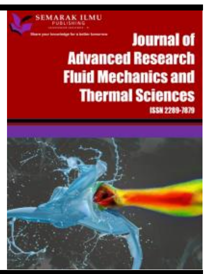
SEMARAK ILMU PUBLISHING

Journal of Advanced Research in Fluid Mechanics and Thermal Sciences

Journal homepage: https://semarakilmu.com.my/journals/index.php/fluid_mechanics_thermal_sciences/index
ISSN: 2289-7879



Improvement of Cork Insulating Properties using Ecological Treatment with Prediction of the Diffusion Coefficient by ANN Approach, under the Effect of the Area and the Direction of the Cut

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ARTICLE INFO

Article history:
Received 23 May 2023
Received in revised form 15 August 2023
Accepted 26 August 2023
Available online 14 September 2023

Keywords:
Cork; THT; diffusion coefficient; modelisation; optimisation; ANN

ABSTRACT

The significance of this work involves improving the mechanical characteristics of cork with a high temperature treatment (THT) ecological treatment taking into consideration different parameters such as the growing area (Medea, Jijel and Skikda), the cutting direction (radial, tangential and longitudinal) and the nature of samples (native and treated). The THT result in the modification of the transport properties particularly the cork mass diffusion coefficient. The value of the apparent diffusion coefficient that best fit the experimental data was evaluated by the calibration of the developed mathematical model results. Thus, it can be concluded that the heat treatment led to a very significant improvement in the diffusion coefficient for treated cork that is grown in Jijel area and cut in the tangential direction. To refine the calculations, all the obtained results were optimized by the Bat-algorithm. The apparent coefficient diffusion ranges from $D_{JTn}=3.05\text{x}10^{-12} m^2 s^{-1}$ to $D_{JTt}=1.17\times10^{-13} m^2 s^{-1}$, is determined with a root mean square error of 10^{-5}. Furthermore, this investigation was completed by developing an artificial neural network model (ANN) in order to predict the impact of the different parameters on the apparent coefficient diffusion. Indeed, the results mentioned above have been confirmed by the neural network of an optimal architecture of (5-5-13-1) with a correlation coefficient value is equal to 0.9995.

1. Introduction

Cork is a biomaterial identical with the other polymeric materials in mass insulation purpose [1,2]. However, the quality-price ratio of the native cork makes it less competitive. To resolve this shortcoming many researchers have set out to study the cork parameters in order to improve its mechanical properties [3,4]. Knowing that weather condition does not affect the chemical composition of cork but have an influence on both is density and the cork oak annual growth, which has been recently confirmed by the impact of the irrigation on cork properties [5-8]. In terms of heat exchange performance, Cortes *et al.,* [9] have studied the thermal insulation effect of production

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https://doi.org/10.37934/arfmts.109.1.177187

cork in building walls. Rosa and Fortes [10] have treated thermally cork in free air at temperatures ranging between 100°C to 300°C. She noticed that the samples swelled and their masses decreased considerably. These findings are due to the swelling of the lenticular canals while the cell walls, initially wavy, become rather rectilinear with modification of their tortuosity. To prevent such effect, it was suggested to treat cork sample under an inert gas (Argon) and examining the effect of other operating parameters such as the cutting direction as well as the optimal high temperature treatment (THT) cycle with boiling on the cork behavior. Kermezli *et al.,* [11] have confirmed the temperature effect of the THT cycle on the insulation properties of cork. Zemirline *et al.,* [12] have examined the impact of the diffusion direction for both native and treated cork samples after subjecting them to THT treatment under inert gas.

The present work is to bring a competitive biomaterial onto the market for insulation purpose after improving its mechanical structure in terms of several parameters, the growing area of cork, the cutting direction of samples and its nature (native and treated). By adopting the concept of the electrical conductivity, the experimental results in transient mode are calibrated with a developed mathematical model to determine the apparent diffusion coefficient (D_{app}). It is worth noting that the effect of the cork treatment is connected to the D_{app} value. As a result of the large number of influential parameters on the insulating properties of the studied material, the analysis is refined by using the artificial neural network model (ANN) which is going to be beneficial [13-16]. It is worth mentioning that the application of the ANN model will predict any material property without necessary conducting practical experiments applied for each sample.

