25	0.85879
Case 2	7	0.99699	16	0.61297
Case 3	8	0.99998	15	0.82186
Case 4	28	0.99997	12	0.81293
Case 5	16	0.99997	29	0.86836
Case 6	7	0.51172	22	0.76551
Case 7	18	0.99783	2	0.58601
Case 8	11	0.51186	10	0.75414

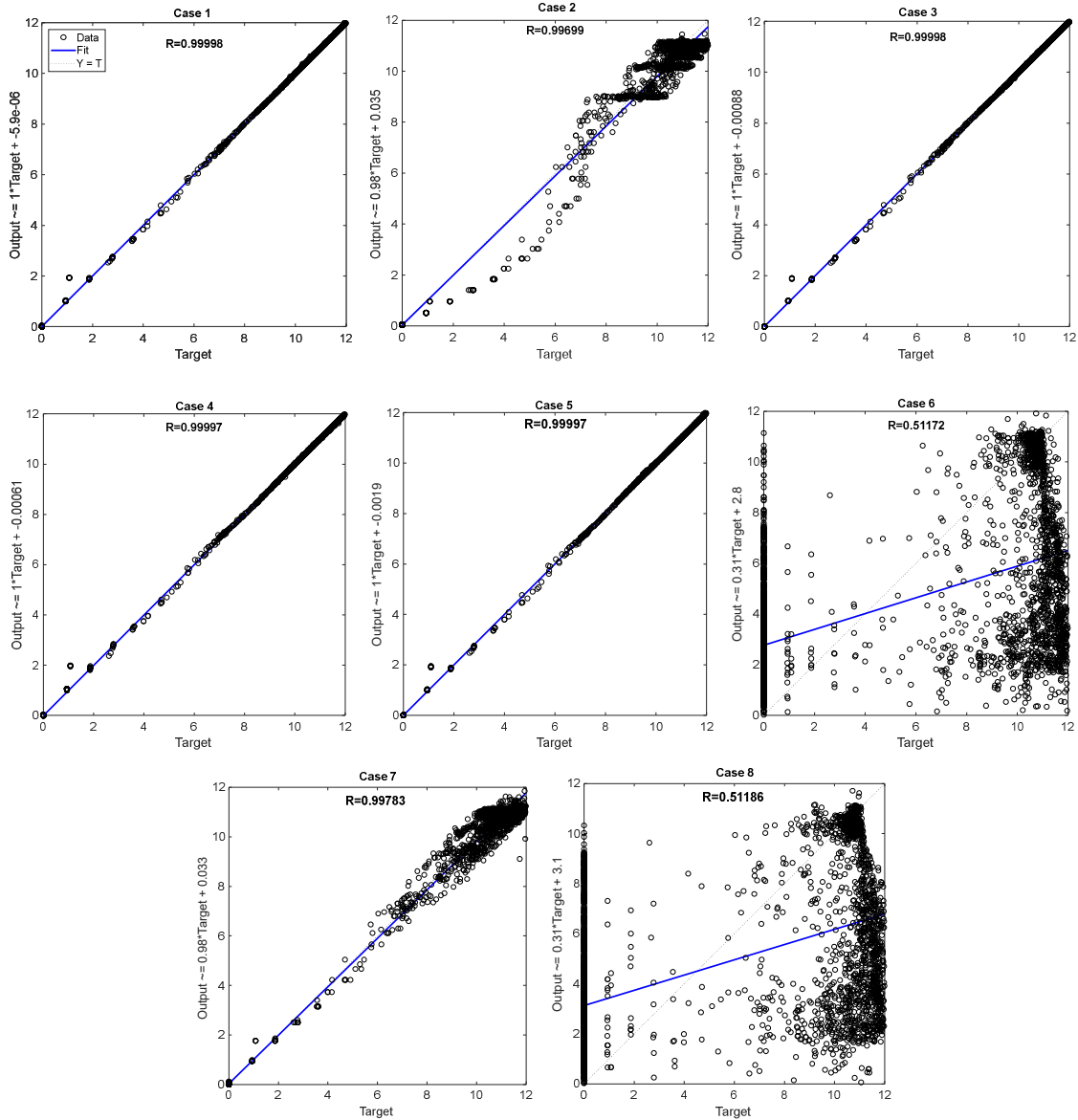
433 The best number of hidden layer neurons for each case is summarized in **Table 4**. Generally,
434 it can be observed that the neural network to predict the electrical efficiency performs well for
435 low number of hidden layer neurons, unlike the neural network to model the thermal
436 efficiency that shows high accuracy for high number of hidden layer neurons. The best
437 number of hidden layer neurons for each case were adopted for the performance assessment in
438 the following sections.



