

# Designing of Open Cell Aluminum Foam Heat Exchanger and Modelling of its Thermal Performance by Using Ann Method

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## ABSTRACT

This study deals with the design and thermal performance modeling of aluminum foam open cell heat exchangers by making use of experimental data where the aluminum featuring different numbers of pores per inch (PPI) was used and the modeling was based on the Artificial Neural Networks (ANN) method. The open celled aluminum foams with 10, 20 and 30 PPI features were shaped into heat exchangers. The heat exchangers were placed into a rectangular groove then hot water was circulated within the heat exchanger tubings and cold air generated from a fan was blown over the tubings at varying rates. For every heat exchanger, the variations of Reynolds number with Nusselt number, pressure drop with air speed, and friction with Reynolds number were presented on graphs. By making use of the experimental data, ANN modeling was carried out for materials with 10, 15, 20, 25 and 30 PPI porous densities. The ANN input parameters for the developed system were  $T_{hin}$ ,  $T_{cin}$ ,  $T_{hinw}$ ,  $u$  and PPI, whereas the output parameters were chosen to be  $T_{hout}$ ,  $T_{cout}$ ,  $T_{houtw}$  and  $\Delta P$ . When the results from the Artificial Neural Networks were analyzed and compared with the experimental results, it was found that a close correlation exists between the two. With the result of this study, it becomes clear that the Artificial Neural Networks numerical modeling can be safely applied to aluminum foam heat exchangers.

**Keywords:** Aluminum foam, heat exchanger, performance, artificial neural network

## Açık Hücreli Alüminyum Köpüğün Isı Değiştiricisi Olarak Tasarımı ve Isıl Performansının Yapay Sinir Ağları Yöntemi ile Modellenmesi

### ÖZ

Bu çalışma, deneysel verilerden yararlanılarak farklı ppi özelliklerine sahip açık hücreli alüminyum köpüğün ısı değiştiricisi olarak tasarımı ve ısı performansının yapay sinir ağı (YSA) ile modellenmesi üzerinedir. PPI 10, 20 ve 30 özelliklerine sahip açık hücreli alüminyum köpükler, ısı değiştirici formuna getirilmiştir. Isı değiştirici bir kanala yerleştirilerek içinden sıcak su geçirilip, üzerine bir fan yardımı ile değişen debilerde hava üflendi. Her ısı değiştirici için; Reynolds - Nusselt, Etkenlik - Hız, Basınç düşümü - Hız ve Sürtünme - Reynolds sayısı değişimleri incelendi. Deneysel veriler kullanılarak 10, 15, 20, 25 ve 30 PPI gözenek yoğunlukları için YSA modellemesi yapılmıştır. Geliştirilen sistemde YSA uygulanan giriş parametreleri  $T_{hin}$ ,  $T_{cin}$ ,  $T_{hinw}$ ,  $u$  ve PPI, çıkış parametreleri ise  $T_{hout}$ ,  $T_{cout}$ ,  $T_{houtw}$  ve  $\Delta P$  şeklindedir. YSA'dan elde edilen sonuçlar ile deneysel verilerin istatistiksel analizleri yapıp mukayese edildiğinde, iki grup verinin uyumlu olduğu tespit edilmiş ve aralarında anlamca fark olmadığı görülmüştür. Bu çalışmanın sonucu Yapay Sinir Ağlarının alüminyum köpük ısı değiştiricilere güvenli bir şekilde uygulanabileceğini açıkça göstermiştir.