2. Materials and Methods

2.1 Experimental Section

With regard to mass transport property, the D_{app} is a potential parameter that plays a significant role in terms of mass insulation. Indeed, cork is an anisotropic porous material and to evaluate its diffusive properties plank of cork classified as Class A in terms of quality were collected from different areas of Algeria namely Medea, Jijel and Skikda [17-19]. The experiments were carried out on chips obtained by cutting planks with an average surface area of 4.4×10^{-2} m^2 and a thickness of 3×10^{-3} m in three directions: Radial, Tangential and Longitudinal. Depending on the cutting direction and the growing area as well, the samples were treated following the treatment protocol using the optimal THT cycle inspired from the thermal cycle obtained by Zemirline *et al.,* [12] as shown in Figure 1. By adopting the conductimetric analysis method, that measures the transient conductivity of a chemical species released by the cork sample, and on the basis of the developed model Eq. (2) which is derived from mass balance in transient mode we defined the parameters influencing the D_{app} while following the evolution of the instantaneous concentration of sodium chloride (NaCl) for different samples [11]. The obtained results are grouped together in a file, which would provide a database for any subsequent numerical processing.

The improvement in insulation was confirmed by scanning electron microscope (SEM) (Quanta 250 from FEI) and infrared tests (IR) (by FT-IR Spectrometer Bruker, Tensor II, Sample Compartment RT-DLaTGS).

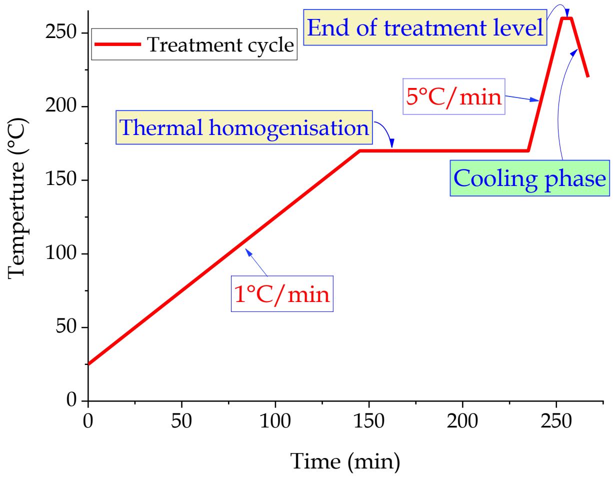


Fig. 1. Optimal heat treatment cycle (THT)

Figure 2(a) and (b) from the SEM analysis depict the cork's cell walls both before and after treatment. The examination of the pictures makes it evident how the THT treatment causes the rigorous shape of the native cork cells (Figure 2(a)) to wrinkle (Figure 2(b)), increasing the cork's tortuosity and, consequently, its insulation. Likewise, the IR test of Figure 3 reveals the attenuation of the intensity of the groups after THT treatment, particularly for the wavelength of 1261.93 and 1034.1 (cm^{-1}), due to the modification in the chemical cork structure.

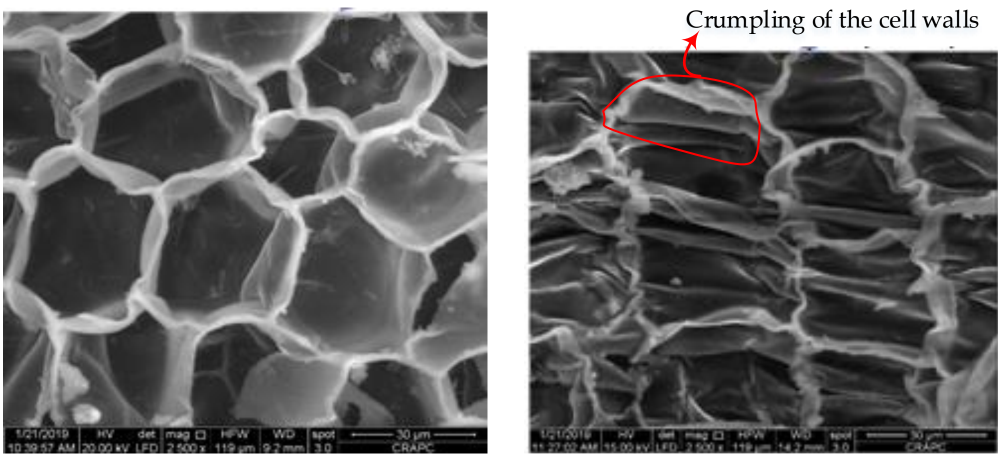


Fig. 2. Effect of treatment on cork cell walls observed by SEM (a) native (b) treated