439
440

Fig.15: Target VS predicted values of the electrical efficiency.

441 **Fig.15** plots the actual values (target) and the predicted values of the electrical efficiency. For
442 each case, the neural network's response is quite similar to the expected value, excepted for
443 case 6 and 8 which represent the weather variables combinations without the solar irradiance.



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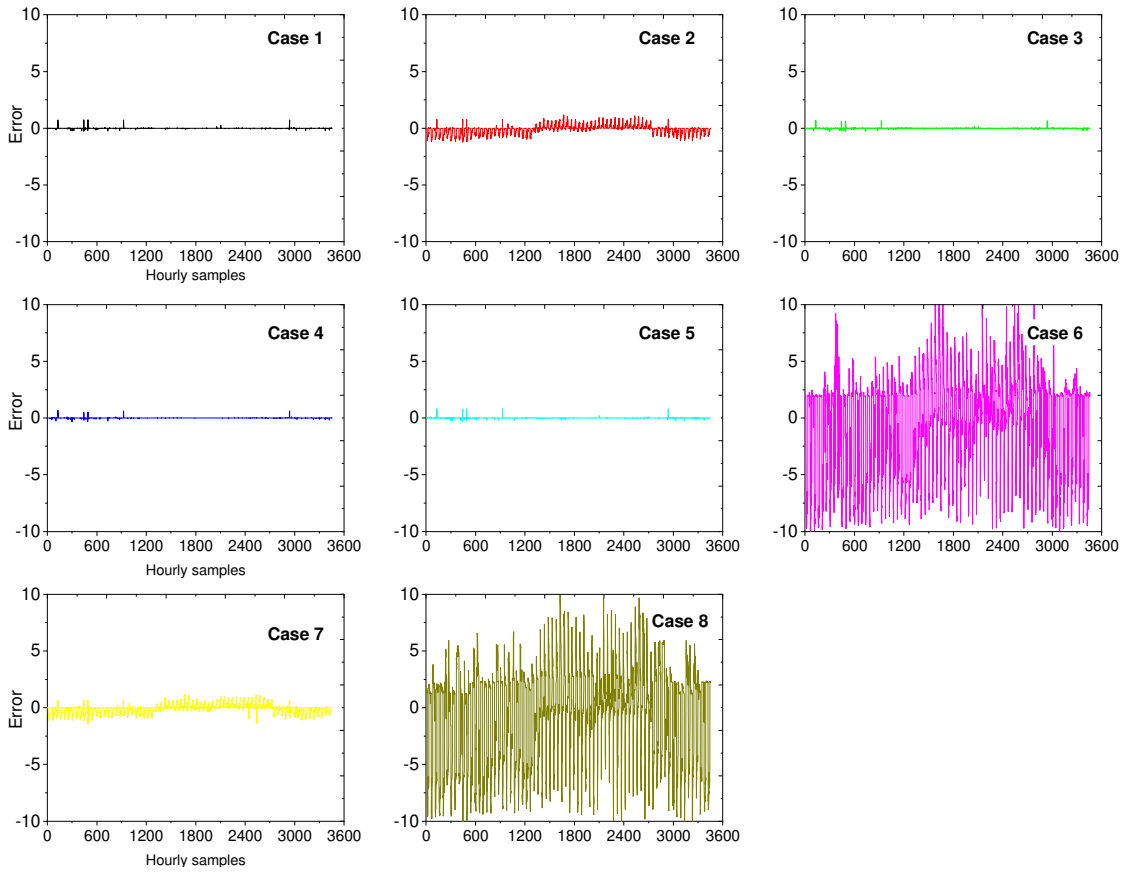
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Fig.16: Regression plot for electrical efficiency

448 **Fig. 16** presents regression plots for electrical efficiency. Mainly the R value is 0.99 excepted

