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Application of Meta-Heuristic Hybrid Artificial Intelligence Techniques for Modeling of Bonding Strength of Plywood Panels

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ABSTRACT

Plywood, which is one of the most important wood based panels, has many usage areas changing from traffic signs to building constructions in many countries. It is known that the high quality plywood panel manufacturing has been achieved with a good bonding under the optimum pressure conditions depending on adhesive type. This is a study of determining the using possibilities of modern meta-heuristic hybrid artificial intelligence techniques such as IKE and AANN methods for prediction of bonding strength of plywood panels. This study has composed of two main parts as experimental and analytical. Scots pine, maritime pine and European black pine logs were used as wood species. The pine veneers peeled at 32°C and 50°C were dried at 110°C, 140°C and 160°C temperatures. Phenol formaldehyde and melamine urea formaldehyde resins were used as adhesive types. EN 314-1 standard was used to determine the bonding shear strength values of plywood panels in experimental part of this study. Then the intuitive k-nearest neighbor estimator (IKE) and adaptive artificial neural network (AANN) were used to estimate bonding strength of plywood panels. The best estimation performance was obtained from MA metric for k-value=10. The most effective factor on bonding strength was determined as adhesive type. Error rates were determined less than 5% for both of the IKE and AANN. It may be recommended that proposed methods could be used in applying to estimation of bonding strength values of plywood panels.

Keywords: Adaptive artificial neural network (AANN), Bonding Strength, Intuitive k-nearest neighbor estimator (IKE), Plywood

Kontrplaklarda Yapışma Direnci Modellenmesinde Meta-Buluşsal Yapay Sinir Ağları Tekniklerinin Kullanılması

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ÖZET

En önemli ahşap kökenli levha ürünlerinden biri olan kontrplak trafik levhalarından inşaata kadar pek çok kullanım yerine sahiptir. Yüksek kalitede kontrplak üretimi için tutkal türüne bağlı olarak optimum pres koşulları altında iyi bir yapışmanın sağlanması gerektiği bilinen bir gerçektir. Bu çalışmada kontrplağın yapışma direncinin tahmin edilmesi için modern meta buluşsal tekniklerden IKE ve AANN metotlarının kullanım imkanları araştırılmıştır. Çalışma deneysel ve analitik olarak iki kısımdan oluşmaktadır. Çalışmada ağaç türü olarak sarıçam, sahil çamı ve karaçam kullanılmıştır. Kaplamalar 2 farklı sıcaklıkta (32°C ve 50°C) soyulmuş ve 3 farklı sıcaklıkta (110°C, 140°C ve 160°C) kurutulmuştur. Kontrplak üretimi için fenol formaldehit ve melamin üre formaldehit tutkalları olmak üzere iki farklı tutkal türü kullanılmıştır. Deneysel olarak kontrplakların yapışma direnci değerleri EN 314-1 standardına göre yapılmıştır. IKE ve AANN teknikleri analitik olarak yapışma direnci tahmininde kullanılmışlardır. En iyi tahmin performansı k değeri 10 için elde edilmiştir. Yapışma direnci üzerine en etkili faktör olarak tutkal türü belirlenmiştir. IKE ve AANN için belirlenen hata oranları %5'in altında bulunmuştur. Çalışma neticesinde uygulanan tekniklerin kontrpalklarda yapışma direnci tahmininde kullanılabilir oldukları tespit edilmiştir.

Anahtar Kelimeler: Adaptif yapay sinir ağı (AANN), Yapışma Direnci, Sezgisel k en yakın komşu tahmincisi (IKE), Kontrplak