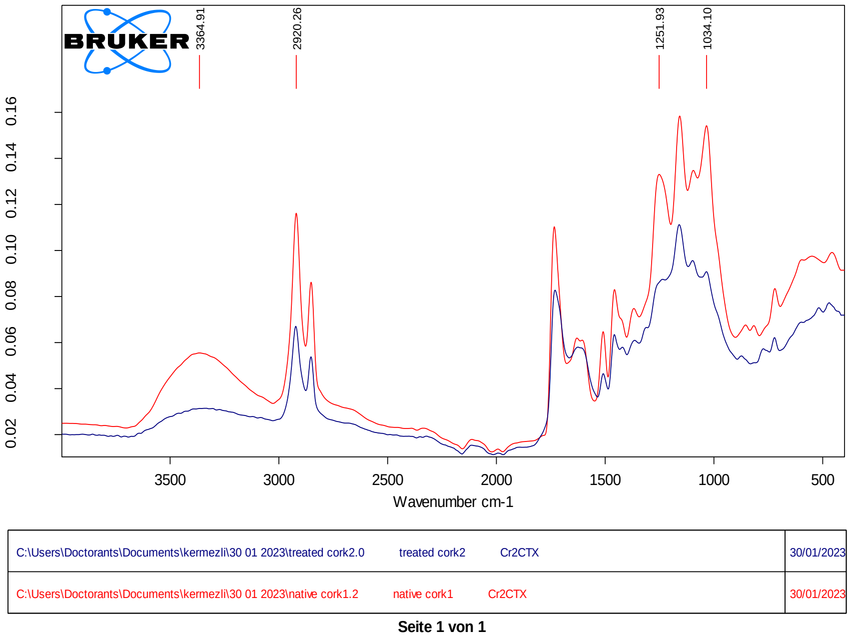


Fig. 3. IR-FT spectrum of native and treated cork samples

2.2 Modeling

The primary objective of the mathematical modeling of mass transfer through the cork chip is to establish the analytical expression for diffusion that links the variation of the electrolyte concentration (NaCl) with the characteristic parameters of the sample such as the D_{app}, characteristic dimension of the cork chip etc. This expression is derived from the mass balance of the chemical diffusion species on the volume element dv in the time interval dt. The resulting balance equation is partial differential equation (PDE) order 2 with no source term known as Fick's second law [20]. Given its complexity and to obtain simple analytical expressions that can be used experimentally, we were compelled to introduce some simplifying assumptions. The balance equation is that:

$$(Accumulation\ term) - (Diffusion\ term) = 0 \tag{1}$$

For homogeneous medium and no chemical reaction, the mass transfer PDE solution is solved by using the Laplace transform method. The spatio-temporal evolution of the electrolyte mass released at the chip wall is expressed by the following analytical expression given by Kermezli *et al.,* [11]:

$$\frac{m_t}{m_\infty} = 1 - \frac{8}{\pi^2}\sum_{n=0}^{\infty}\left\{\frac{1}{(2n+1)^2}.\exp\left(-\frac{(2n+1)^2.\pi^2.D_{iapp}}{4l^2}.t\right)\right\} \tag{2}$$

With: *l* is the half thickness of the sample; m_t the mass of the substance released at the time t; m_∞ the mass of the substance transferred after total desorption of the sample at infinite time (at the equilibrium) under the operating conditions. We specify that it is possible to establish a relationship between the instantaneous mass m_t and the concentration C_t:

$$\frac{m_t}{m_\infty} = \frac{C_t}{C_\infty} \tag{3}$$

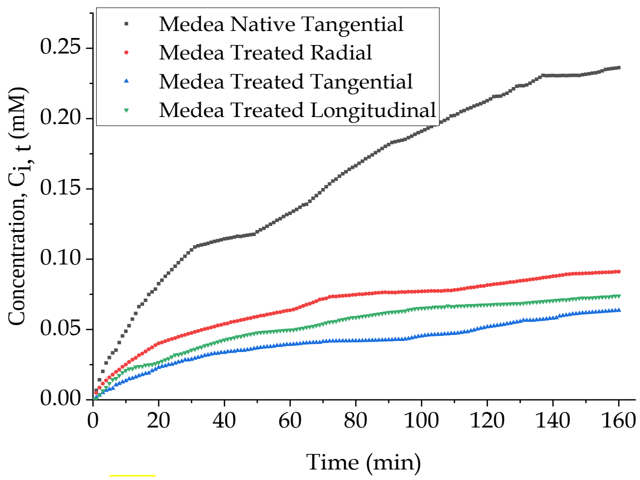
2.3 ANN Approach

ANNs are computational systems inspired by the learning algorithm of biological neurons [16]. ANN it is powerful modeling technique widely used for solving many classes of complex problems relating to modern industry [21]. To estimate the mass isolation of cork as a function of the operating conditions presented in the experimental section, we will create a statistical method based on ANNs. Our test database has 2880 data points. The input of the ANN neuron combines the morphological characteristics of the cork and the operating conditions: direction of diffusion, growth zone, nature (native and treated) and time whereas the output of the ANN is the Dapp.

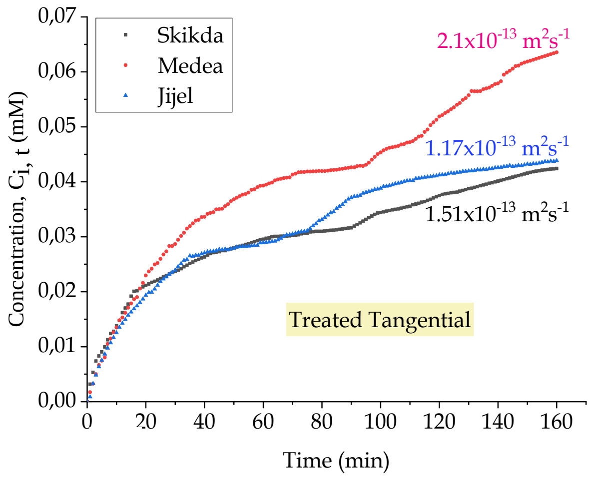
3. Results and Discussion

3.1 Modeling and Experimental

The D_{app} is determined by calibration between the instantaneous concentration of NaCl evaluated from the model of Eq. (2) and the concentration collected from experimental measurements. Thus, the obtained results are presented in Figure 4(a), where the effect of heat treatment and the cutting direction on the D_{app} is identified. As a result, the treated cork is characterized by a better D_{app} compared to native cork. In addition, the chips whose cut in tangential direction present a better diffusion coefficient than the other directions. Furthermore, the effect of the growth area on the D_{app} is investigated as depicted in Figure 4(b), which indicates that the cork grown in Jijel and Skikda lead to better results.



(a)



(b)

Fig. 4. Variation in concentration with respect (a) Cutting direction (b) growing area

There is a very good agreement between the experimental instantaneous electrolyte concentration profile with that obtained by the model as shown in Figure 5. Thus, the model faithfully describes the mass transfer phenomena in the cork sample.

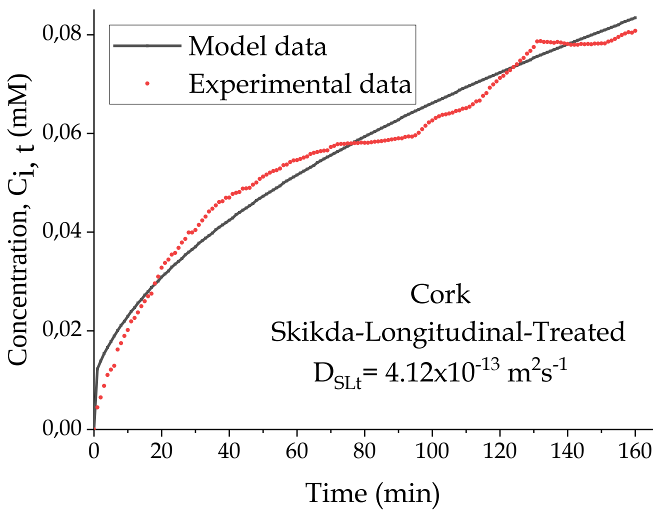


Fig. 5. Calibration of the experimental results with the diffusion model

Table 1 sets the obtained D_{app} for different operating conditions after performing the Bat-Algorithm optimization [22].