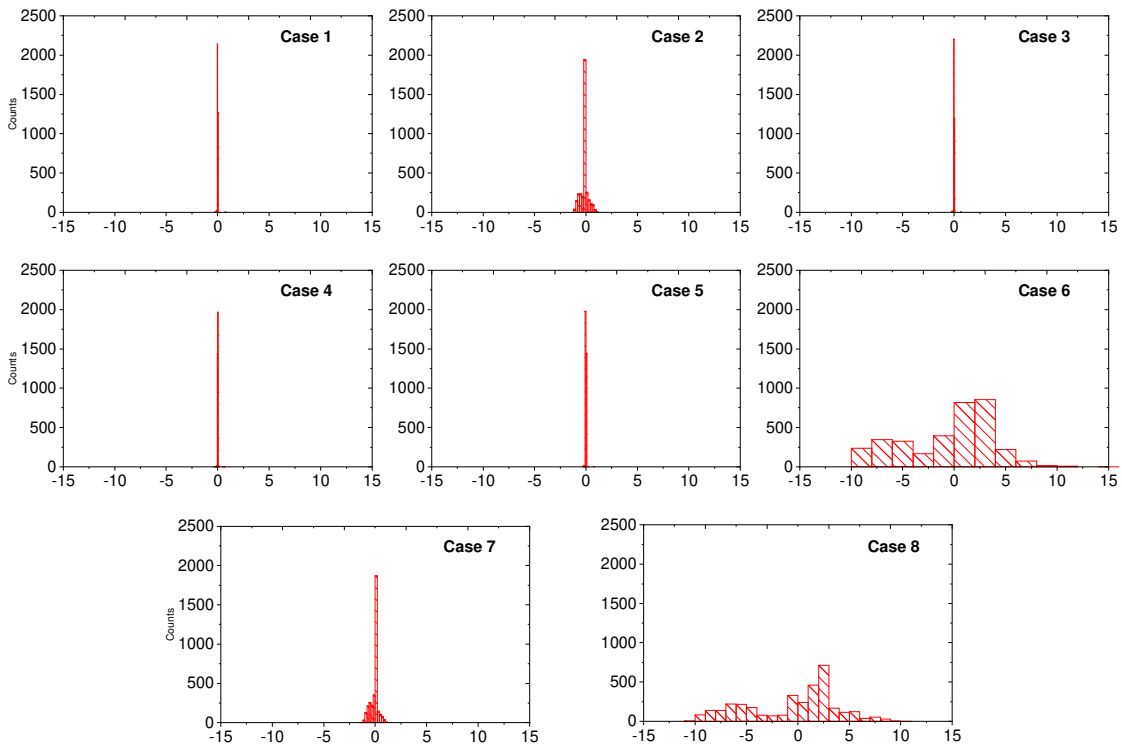
449 0.51 for case 6 and 8.



450

451

Fig.17: Electrical efficiency error



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Fig.18: Electrical efficiency error histograms

455 In **Fig. 17** the errors generally are very low, exhibiting good compliance between target and
456 output, but evident spikes can be observed between -10% and 10% in case 6 and 8. In fact the
457 error histograms (**Fig. 18**) demonstrate that the error distribution is mainly peaked and
458 centered to zero, unlike it is flat for case 6 and it is very flat for case 8.