INTRODUCTION

One of the most popular wood based panels, plywood, has been used from traffic signs to building constructions (Demirkır 2012). World plywood production in 2010 was more than 81 million cubic meters with a market value of approximately 19 billion dollars in both exports and imports (Fernandez et al. 2012). The quality of plywood panels is crucial because it classifies boards as suitable or not for using areas. It is known that the high quality plywood panel manufacturing has been achieved with a good bonding under the optimum pressure conditions depending on adhesive type. There are many studies about the factors such as wood specie and density, relative moisture content, adhesive type, veneer peeling temperature, veneer drying temperature affecting the bonding quality of plywood panels (Toksoy et al. 2006; Jin and Dai 2004; Chow and Chunsi 1979; Namara and Waters 1970; Vick 1999; Aydın et al. 2006). However few studies are available about the effect of which factor are the weightiest on bonding strength of plywood panels. Some techniques such as artificial neural networks (ANNs) have been used to model mechanical properties of wood based materials. Artificial neural networks (ANNs) are used for modeling the parameters of nonlinear systems in various fields, as well as engineering and computer science (Babu and Suresh 2013; Iyer and Sharda 2009; Peng and Dubay 2012). A classic ANN is composed of layers (input, hidden, and output), processing units (nodes and activation functions) and node connections (weight coefficients). In general, most of the non-experts face major difficulties in modeling of a non-linear system by using the ANNs. A major challenge in modeling is how to design ANN accurately and efficiently considering network components and problem parameters that provide optimum and stable decisions. Determination of number of hidden layers, nodes and activation function types are the essential problems in ANN-based system modeling. Therefore, numerous test and experimental study is executed to explore the best ANN model. These are the basic constraints of ANN-based modeling studies. Nevertheless, ANNs have been widely used in the field of wood, in the prediction of mechanical properties both from manufacturing parameters (Esteban et al. 2011) in the recent years. However the method alone is insufficient to determine the weight ratio of factors on bonding strength of plywood panels. Some artificial intelligence (AI) techniques have been developed to solve such problems.

The intuitive k-nearest neighbor estimator (IKE) and adaptive artificial neural network (AANN) are efficient AI-based estimation methods which have been successfully developed and tested in different engineering problems recently. One of the most important and specific ability of IKE method is to explore the relationships among problem or system parameters. Thus, it determines impact factors or weight values of input parameters (features) on output parameter(s) independently (Kahraman et al. 2012a; Aksoy et al. 2012; Kahraman et al. 2012b). IKE algorithm uses the distances between a test observation and the training observations, then it calculates the nearest neighbors of test observation for user defined *k*-value, and finally it estimates its bonding value by using the bonding values of the nearest observations in the "root average sum of squares" method.

AANN-based method was developed to easily design the ANN and explore its optimum parameters. It has a multilayered feed-forward neural network and the meta-heuristic exploring unit. Heuristic algorithms might be used to create the candidates of ANN which has different network structure, hidden layer, node number, and combination of activation function types. The major obstacle of the heuristic units is the limited adaptation capability in the AANN-based previous studies. The adaptation effect can only be used to the adaptive selection of activation functions of processing nodes in network. Therefore, the heuristic unit has been extended. In the proposed heuristic unit, the activation function types of the nodes are heuristically changed as well as previous studies (Ustun 2009; Bayindir et al. 2012). Additionally, the number of hidden layers and nodes are also adaptable by the genetic algorithm-based (GA) heuristic exploring unit. In this study, a GA-based heuristic approach was extended to explore the optimum parameters of ANN (Ustun 2009; Bayindir et al. 2012; Goldberg 1989; Tu and Lu 2004; Mitchell 1997; Babu and Suresh 2013; Iyer and Sharda 2009; Peng and Dubay 2012). The first aim of the study is to determine the using possibilities of IKE and AANN methods for prediction of bonding strength of plywood panels. The other one is to be estimated the weight ration of factors affecting the plywood properties on bonding strength of plywood panels through IKE technique by using the values obtained from experimental studies. Finally, it can be determined that the factors could be considered to supply required bonding strength values for using places in plywood manufacturing.

MATERIALS AND METHOD

Wood Material and Manufacturing of Plywood Panels

Scots pine (*Pinus slyvestris*), Maritime pine (*Pinus pinaster*), and European black pine (*Pinus nigra*) were used as wood species in this study. Logs for veneer manufacturing with an average diameter at breast height of 40 cm were obtained from Sinop, located at the most northern point of the Black Sea Region in Turkey. The logs were steamed and divided into two groups according to their temperatures before the veneer clipping process. Two different log temperatures were chosen as 32°C and 50°C for this study. Then veneer sheets with dimensions of 55 cm by 55 cm by 2 mm were clipped. A rotary peeler with a maximum horizontal holding capacity of 80 cm was used for veneer manufacturing. The vertical opening was 0.5 mm and horizontal opening was 85% of the veneer thickness in the veneer manufacturing process. After rotary peeling, veneers were dried at three different temperatures: 110°C, 140°C, or 160 °C. Veneer sheets were conditioned to approximately 5-7% moisture content in a conditioning chamber before gluing. Five-layer-plywood panels with 10 mm thick were manufactured by using phenol formaldehyde (PF) glue resin with 47% solid content and melamine urea formaldehyde (MUF) with 55% solid content. The formulations of adhesive mixtures used for plywood manufacturing are given in Table 1. Two replicate panels were manufactured for each test group. Approximately 160 g/m^2 adhesive mixture was spread on single surfaces of veneers by using a gluing machine. In the manufacturing of plywood panels, hot press time and pressure were 10 min, 8 kg/cm^2, respectively. Press temperature was applied 110°C, 140°C for MUF and PF adhesives, respectively.