Table 1
D_{app} depending operating conditions

Zone	Direction	Native	Treated
		Dapp (m^2s^{-1})	Dapp (m^2s^{-1})
Skikda	Tangential	2.25×10^{-12}	1.51×10^{-13}
	Longitudinal	5.19×10^{-12}	4.12×10^{-13}
	Radial	6.23×10^{-12}	5.95×10^{-13}
Jijel	Tangential	3.05×10^{-12}	1.17×10^{-13}
	Longitudinal	3.6×10^{-12}	2.62×10^{-13}
	Radial	5.07×10^{-12}	4.50×10^{-13}
Medea	Tangential	2.6×10^{-12}	2.10×10^{-13}
	Longitudinal	2.9×10^{-12}	3.93×10^{-13}
	Radial	3.4×10^{-12}	4.57×10^{-13}

3.2 ANN Modeling

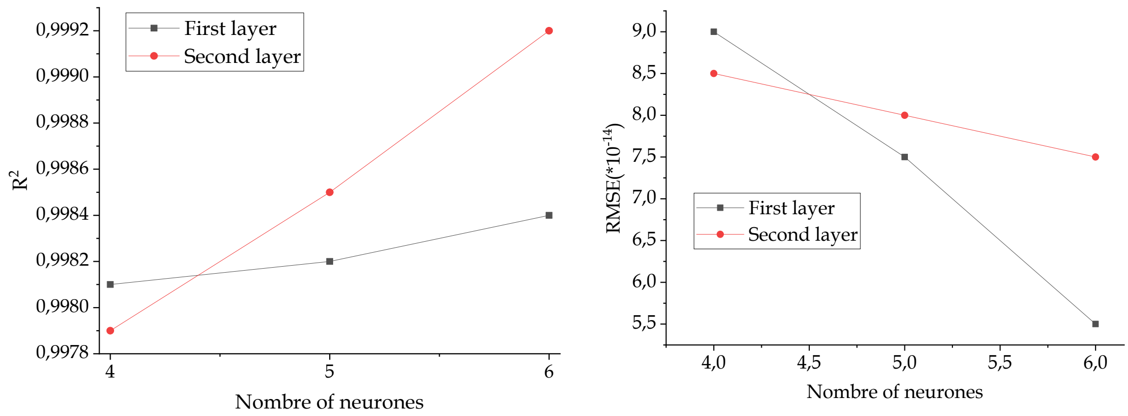
The ANN Multilayer perceptron (MLP) network method was implemented by applying five neurons to the input layer: growing area, cutting direction, nature, diffused concentration and the time [23,24]. Whereas, the output layer contains only single neuron, which is the D_{app}. 60% of our experimental database is used for training, 20% for testing and 20% for validation. The main objective is to design an optimal network that makes accurate predictions of D_{app} for other input various values.

The mean squared error (RMSE) and the correlation coefficient (R^2) are used as criteria to evaluate the quality of the neural network model. The $R^2$and the RMSE are expressed by:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(C_i^{cal} - C_i^{\exp}\right)^2}{\sum_{i=1}^{N}\left(C_i^{cal} - \overline{C_i^{\exp}}\right)^2} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(C_i^{\exp} - C_i^{cal}\right)^2} \tag{5}$$

where, C_i^{cal} is the concentration calculated by the model, C_i^{exp} is the instantaneous concentration registered experimentally and $\overline{C_i^{exp}}$ is the average value of concentrations obtained for a given experiment. To optimize the architecture of network, the values of R^2 and RMSE were tested successively for one and two hidden layers using 4, 5 and 6 neurons for each layer [25]. The analysis of the results depicted in Figure 6(a) and (b) shows that the best results were obtained in the case of two hidden layers that will be adopted for the further architecture optimization.



(a) (b)

Fig. 6. Determination of the number of hidden layers based on (a) R^2 and (b) RMSE

In addition, Figure 7 illustrates the variation of R^2 as a function of the number of neurons. The optimal R^2 is obtained from the combination of the number of neurons in first and second layer (nnh1, nnh2) which is respectively 5 and 13 (neurons in the hidden layer).