**Anahtar Kelimeler:** Alüminyum köpük, ısı değiştirici, performans, yapay sinir ağı

### 1. INTRODUCTION (GİRİŞ)

Materials with cellular nature are among the most important improved surfaces due to their multifunctional features. Some of these valuable features are improved heat transfer area to volume ratio,

good stiffness and strength, as well as enhanced flow mixing capability. With the advancing technology, these materials can find diverse application areas including being used as heat exchanger materials ( as used in this study); used in combustion chambers and cryogenics, as cladding materials on structures, used for strain isolation, geothermal operations, petroleum reservoirs,

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catalytic beds, compact heat exchangers for airborne equipment, air-cooled condensers for air conditioning and refrigeration systems, and as compact heat sinks for power electronics [1]. The use of open-cell metal foams has been widely increasing given by its diverse properties in various areas including aerospace, electronics and automotive among others. They are a relatively new class of materials with very promising applications in which their low densities and other thermal, mechanical, electrical and acoustical properties make them an excellent means of performance improvement [2]. Sertkaya et al. carried out a study on experimental investigation of thermal performance of aluminum finned heat exchangers and open-cell aluminum foam heat exchangers. They found that for both types of heat exchangers, as the velocity of refrigerant increases, the effectiveness drops and pressure loss increases. They also found that the effectiveness was higher at lower Reynolds numbers. It was found that aluminum fin heat exchangers transfer more heat than their aluminum foam counter parts [3]. Babcsan et al. conducted a study on thermal and electrical conductivity measurements of aluminum foams [4]. Dukhan and Quinones carried out a convective heat transfer analysis of open cell metal foam for solar air heaters [5].

Artificial neural networks (ANN), can be described as a mathematical model that tends to be influenced by the structure and /or functionalities of biological neural networks. The ANN is composed of interrelated groups of artificial neurons, which excute and transfer information using a connectionist approach to computation. Generally speaking, ANN is an adaptive system that changes its structure on the basis of external or internal information conveyed within the network during the learning phase. Nowadays, the neural networks encountered tend to have statistical data modeling tools with a non-linear nature.

Ismail et al. investigated design and optimization of an Atkinson cycle engine with the Artificial Neural Network Method [7]. Sözen et al. studied Solar-energy potential in Turkey. They investigated meteorological and geographical data developed to determine the solar-energy potential in Turkey using artificial neural-networks (ANNs) [8].

In this study, aluminum foams with varying PPI features were shaped into heat exchangers and experimental data were used to model their thermal performances by using Artificial Neural Networks. The experimental data were used to carry out the ANN modeling for samples with PPI values of 10, 15, 20, 25 and 30. The obtained numerical results were closely compatible with the experimental data.

## 2. EXPERIMENTAL STUDY (DENEYSEL ÇALIŞMA)

The experimental setup used in this study is illustrated in Fig. 1. In this study, heat capacity of open cell aluminum foam heat exchangers were examined experimentally for the best thermal performance. Three different heat exchangers were investigated, where open-cell aluminum metal foams with 10, 20 and 30 pores per inch (PPI) and the dimensions of 200x200x100 mm acted as cooling fins. Each heat exchanger contained 18 tubes of 10 mm diameter that were used as passages for hot water. These tubes were imbedded in the aluminum foam to create three parallel passages. During the tests, a fan was used to blow cold air at variable flow rates over the heat exchangers in the experimental channel. The surface areas per unit volume  $\sigma$  of these materials were 1200, 1500 and 1800  $\text{m}^2/\text{m}^3$  for PP 10, PP 20 and PP 30 types, respectively. Each heat exchanger with 6 parallel pipes forms a trajectory such that the coolants follow an S-curve. After insertion, the aluminum pipes were blown

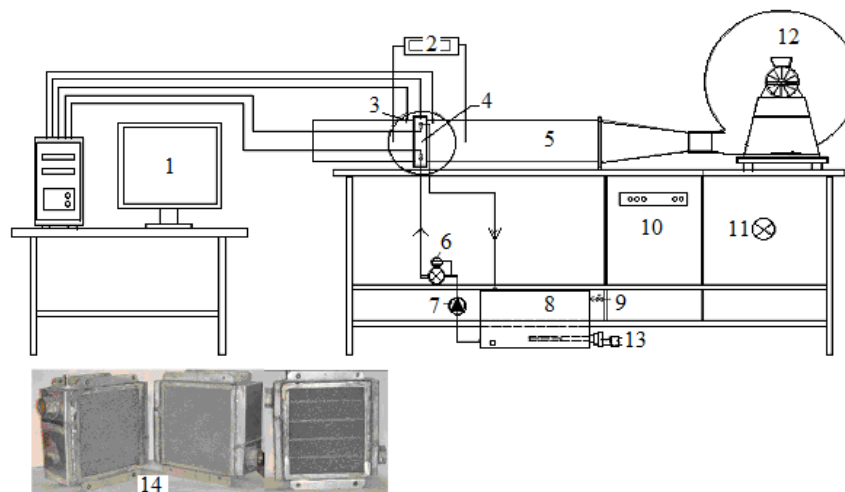


Figure 1. Experimental set-up (Deneysel Düzenek)