Table 1. The formulation of Melamine urea formaldehyde (MUF) and Phenol formaldehyde (PF) used for the manufacturing of plywood panels

Glue Type	Adhesive Ingredient	Parts by weight
MUF glue	MUF resin (with 55 % solid content)	100
	Wheat flour	30
	NH4Cl (with 15 % concentration)	10
PF glue	47 % solid content	100

Method

Bonding Strength

The bonding strength of plywood panels was determined according to EN 314 with a universal testing machine (EN 314-1 1998). Samples manufactured with PF resin were tested after immersion in boiling water for 6 hours and the panels samples manufactured with MUF resin were tested after immersion in water at 20°C for 24 hours. Twenty-five specimens were used for the evaluation of bonding strength tests.

Applying the AI-techniques to bonding estimation

A decision support system was developed on MS Visual Studio NET Environment by using both of the IKE and AANN-based AI techniques for this study.

IKE technique: Application steps of IKE algorithm are shown in the Figure 1.

Modeling and representation of wood specie parameters: Seven parameters were used for developing the estimation model in this study. They are wood specie (ws), peeling temperature (pt), drying temperature (dt), adhesive type (at), density (dn), moisture content (mc), and bonding strength (bs). The 'bn' is target parameter and 'ws, pt, dt, at, dn, mc' are used for estimation model as input parameters. The input parameters and target parameters were represented by set of F_{wood} and T_{wood} in IKE and AANN techniques, respectively (Table 2).