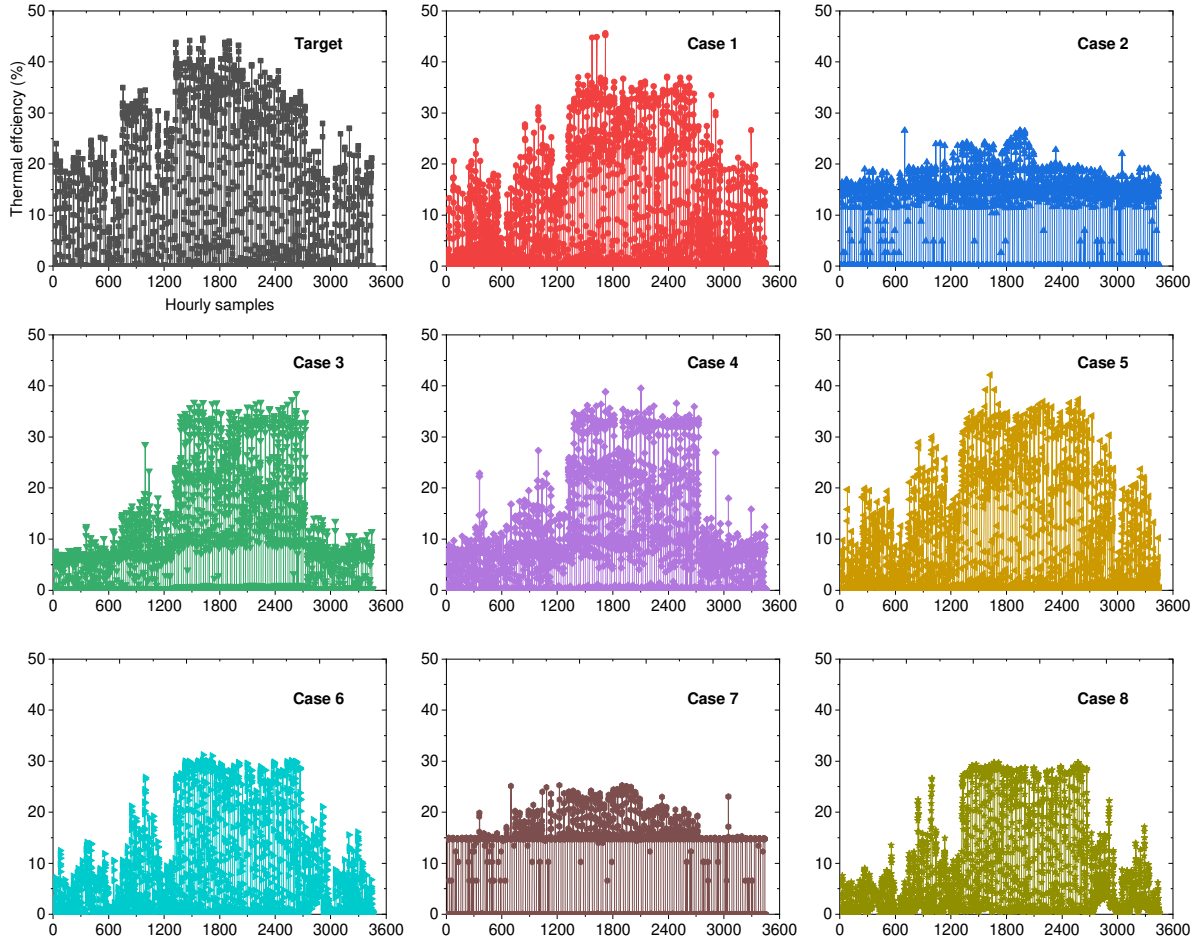
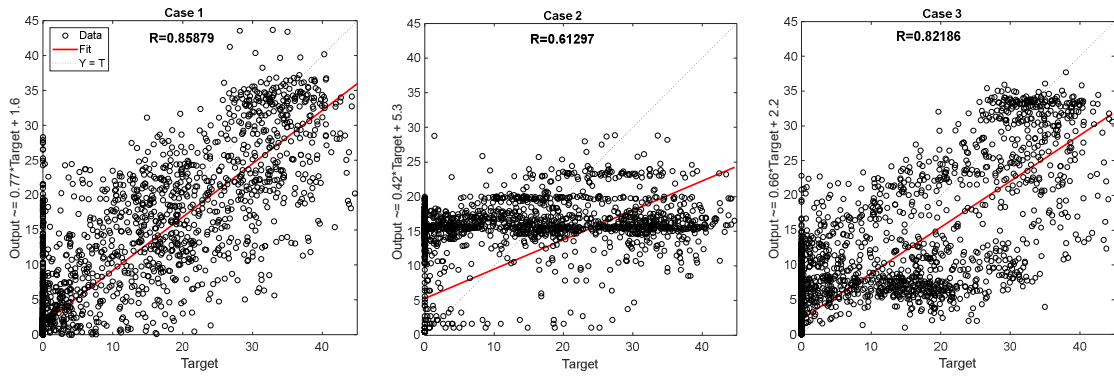


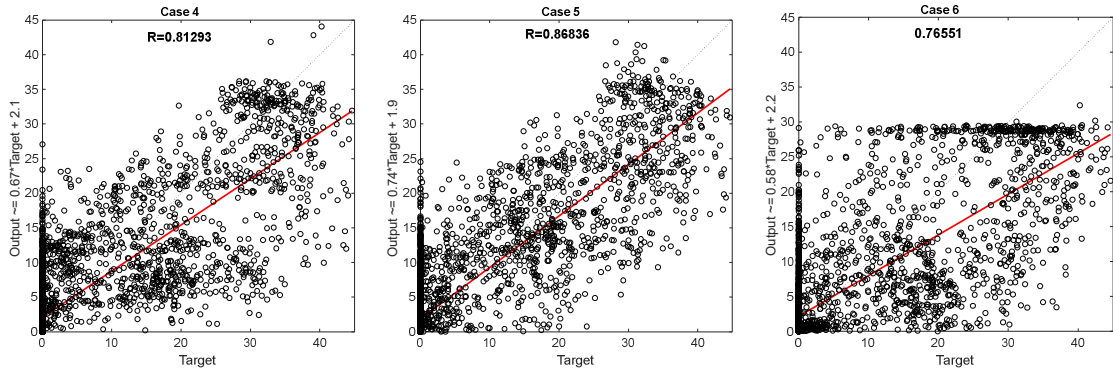
Fig.19: Target and predicted values of the thermal efficiency