They are usually used to model complex relationships between inputs and outputs or to find patterns in data [6].

up to allow a good contact surface with the foam. In each system, water was used as hot fluid and air as cold

fluid. A pump was used to maintain water circulation in and out of tank. When water had reached a desired temperature value, air which was controlled with an inverter, was blown across the heat exchangers. The air velocities were set between 0,5 m/s and 5,5 m/s and adjusted by varying the air speed of the blowing fan. Values obtained from the measurements of pressure, velocity and temperatures were used in the calculations [9]

(1.Computer, 2.Digital manometer, 3.Termokuples, 4.Exchanger-test section, 5.Canal, 6.Digital flow meter, 7.Pump, 8.Water tank, 9.Water filling, 10.Electricity board, 11.air speed control, 12.Fan, 13. Heater, 14.Aluminum foams heat exchangers.)

## 2.1 Aluminum foam theory (Alüminyum Köpük Teori)

In a porous medium, heat transfer between filaments is through conduction while the transfer between the filaments and the environment takes place by means of convection method. The following equations were used for plotting the graphs and offering necessary comments from the study. Reynolds number ( $Re$ ) can be given as

$$Re = \frac{d_h u}{\nu} \quad (1)$$

where  $u$  is air velocity,  $d_h$  is hydraulic diameter and  $\nu$  is kinematic viscosity of the air.  $d_h$  can be calculated from,

$$d_h = \frac{4A}{P} \quad (2)$$

where  $A$  is cross section area of the duct and  $P$  is wetted perimeter of the duct.

Nusselt number ( $Nu$ ) can be defined as follows:

$$Nu = \frac{h d_h}{k} \quad (3)$$

where  $h$  is heat transfer coefficient,  $k$  is thermal conductivity. Convective heat transfer is expressed as follows

$$q = h A \left( \frac{T_{hinw} + T_{houtw}}{2} - \frac{T_{cin} + T_{cout}}{2} \right) \quad (4)$$

$$q = \bar{h} (\pi N d Z) \left( \frac{T_{hinw} + T_{houtw}}{2} - \frac{T_{cin} + T_{cout}}{2} \right) \quad (5)$$

Similarly, the cold fluid receives heat expressed as follows

$$q = \rho_c N_T S_T Z u_\infty c_{pc} (T_{cout} - T_{cin}) \quad (6)$$

$\bar{h}$  has been defined as

$$\bar{h} = \frac{\rho_c N_T S_T Z u_\infty c_{pc} (T_{cout} - T_{cin})}{(\pi N d Z) \left( \frac{T_{hinw} + T_{houtw}}{2} - \frac{T_{cin} + T_{cout}}{2} \right)} \quad (7)$$

where  $N_T$  is the number of cylinders in the transverse direction of a bank,  $S_T$  is transverse pitch in a bank of cylinders,  $N$  is the number of cylinders in a bank,  $d$  is pipe diameter and  $Z$  is depth.

Friction factor ( $f$ ) can be written as follows:

$$f = \frac{\Delta p}{4 \left( \frac{L}{d_h} \right) \left( \frac{\rho_c u^2}{2} \right)} \quad (8)$$

where,  $\Delta p$ ,  $L$ ,  $d_h$ ,  $\rho_c$  and  $u_\infty$  denote pressure drop, channel length, diameter of the hydraulic cylinder, air density and air speed, respectively.