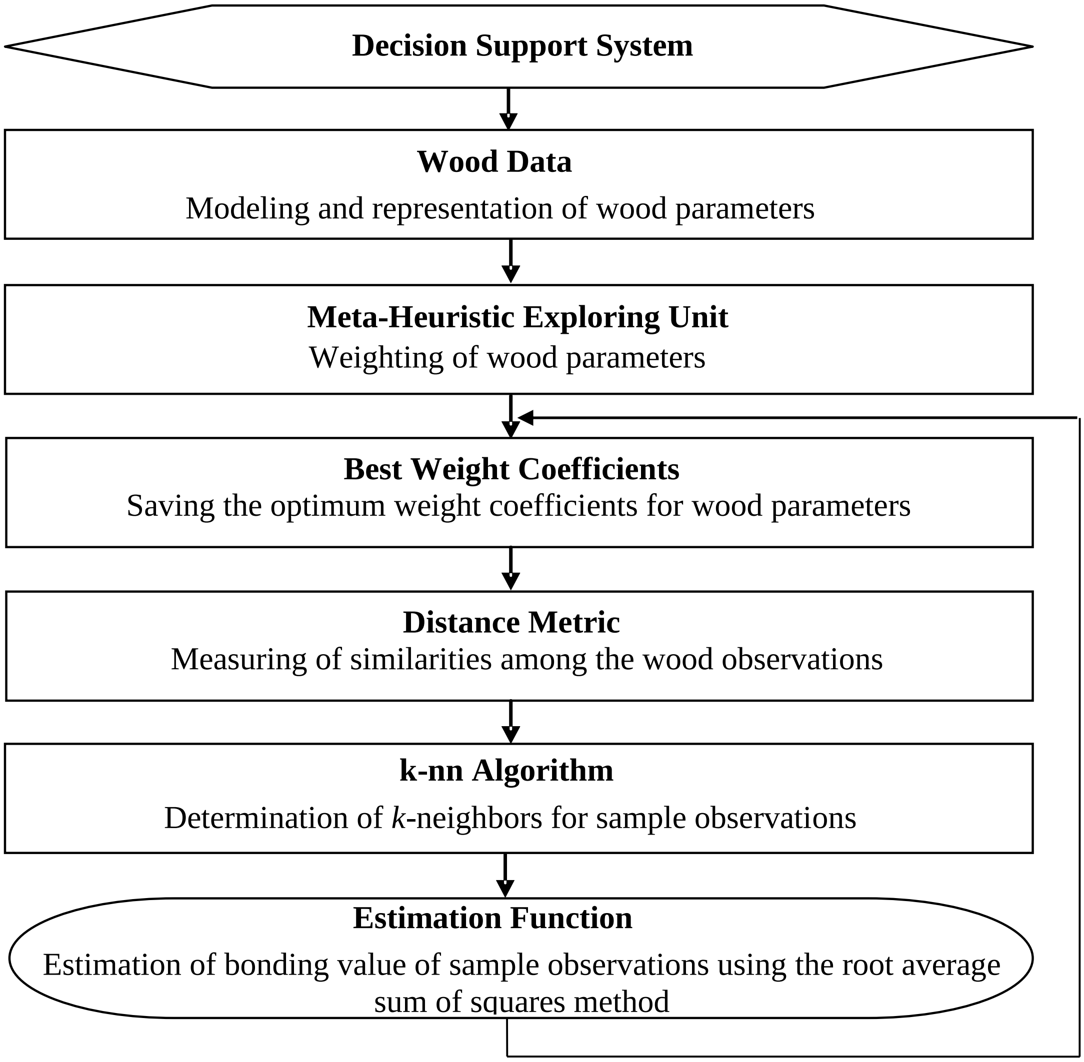

Figure 1. Steps for weighting and prediction of wood parameters in the decision support system

Table 2. Representation of input (F_{wood}) and target parameters (T_{wood}) for the model

Set of F_{wood} (input parameters)						**T_{wood}**
wood specie	peeling temperature	drying temperature	adhesive type	density	moisture content	bonding
ws	pt	dt	at	dn	mc	bs

A sample dataset (D_{wood}) was given in Eq. (1) depending on the parameters of estimation model.

$$D_{wood\,[i,7]} \equiv \begin{bmatrix} F_{ws\,[1,1]} & F_{pt\,[1,2]} & F_{dt\,[1,3]} & F_{at\,[1,4]} & F_{dn\,[1,5]} & F_{mc\,[1,6]} & T_{bs\,[1,7]} \\ & & & \vdots & & & \\ F_{ws\,[i,1]} & F_{pt\,[i,2]} & F_{dt\,[i,3]} & F_{at\,[i,4]} & F_{dn\,[i,5]} & F_{mc\,[i,6]} & T_{bs\,[i,7]} \end{bmatrix} \quad \ldots\ldots\ldots\ldots (1)$$

Where, "*i*" *is the total number of observations in dataset.*

Meta-heuristic exploring unit: The task of this unit is to explore the optimum weight coefficient of each input parameter <F_{ws}, F_{pt}, F_{dt}, F_{at}, F_{dn}, F_{mc}> on the target parameter <T_{bs}>. An array of weight coefficients shown the form of Eq. (2) is created by the meta-heuristic exploring unit.

$$W_{factors[6]} \equiv \left[W_{ws}, W_{pt}, W_{dt}, W_{at}, W_{dn}, W_{mc}\right] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where, "$W_{factors[6]}$" represents the best weight coefficients for the parameters.

Every parameter represented by W_{ws}, W_{pt}, W_{dt}, W_{at}, W_{dn}, W_{mc} means the optimum weight coefficient on the bonding value. Genes belonging to an individual are the weight coefficients of input parameters in the set of F_{wood}, while fitness value is suitability degree of the individual for the bonding estimation. The individual was represented by six genes and a fitness value as given in Table 3.

Table 3. Representing the genes of an individual

Gene 1	Gene 2	Gene 3	Gene 4	Gene 5	Gene 6	Fitness Value
W_{ws}	W_{pt}	W_{dt}	W_{at}	W_{dn}	W_{mc}	FV

According to Table 3, the population ($P_{wood\,[m,7]}$) was given shape of matrix form in Eq. (3) where 'm' represents the number of individuals or candidates in the population.

$$P_{wood[m,7]} \equiv \begin{bmatrix} W_{ws\,[1,1]} & W_{pt\,[1,2]} & W_{dt\,[1,3]} & W_{at\,[1,4]} & W_{dn\,[1,5]} & W_{mc\,[1,6]} & FV_{bs\,[1,7]} \\ & & & \vdots & & & \\ W_{ws\,[m,1]} & W_{pt\,[m,2]} & W_{dt\,[m,3]} & W_{at\,[m,4]} & W_{dn\,[m,5]} & W_{mc\,[m,6]} & FV_{bs\,[m,7]} \end{bmatrix} \quad (3)$$

Each row (individual) in the matrix (Eq. (3)) corresponds to a solution. The last column of rows is the fitness value of solution. A fitness function is used to evaluate the suitability value of weight coefficients of each individual.