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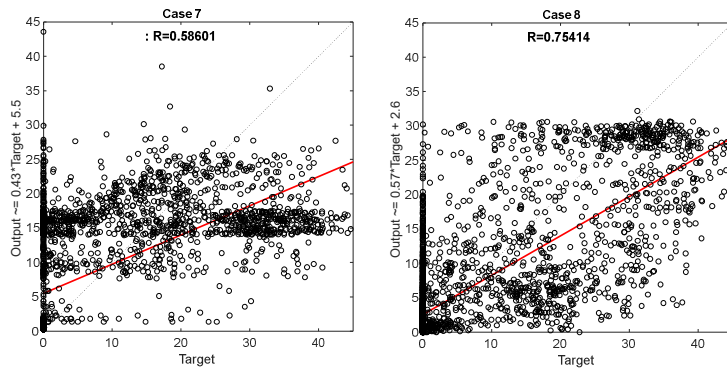


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Fig.20: Regression plot for thermal efficiency

474 The target and the predicted value of the thermal efficiency are presented in **Fig.19**. The
 475 implemented neural networks show different responses of the thermal efficiency for the 8
 476 cases. The regression plots (**Fig.20**) illustrate R values up to 0.86 (case 5) and 0.85 (case 1).
 477 The worst R value (0.58) is for case 7 that does not consider the module temperature as input
 478 of the neural network (see **Table 3**).