## 2.2 Artificial Neural Networks (Yapay sinir Ağları)

Artificial Neural Networks (ANN) is a generic name given to scientific studies aimed at creating mathematical model, capable of imitating human brain by taking into account all angles of the human cells operating mechanism. The ANN can be modeled to mimic the human brain and its functional principles both in terms of software and hardware.

ANNs are systems in which the artificial neural cells are interconnected to each other. Basically, this system is composed of three layers, input layer, hidden layers and output layer. The input layer is where the ANN data are uploaded. The data entering this layer are not processed, there is as many number of inputs as the artificial cells in this layer. Hidden layers are responsible for the processing of the data from the input layer. The number of layers to be established varies from a problem to problem. The number of layers is independent of the input and output data. Every layer processes the data, and then conveys them to the next layer. The number of cells in the hidden layers can be more than one. Each cell is connected to all cells in the previous layer. Input data is established into every cell by multiplying the data from the previous layer by the weights and taking their sum.

$$net_j^k = \sum_i w_{ij}^{k-1,k} o_i^{k-1} + \theta_j^k \quad (9)$$

If logarithmic sigmoid is used as activation function, the neuron output is then computed as follows:

$$o_j^k = f \left( net_j^k \right) = \frac{1}{1 + \exp \left( -net_j^k \right)} \quad (10)$$

where  $o_i^{k-1}$  is the output of the  $i$ th neuron of the  $(k-1)$ th layer,  $w_{ij}^{k-1,k}$  is the weight connecting the  $i$ th neuron of

the (k-1)th layer to the  $j$ th neuron of the  $k$ th layer.  $net_j^k$  and  $\theta_j^k$  are the input and threshold values, respectively, for the  $j$ th neuron of the  $k$ th layer. The output layer executes the data from the hidden layers and converts them into suitable outputs. There is one output for every single output cell. There are different learning algorithms that can be applied to train a neural network. The most popular of them is the back propagation algorithm, which has different variants. Standard back propagation is a gradient descent algorithm. It is very difficult to know which training algorithm will be the fastest for a given problem, and the best one is usually chosen by trial and error. An ANN with a back propagation algorithm learns by changing the connection weights, and these changes are stored as knowledge.

To calculate the error during the learning, the root-mean-squared error (RMSE) is used. RMSE is defined as follows.

$$RMSE = \left( \frac{1}{n} \sum_{j=1}^n |a_j - p_j|^2 \right)^{1/2} \quad (11)$$

In addition, absolute fraction of variance ( $R^2$ ) and mean absolute error (MAE) are defined as follows, respectively:

$$R^2 = 1 - \left( \frac{\sum_{j=1}^n (a_j - p_j)^2}{\sum_{j=1}^n (p_j)^2} \right) \quad (12)$$

$$MAE = \frac{1}{n} \sum_{j=1}^n \left| |a_j| - |p_j| \right| \quad (13)$$

Mean relative error (MRE,%) may be written as:

$$MRE(\%) = \frac{1}{n} \sum_{j=1}^n \left( 100 \times \frac{a_j - p_j}{a_j} \right) \quad (14)$$

where  $a_j$  is the actual value and  $p_j$  is the predicted value respectively.

$$x_N = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (15)$$

where  $x_N$  is the normalized value of a variable,  $x$  is a real value in a parameter,  $x_{\max}$  and  $x_{\min}$  are the maximum and

minimum values of  $x$ , respectively. Obtained statistical results for testing parameters are illustrated in Table 1.

### 3. RESULTS (SONUÇLAR)

In this study thermal performance modeling of open celled aluminum foam heat exchangers was investigated by using the Artificial Neural Networks where the foams used possessed 10, 15, 20, 25 and 30 PPI pore density features. The study benefitted from experimental data where even the values within the 15 PPI and 25 PPI range were applied to the ANN. Fig 2 shows the ANN model for the problem.