Distance measurement with weighted parameters: Optimum weight coefficients obtained from Meta-heuristic exploring unit were used to increase distance measurement accuracy of Euclidean (EU) and Manhattan (MA) metrics. Distance between the test observation (qt) and the sample/training observation (qs) were calculated as below (Eq. (4)):

$$EU{:}\, d(q_t, q_s) = \sqrt{\begin{matrix} W_{ws}\,(Fq_{t\,(ws)} - Fq_{s\,(ws)})^2 + W_{pt}\,(Fq_{t\,(pt)} - Fq_{s\,(pt)})^2 + \\ W_{dt}\,(Fq_{t\,(dt)} - Fq_{s\,(dt)})^2 + W_{at}\,(Fq_{t\,(at)} - Fq_{s\,(at)})^2 + \\ W_{dn}\,(Fq_{t\,(dn)} - Fq_{s\,(dn)})^2 + W_{as}\,(Fq_{t\,(as)} - Fq_{s\,(as)})^2 \end{matrix}} \quad \text{.................. (4)}$$

It is supposed that $U_{wood[e]}$ is a set of training observations and '*e*' is the number of samples in the set. An *e*-dimensional distance array is obtained from distance measurements between the (q_t) and $U_{wood[e]}$ as given in Eq. (5).

$$d(q_t, U_{wood[e]}) \equiv \left[d_{q_t U_{wood\ [0]}}, d_{q_t U_{wood\ [1]}}, d_{q_t U_{wood\ [2]}}, \dots, d_{q_t U_{wood\ [m]}}\right] \text{........................(5)}$$

The distance values in the d $(q_t, U_{wood[e]})$ are used to determine the *k* neighbors of q_t.

Determining of nearest neighbors: The '*k*' means the number of nearest neighbors for a test observation. Depending on the *k*-value, the nearest neighbors of q_t were selected by using the array of $d(q_t, U_{wood[e]})$. The bonding values of selected *k*-neighbors were used to estimate the bonding value of q_t. The selected bonding values were represented an array with *k*-dimensional as given in Eq. (6).

$$q_{t(Tbs)[k]} \equiv \left[T_{bn\,[0]}, \dots, T_{bs\,[k]}\right] \qquad (6)$$

Estimation function: The root average sum of squares method was used to estimate the bonding value of a test observation. After determining the bonding values of *k*-neighbors of q_t, its bonding value estimation was calculated with Eq. (7):

$$q_{t\,Tbn} = \sqrt{\sum_{i=1}^{k} (q_{t(Tbs)[k]})^2 / k} \ \dots (7)$$

AANN technique: The structure and basic elements of the designed AANN are shown in Figure 2.

As shown in Figure 2, the population generated with the GA-based heuristic unit has alternative combinations of network with 6-inputs and single. It is composed of individuals composing of genes which are represents the candidate solutions for the problem. The genes, a network parameter, of an individual are designed as given in Table 4.