Figure 8 delineates the variation of RMSE with the number of neurons in the two hidden layers. The RMSE reaches a minimum value of 0.0141×10^{-12} when: nnh1 has 5 and nnh2 has 13neurons.

From the obtained results depicted in Figure 7 and 8, it is apparent that the optimal architecture for the neural model is (5-5-13-1).

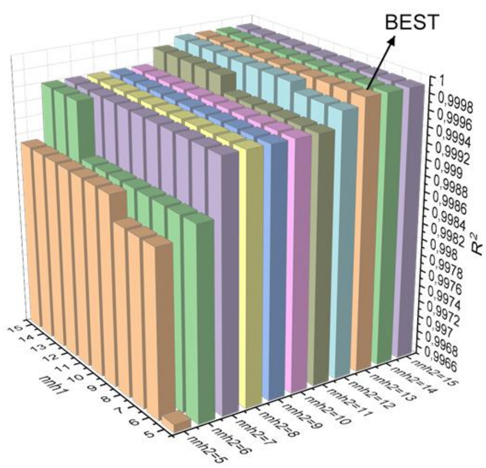


Fig. 7. Optimization of R^2 according to the network architecture

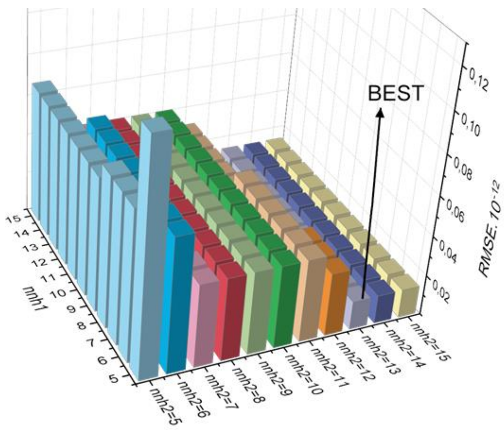


Fig. 8. Variation of RMSE with respect to the network architecture

Table 2 summarizes the parameters involved in determining the optimized model ANN.

Table 2
Model structure optimized by ANN

Network type	Algorithm	Input layer	1st hidden layer		2nd hidden layer		Output layer	
		Neurons number	Neurons number	AF	Neurons number	AF	Neurons number	AF
FFBP NN (newff)	SCG (trainscg)	5	5	purelin	13	purelin	1	trainlm

Figure 9 shows the R^2 values for the data analysis phases (training, validation and testing) are close to 1 (R^2=0.9999). Hence, the implementation of the ANN was deemed to be very satisfying and robust.