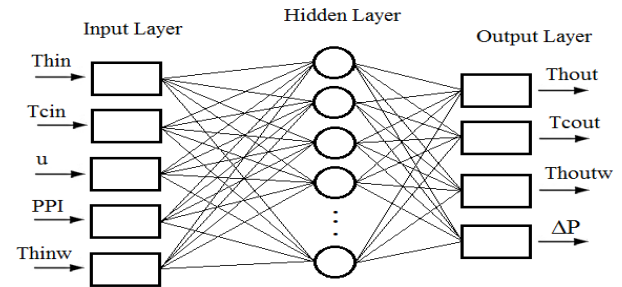


Figure 2. ANN architecture (YSA ağı)

As seen on Fig.3, the correlation value,  $R$  produced by the ANN is 0.98614.

This shows that this problem can perfectly be applied to the Artificial Neural Networks at the given value.

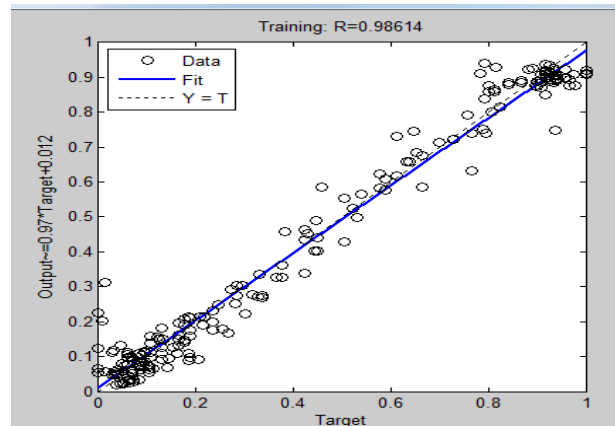
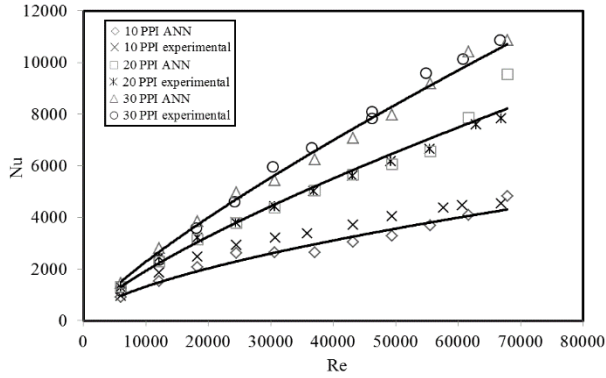


Figure 3. Comparison of test data with experimental and ANN results (DeneySEL ve YSA sonuçları ile deney verilerinin karşılaştırılması)

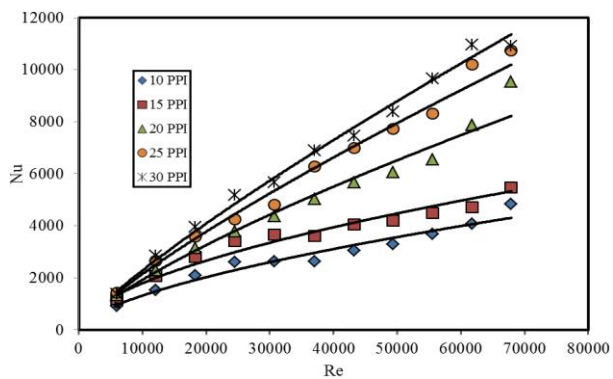
Table 1. Obtained statistical results (Elde edilen istatistik sonuçlar)

	RMSE	MAE	$R^2$	MRE
Thout	0,9861	0,0143	0.9725	0,2300
Tcout	1,2662	0,01397	1.6711	0,3568
Thoutw	1,8263	0,0311	3.3356	1,0749
Δp	0,0062	4,19E-06	3.88E-05	8,2380



**Figure 4.** Comparison of the variation of Reynolds number with Nusselt number for the experimental and ANN results under PPI features of 10-20-30 (PPI 10,20 30 için deneysel ve YSA sonuçlarına göre Nusselt -Reynolds sayısının değişiminin karşılaştırılması)

In Fig. 4, the variation of Reynolds number with Nusselt number for open celled aluminum heat exchangers with 10, 20, 30 PPI features is plotted, where the experimental results and those obtained from the ANN are shown on the same graph. As the porous density increases, the distance covered by air (cold refrigerant) between the heat exchanger entrance and exit, increases too. This situation maintains longer contact between the hot and cold fluid. Moreover; as the porous density increases, the surface area per unit volume increases as well. The increase in Nusselt number indicates that the heat transfer rate increases [3,10]. The best heat transfer occurred with PPI feature of 30, and then successively followed by 20 PPI and 10 PPI. In three heat exchangers dealt with in this study, it was found that the Reynolds number increases with the Nusselt number. In addition; the study found out that the experimental results cope well with the results obtained with the artificial neural networks method.