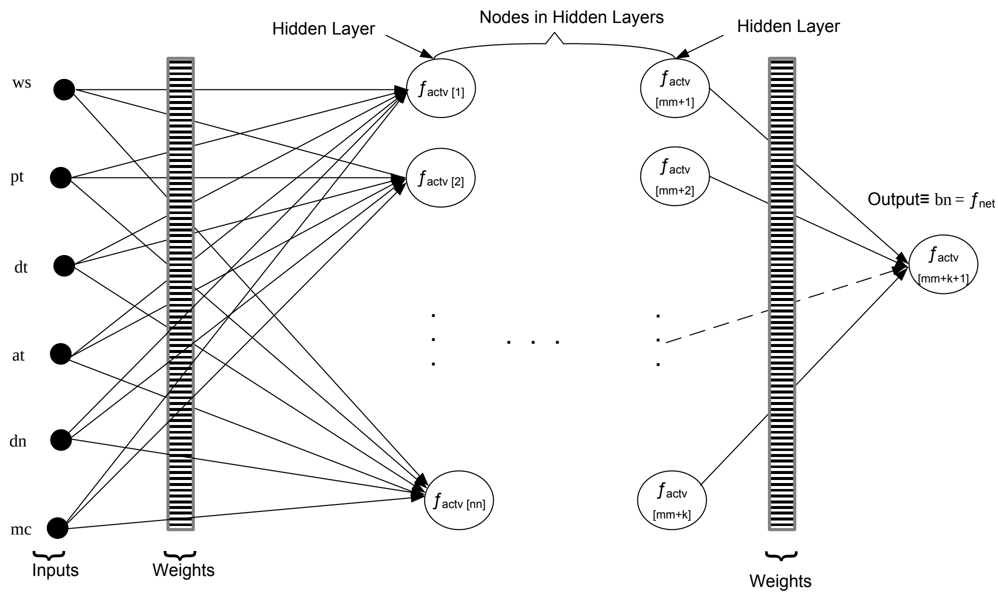

Figure 2. The structure and basic elements of the AANN designed for the study

Table 4. The genes of an individual in population

gene [1]	gene [2]	gene [3]	gene [4]	...	gene [n]	gene [n+1]
hidden layer number	node number	activation function type for node 1	activation function type for node 2	...	activation function type for node n	fitness value

The fitness value seen in Table 4 was calculated according to parameter values of others genes. It shows the suitability degree of genes of a candidate solution (individual) for problem. There are three different adaptation types such as "hidden layer number", "node number" and "activation function types" as given in Table 4. Parameter values are given in Table 5 according to adaptation types.

Table 5. Adaptation types and parameter values in the extended GA-based AANN method

Adaptation Types	Number of Hidden Layers	Number of Nodes	Activation Functions	
Parameter values	Min: 1 Max: 3	Min: 2 Max: 10	Linear	$f(x)=x$
			Treshold or Sign	$f(x)=\begin{cases}1 & if\ x \geq 0\\ 0 & if\ x < 0\end{cases}$
			Logistic sigmoid	$f(x)=\frac{1}{1+e^{-x}}$
			Sinus	$f(x)=\sin(x)$
			Hyperbolic tangent	$f(x)=\frac{1-e^{-2x}}{1+e^{-2x}}$
			Radial bases	$f(x)=e^{-x^2}$
			Tan-Sigmoid	$f(x)=\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$

A population was created by using the genes in Table 4 and parameter values in Table 5 as seen Eq. (8). The Eq. (8) was used to search the best values of optimization parameters in this study.

$$P_{wood[y,n]} \equiv \begin{bmatrix} gene_{wood\ [1,1]} & gene_{wood\ [1,2]} & \cdots & gene_{wood\ [1,n]} \\ & & \vdots & \\ gene_{wood\ [y,1]} & gene_{wood\ [y,2]} & \cdots & gene_{wood\ [y,n]} \end{bmatrix} \quad \ldots\ldots\ldots\ldots(8)$$

Where, "y" is number of individuals in "P_{wood}" population.

RESULTS AND DISCUSSION

Experimental Results of IKE

The *k* values were determined as 7, 8, 9, and 10 to generate the best estimation model for this study. The optimum weight coefficients ($W_{wood[6]}$) are given in Table 6.

Table 6. The optimum weight coefficients for different metrics and *k*-values

k-value	Metric	W_{ws}	W_{pt}	W_{dt}	W_{at}	W_{dn}	W_{mc}
7	EU	0.004117	0.625308	0.964259	0.559797	0.842246	0.201244
	MA	0.030971	0.382925	0.643251	0.734249	0.501932	0.062842
8	EU	0.023061	0.765107	0.033919	0.523658	0.949571	0.174087
	MA	0.052524	0.171320	0.235553	0.572705	0.912694	0.140993
9	EU	0.005056	0.520246	0.009166	0.037818	0.812398	0.105377
	MA	0.066676	0.037194	0.718135	0.922387	0.871275	0.261593
10	EU	0.007593	0.468617	0.677802	0.971943	0.995543	0.619883
	MA	**0.062222**	**0.040632**	**0.832567**	**0.867202**	**0.832567**	**0.577171**

The optimum weight values were used to test the estimation performance of IKE for different metrics and *k*-values. The best estimation performance was obtained from MA metric for *k*-value=10. As shown in Table 6, the most effective factor on bonding strength is adhesive type. It was known that wood adhesives such as adhesive type, content, jell time have also effect on the bonding strength (He et al. 2007). This study demonstrated that the most important manufacturing parameter was adhesive type. Therefore, firstly for a good bonding, adhesive should be considered. Next parameters following the adhesive type are density and drying temperature. A number of researchers stated that drying temperatures and density affect the bonding strength of plywood (Aydın and Colakoglu 2005; Christiansen 1990; Lehtinen 1998; Chow and Chunsi 1979; Namara and Waters 1970). According to Table 6, peeling temperature had an effect on the bonding strength but not as much as other factors.

The values giving the best performance were used to estimate analytically the bonding values of test observations. Table 7 shows that the percentage of mean error rates and standard deviations of bonding strength values estimated from the model.