479

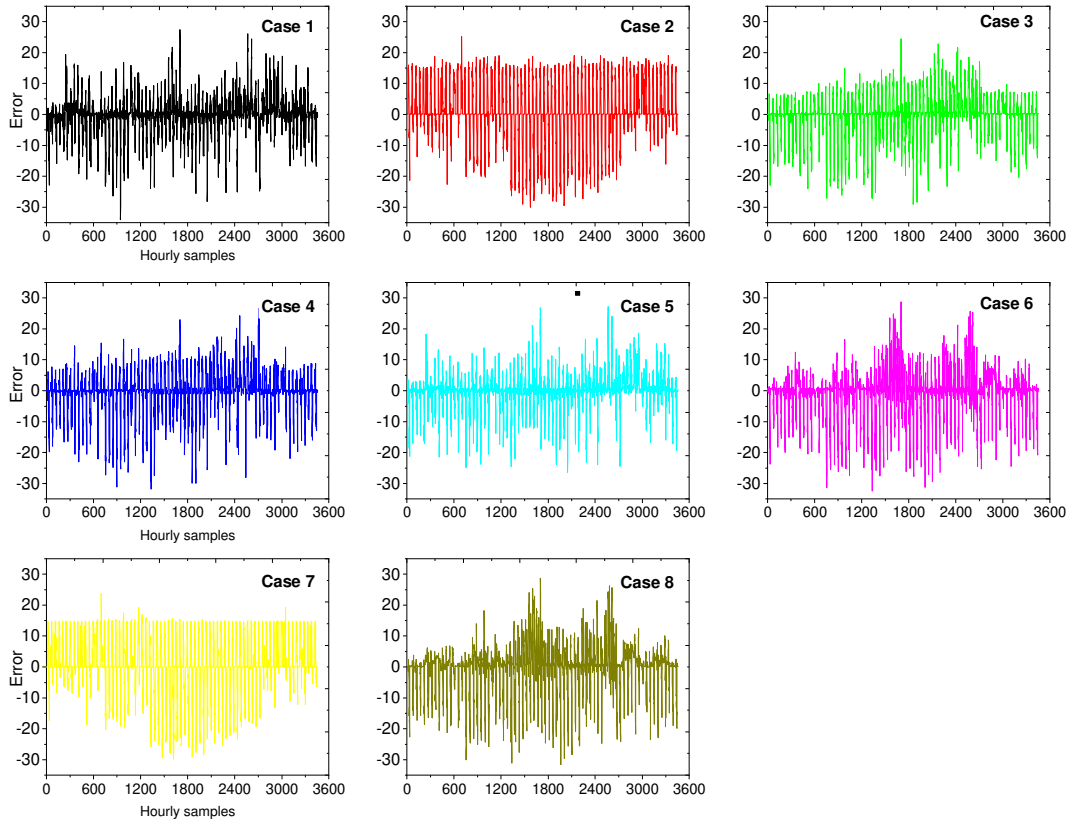


Fig.21: Thermal efficiency error

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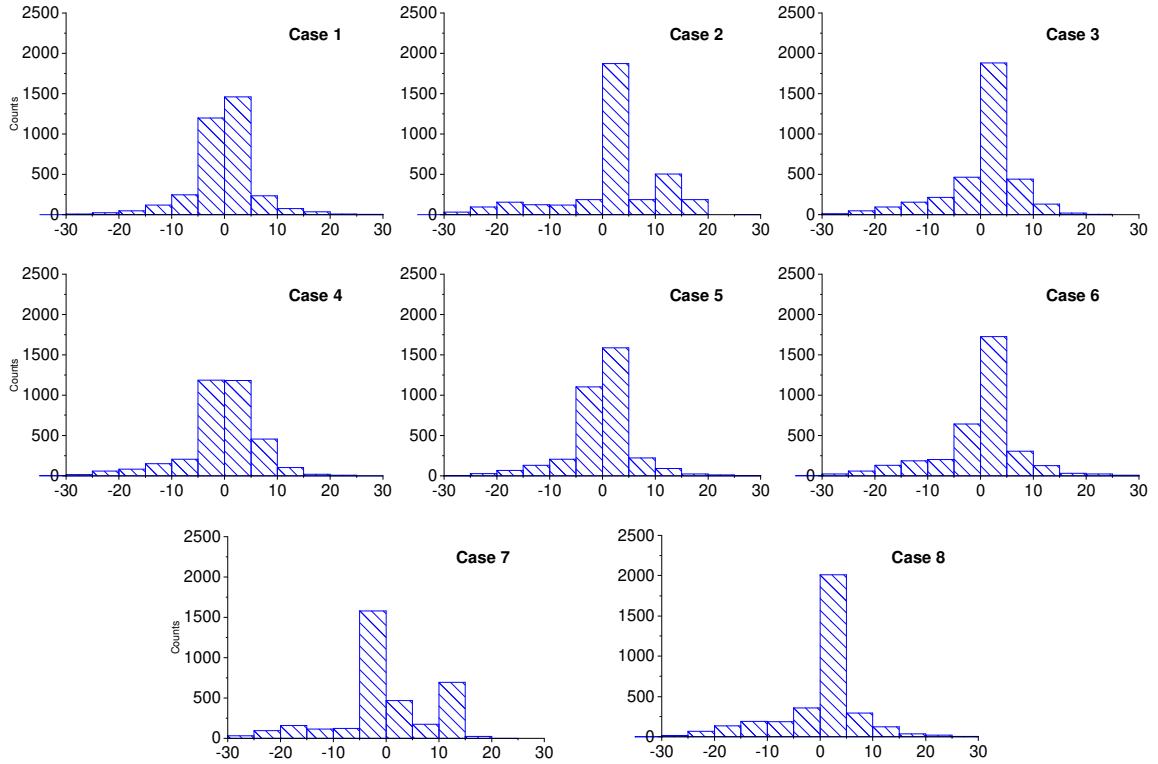
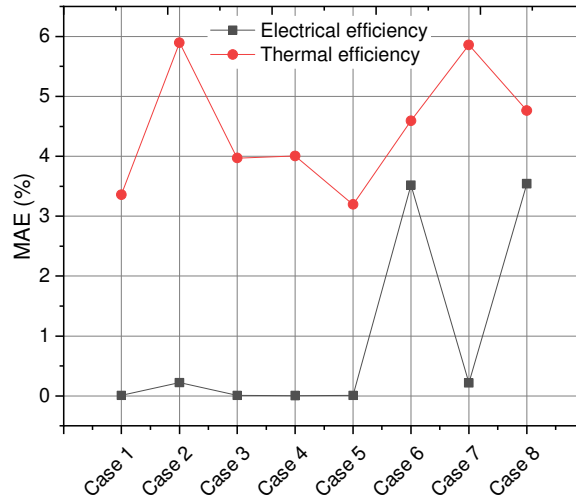


Fig.22: Thermal efficiency error histograms

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485 **Fig.21** depicts the errors and confirms that the case 7 presents low error, the remain cases are
 486 affected by evident spikes. The thermal efficiency error histograms (**Fig.22**) are left shift:
 487 This means that it is more probable to underestimate the thermal efficiency than to
 488 overestimate it. Furthermore, the histograms are low with not evident peaks, so positive and
 489 negative errors occur with comparable probability.