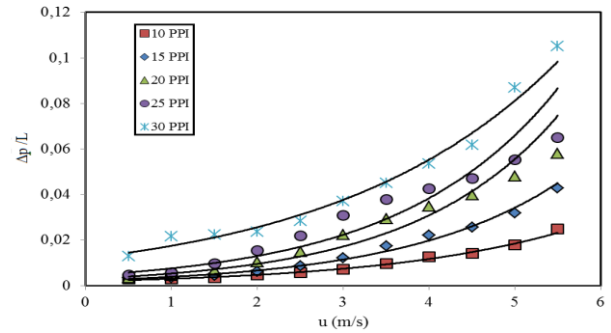
**Figure 5.** Variation of Re number with Nu number based on the ANN data (YSA verilerine göre Nu -Re sayısının değişimi)

Fig. 5. Shows the relationship between Reynolds number and Nusselt number with respect to the ANN data. The ANN was applied for PPI values of 10,15,20,25 and 30 by making use of the experimental

data. The graphs obtained showed that as the Reynolds number increases, so does the Nusselt number. According to the ANN results, the graphs plotted tend to show similar trends with those drawn from experimental data [3,10,11]. The correlation equations between Reynolds number and Nusselt number for the graphs drawn based on the ANN data are presented in Table 2.

**Table 2.** Reynolds – Nusselt correlation equations (Reynolds - Nusselt korelasyon denklemleri)

Material	Correlation equation ( $\epsilon_e$ )	R <sup>2</sup> (%)
10 PPI	$Nu = 4.447 Re^{0.6174}$	97.06
15 PPI	$Nu = 8.475 Re^{0.5774}$	98.71
20 PPI	$Nu = 1.8184 Re^{0.7565}$	98.89
25 PPI	$Nu = 1.2139 Re^{0.8121}$	99.26
30 PPI	$Nu = 1.0399 Re^{0.8358}$	99.44



**Figure 6.** Variation of air speed with pressure drop on the basis of ANN data (YSA verilerine göre basınç düşüşü ile hava hızı değişimi)

In Fig. 6, the curves showing variation of pressure drop per unit length with air speed in the aluminum foam heat exchangers are shown. The curves have been drawn by using the ANN data. It is clear that as the porous density level increases the pressure drop becomes more acute. On the other hand, as the surface area per unit volume increases the pressure loss increases as well. The highest pressure loss was observed at the porosity of 30 PPI while the least pressure loss occurred at the porosity of 10 PPI. On top of that, for all the heat exchangers considered, it was found that the increase in the air speed leads to corresponding increase in the pressure drops and that at higher air speeds this increase becomes quite substantial. The results of ANN are compatible with experimental references in literature [2,3,12]. The correlation equations between pressure drop per unit length with pressure drop for the graphs drawn with respect to the ANN results are given in Table 3.

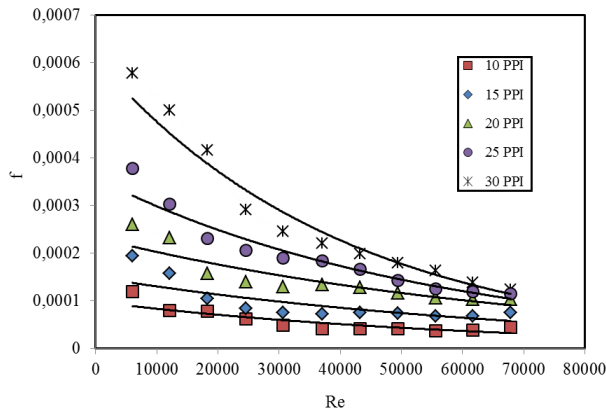
**Table 3.** Correlation equations between pressure drop and air speed (Basınç düşüşü ve hava hızı arasındaki korelasyon denklemleri)