Table 7. The percentage of mean error rates and standard deviations

Distance Metric	Mean Error Rates (%)		Standard Deviations (%)	
k-value	**EU**	**MA**	**EU**	**MA**
7	2.94	3.00	2.08	2.06
8	2.99	2.94	2.09	2.05
9	2.89	2.90	2.11	2.01
10	2.94	2.89	2.03	2.03

According to Table 7, the lowest mean error rates and standard deviation were determined in IKE method with MA metric for *k*=10. The error rate was calculated less than 5% in most of the test observations. Consequently, the estimation accuracy was very high in IKE method. The real (measured) and the estimated bonding values estimated with IKE method were shown in Figure 3.

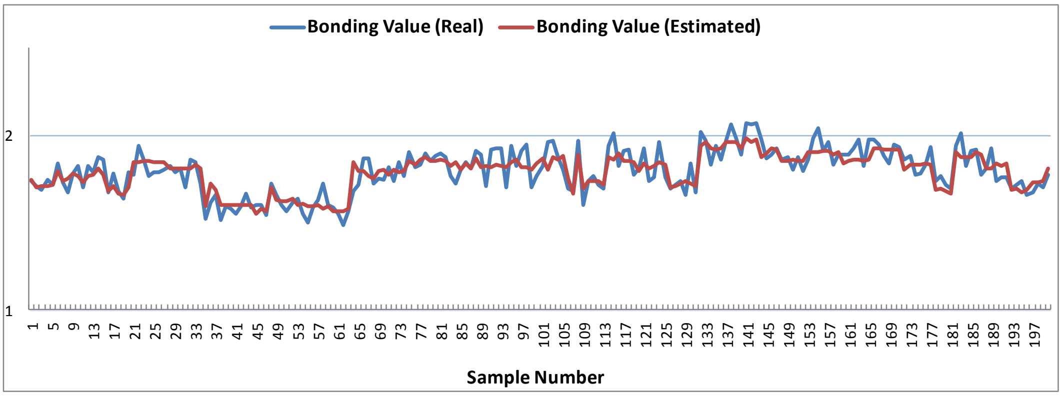

Figure 3. The real (measured) and the estimated bonding values in IKE method

Experimental Results of AANN

The number of hidden layers, the number of neurons per layer, and the types of activation functions were explored by the heuristic unit of AANN. The optimum number of hidden layers and the optimum number of nodes was determined as two and five for the first and second layers, respectively. The function types for each node in the hidden layers were also given in Table 8.

Table 8. The optimum values of network parameters

Number of Hidden Layers	Number of Nodes		Activation Functions
2	First Layer	5	Log-Sigmoid Function
			Tan-Sigmoid function
			Sinus
			Hyperbolic tangent
			Tan-Sigmoid function
	Second Layer	5	Tan-Sigmoid function
			Hyperbolic tangent
			Radial bases
			Radial bases
			Tan-Sigmoid function

The best network was designed to estimate the bonding values of test observations depending on the parameter values given in Table 8. The estimation accuracy was very high in AANN method, since the error rate was determined less than 5% in the test observations. The real (measured) and the bonding values estimated with AANN method were shown in Figure 4.

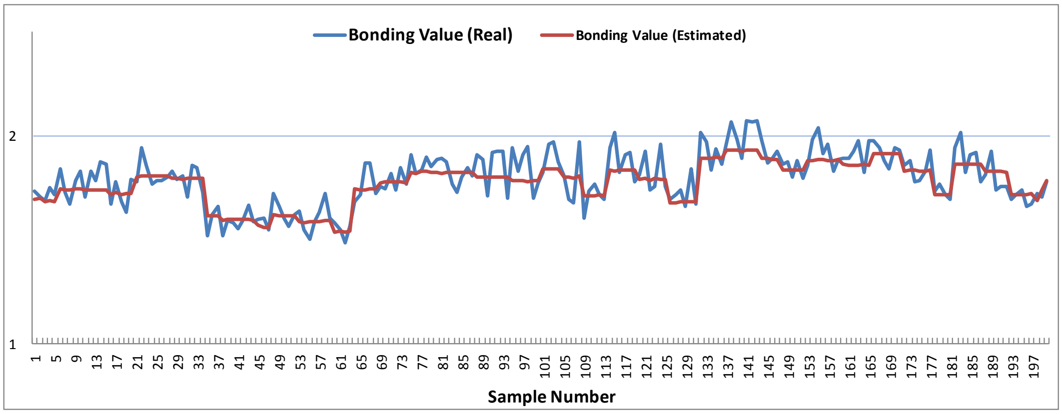

Figure 4. The real (measured) and the estimated bonding values in AANN method

Comparisons

The comparisons between the IKE and AANN methods are shown in Figure 5 and 6 according to the standard deviations and percentage of mean error rates.