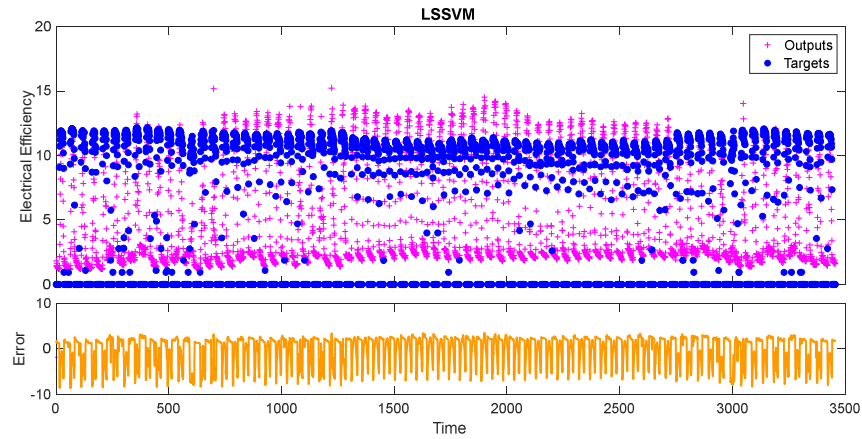
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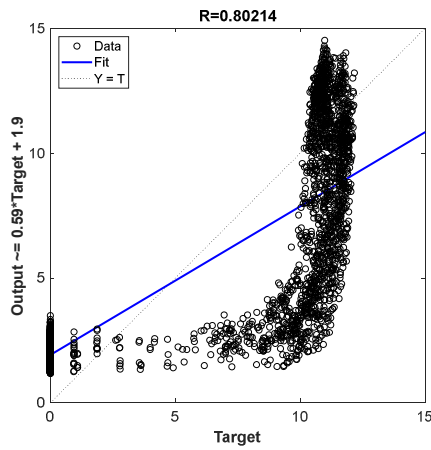
Fig.23: MAE for electrical and thermal efficiency for 8 cases

492 The MAEs of each case, calculated by **Eq.(23)**, are plotted in **Fig. 23**. Regarding the electrical
 493 efficiency, the case 1, 3, 4 and 5 show the best performances in term of MAE closed to zero.
 494 For such cases, solar irradiance and module temperature are the common variables, so
 495 humidity and wind variables are not essential to obtain high accuracy. High MAEs (up to
 496 3.5%) are remarked in the case 6 and 8 which not consider the solar irradiance as input of the
 497 neural network. MAEs of 3.2% can be obtained for thermal efficiency in case 1 and 5 which
 498 include the solar irradiance, module temperature and humidity as input. High MAEs (5.9 %)
 499 are reported for the cases 2 and 7 which not include module temperature. Such results are in
 500 accord with the correlations shown in **Fig.8**, where the electrical efficiency is strictly
 501 correlated with the irradiance, the thermal efficiency is correlated with the module
 502 temperature.

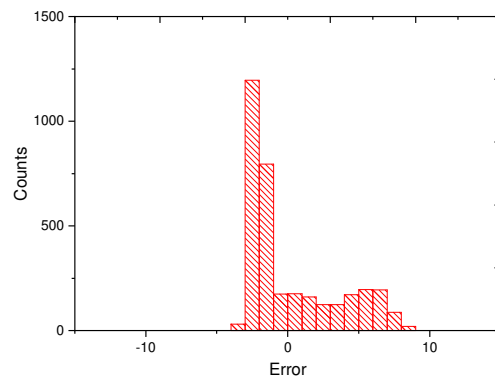
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(a)



(b)



(c)

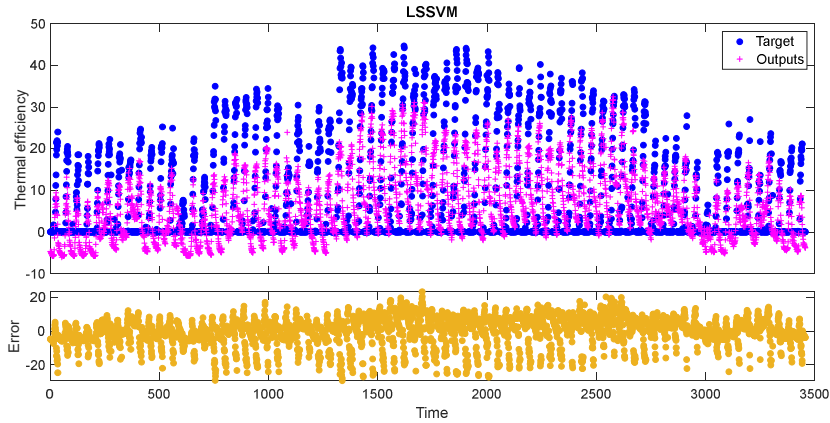
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Fig.24: Actual VS predicted (a) R (b) and Error histograms (c) of the electrical efficiency by LSSVM.