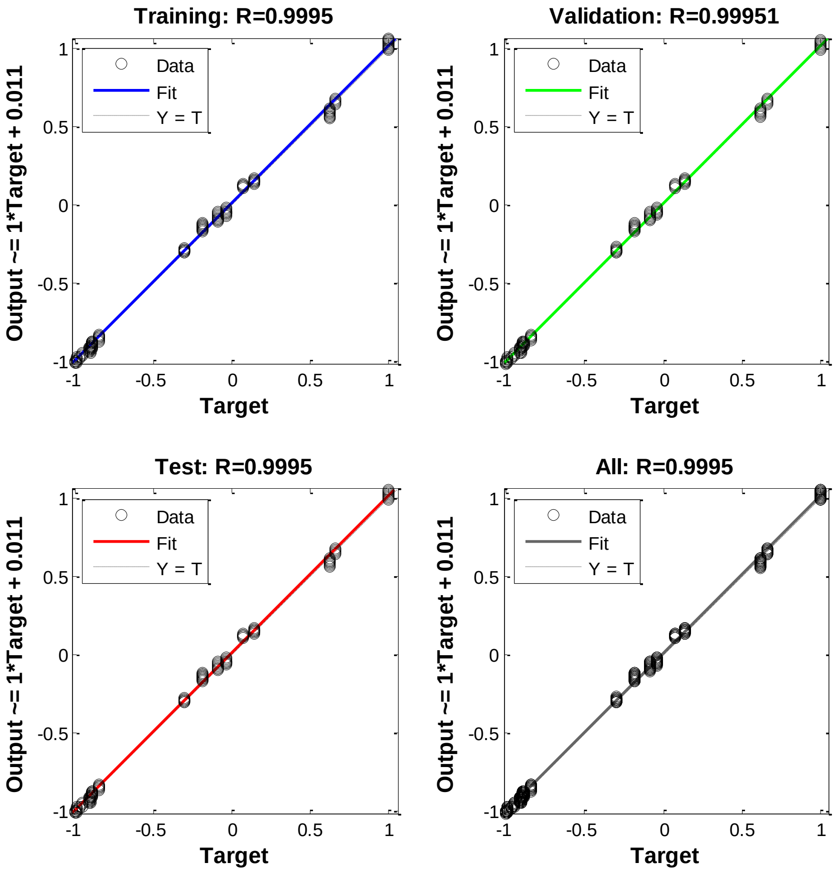


Fig. 9. Regression plots

Figure 10 shows the graph related to the validation performance of the results referring to the obtained D_{app} values. In carrying out the neural network technique, a better performance is obtained by adopting the MSE as criterion.

The results illustrated in Figure 10 provides information on the value of the root mean square error during training, validation, and testing against the number of epochs. The training network gave the minimum validation root mean square error (MSE) of about 0.51191x10^{-3} at the 9th epoch. The MSE is quite small, showing that the training network did not experience any over fitting issues. It can be pointed out that, up to 9 epochs, despite the few deviations in the MSE formation, the validation and the MSE test in extrapolation remain in a straight line, which indicates that there is an absence of network over fitting.

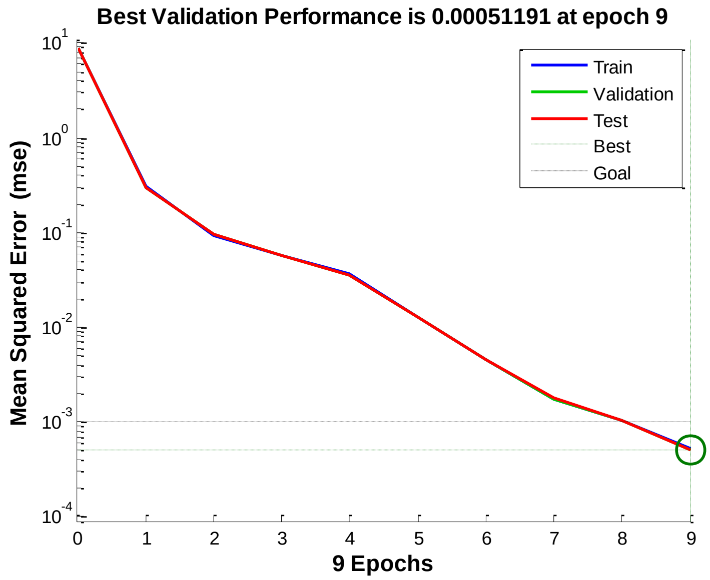


Fig. 10. Performance curve

4. Conclusion

In the present work, an experimental investigation was carried out to improve the cork properties by analyzing its diffusion coefficient D_{app} for insulation purpose. This study focuses on the influence of several parameters that have a great impact on the material insulation performance, such as the growing area (Medea, Jijel and Skikda), the cutting direction (longitudinal, transversal and radial) and the nature of the cork (native and treated). The experimental results have clearly established that the insulation characteristic of cork is improved after its treatment by THT whatever the growing area. Indeed, the Dapp of the treated cork is about of $10^{-13}m^2s^{-1}$. Noting that the values of D_{app} were obtained by calibration between the model results and the experimental data collected by conductmetric method and refined by Bat-Algorithm with an accuracy of 10^{-5}. The experimental investigations have shown that the cutting direction of the samples has a direct impact on its diffusion coefficient, which follows the following trend: $D_{Tt}<D_{Lt}<D_{Rt}$. The impact of the growing area has been studied where the obtained results are as follows: $D_{JTt}=1.17x10^{-13}<D_{STt}=1.51x10^{-13}<D_{MTt}=2.1x10^{-13}(m^2s^{-1})$. This trend indicates that the cork collected from Jijel is more efficient for insulation use than the others regions. Moreover, given to the interaction of the parameters and for the purpose of analyzing their effect, it seemed necessary to use the ANN modeling. In this section and through our experimental database, it emerged that the optimized architecture is (5-5-13-1) with a correlation coefficient (R^2=0.9995) close to unity. Having also opted for RMSE=$0.0141x10^{-12}$ as a performance criterion.

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