Material	Correlation equation ( $\Delta p / L$ )	R <sup>2</sup> (%)
10 PPI	$(\Delta p / L) = 0.0019 e^{0.4583 U}$	98.90
15 PPI	$(\Delta p / L) = 0.0022 e^{0.5486 U}$	98.85
20 PPI	$(\Delta p / L) = 0.0029 e^{0.5974 U}$	97.08
25 PPI	$(\Delta p / L) = 0.0043 e^{0.5545 U}$	94.67
30 PPI	$(\Delta p / L) = 0.0119 e^{0.3846 U}$	97.78

**Table 4** Correlation equations for Reynolds number with frictional factor (Sürtünme faktörü-Reynolds sayısı için korelasyon denklemleri)

Material	Correlation equation ( $\Delta p / L$ )	R <sup>2</sup> (%)
10 PPI	$f = 2E-14 Re^2 - 2E-09 Re + 0,0001$	96.17
15 PPI	$f = 3E-14 Re^2 - 3E-09 Re + 0,0001$	95.19
20 PPI	$f = 2E-14 Re^2 - 3E-09 Re + 0,0002$	96.38
25 PPI	$f = 8E-14 Re^2 - 9E-09 Re + 0,0004$	96.06
30 PPI	$f = 1E-13Re^2 - 2E-08Re + 0,0007$	98.16

The variation of frictional factor with Reynolds number drawn on the basis of ANN data is shown on Fig. 7. It is seen that friction is higher on areas with higher porous densities and decreases as the porosity becomes low. The maximum frictional loss was recorded at the PPI value of 30 and the minimum occurred at porous density value of 10. In all the heat exchangers, the frictional losses were higher on low Reynolds numbers and vice versa. The higher frictional values on higher porous densities are due to the narrowed inter-distances among the filaments and the long way taken by the cold fluid during circulation. The ANN results again proved to be consistent with experimental studies [2,3,10]. Table 4 shows the correlation equations for the variation of Reynolds number with frictional factor belonging to the graphs plotted with the ANN data.

**Figure 7.** Variation of frictional factor with Reynolds number based on ANN data

(YSA verilerine göre Reynolds sayısı sürtünme katsayısı değişimi)

#### 4. DISCUSSION (TARTIŞMA)

This study has based on designing open cell aluminum foam heat exchangers from experimental data featuring different PPI properties of the material and usage of the artificial neural networks (ANN) to model thermal performances of the designed heat exchangers. The modeling was made based on experimental data for materials with PPI values of 10, 15, 20, 25 and 30. The results found are summarized below:

- Reynolds number increases with the Nusselt number. An increase or decrease in Nusselt number is an indication of the amount of heat transferred. The highest Nusselt number occurs at the PPI value of 30 whereas the lowest takes place at 10 PPI. As the porous density (PPI) increases, the heat transfer rate increases too (Figs. 4-5).
- In the open celled aluminum foam heat exchangers, when the porous densities increase the pressure losses increase. The maximum pressure loss occurs at 30 PPI while the minimum is recorded at 10 PPI. An increase in air speed leads to a corresponding increase in the pressure loss which becomes intensive at higher air speeds (Fig. 6).
- The frictional losses in the aluminum foam heat exchangers increase with the increasing porous density values. Maximum frictional loss occurs at 30 PPI with the minimum loss recorded at 10 PPI. Air speed and frictional loss seem to have inverse proportional relationship in which the increase in air speed causes a decrease in the frictional loss; and at higher air speeds the frictional loss becomes much less (Fig. 7).

When the results from the ANN model are analyzed and compared with the experimental results, it is found that the two indicate a consistent common result. With this study, it has been shown that the ANN can be reliably used for analyzing aluminum foam heat exchangers and the ANN modeling can be applied without necessitating numerous experimental studies.

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