The percentage of mean error rate and the standard deviation were calculated as 2.89% and 2.11% in the IKE method, respectively. They were also determined in the AANN method as 3.13% and 2.26%, respectively. Upper limit value was chosen as 5% for error rate before the study was launched, because this value was supported as acceptable upper limit in several studies about the using of AI techniques (Kahraman et al. 2012a; Aksoy et al. 2012; Kahraman et al. 2012b; Bayindir et al. 2012). Since the calculated values were less than 5%, it may be recommended that both of the proposed methods could be used in applying to the estimation of bonding strength values of plywood panels.

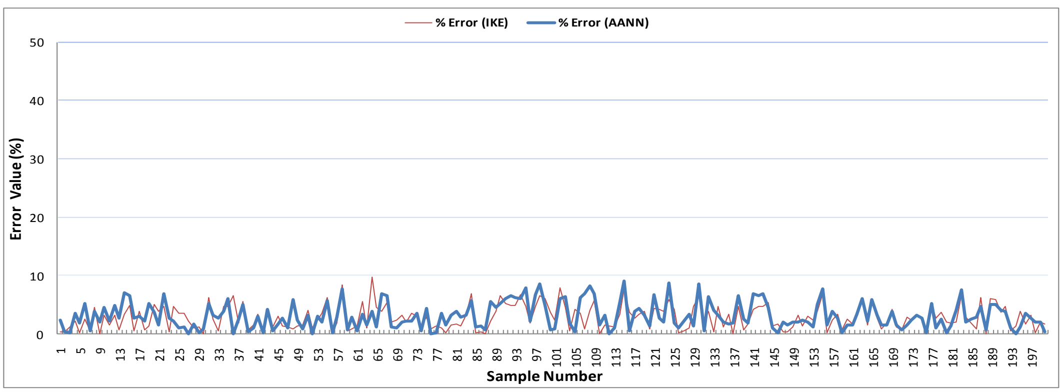

Figure 5. The percentage of mean error rate for IKE and AANN-based methods

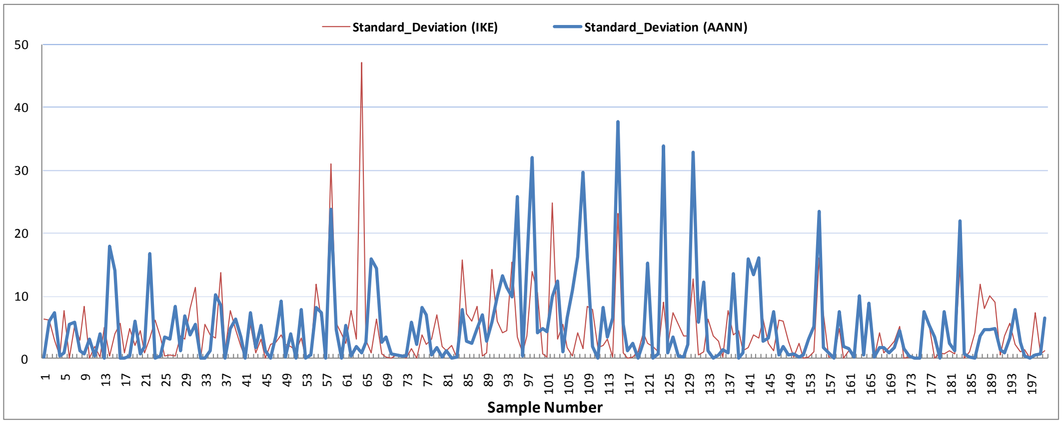

Figure 6. Standard deviations for bonding estimation in IKE and AANN-based methods

CONCLUSIONS

This is a study of determining the using possibilities of modern meta-heuristic hybrid artificial intelligence techniques such as IKE and AANN methods for prediction of bonding strength of plywood panels. The best estimation performance was obtained from MA metric for k-value=10. The most effective factor on bonding strength was determined to be adhesive type. Error rates were determined less than 5% for both of the IKE and AANN. It is concluded from this study that proposed methods can be used in applying to the estimation of bonding strength values of plywood panels.

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