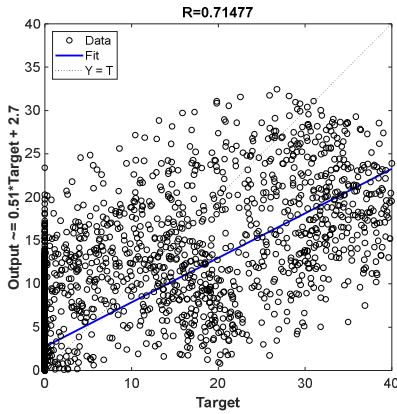
508 In order to demonstrate the high performance of the discussed neural network-based model, a
509 comparison with the LS-SVM technique is illustrated. Solar irradiance, module temperature,
510 humidity and wind (case 1) were used as input for the LS-SVM model. **Fig.24.a** plot the
511 electrical efficiency targets and outputs. It is evident that the response of the LS-SVM model
512 is very spread if it is compared with the actual electrical efficiency as the R value of 0.80214
513 confirms (**Fig.24.b**). The error distribution is left shift (**Fig.24.c**) that means most of all the
514 predicted values underestimate the actual electrical efficiency.

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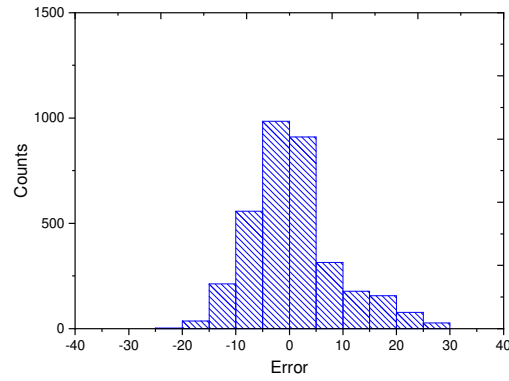
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(a)



(b)



(c)

Fig.25: Actual and predicted values of the thermal efficiency by LS-SVM (a) R value (b) and Error histograms (c) of the thermal efficiency by LS-SVM

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522 The actual and predicted thermal efficiency by LS-SVM is illustrated in **Fig.25.a**.
523 Furthermore, the low R coefficient (0.71477) confirms that exists a not strong correlation
524 (**Fig. 25.b**) and a quite similar probability to underestimate and overestimate the thermal
525 efficiency as seen by the symmetric error distribution (**Fig.25.c**).

526

Table 5: ANN vs LS-SVM

	ANN		LS-SVM	
	Electrical Efficiency	Thermal Efficiency	Electrical Efficiency	Thermal Efficiency
MAE (%)	0.0078	3.3607	2.6936	6.1546

527

528 The **Table 5** summarizes the MAE for ANN and LS-SVM using the prediction models for
529 both electrical and thermal efficiency. The results of the case 1 were adopted to compare the
530 performance of the NN-based model. It can see that the ANN outperforms the LS-SVM
531 showing very low MAE values for both efficiencies. The accuracy assessment confirms that
532 the electrical and thermal efficiency of a PVT air system can be predicted with higher

533 performance by using an ANN than LS-SVM based-model, with a reducing up to 2.7% for
534 electrical efficiency and up to 2.8% for the thermal efficiency.

535 **Conclusion**

536 The study presents the results of an ANN model to predict the electrical and thermal
537 efficiencies of PVT air systems. The first part of the paper introduces a method to model the
538 electrical and the thermal efficiencies. Such method is evaluated by using actual
539 measurements of weather conditions. Then the efficiency modeled values are applied to train
540 and test a predictive model based on ANN using the weather data as an input for the neural
541 networks. Different combinations of the weather variables were considered to assess the
542 performance of the ANN- based model. The results are presented, and an accuracy analysis is
543 performed by RMSE, R coefficient and MAE. The outcomes demonstrate that the choice of
544 the variables as input of the neural network is very important to perform a model with low
545 error. Furthermore, the solar irradiance and the module temperature are the most important
546 variables to consider as input in a NN-based model respectively. The results also demonstrate
547 higher performance of the ANN than LS-SVM. Furthermore, the electrical efficiency can be
548 predicted with higher accuracy than the thermal efficiency.

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