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Prediction of Women's Fashion Product Expense in Hanoi City Using Artificial Neural Network

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Abstract

A person's fashion product expense plays an important role in building a garment company's product and pricing strategy. This article presents the results of predicting the fashion expenses of women aged 25 to 55 in Hanoi city. A linear multivariable model determined by the Bayesion Model Average (BMA) was applied to predict expenditures based on a set of 150 women survey data. The 3 layers feed-forward neural network model with 8 input neurons, 4 (+1) hidden layer neurons, and 1 output layer neuron, The Sigmoid activation function, trained by the error backpropagation algorithm has been established on software R specifically predicts the value of women's fashion expense with the above data set. The results show that the artificial neural network (ANN) has been set up allowing to prediction of fashion expenses accurately. The expenditure values predicted by the ANN and the actual value are linearly correlated with R^2 = 0.987; The prediction results by ANN are more accurate than the defined multivariable linear model.

Keywords: Artificial neural network, expense for fashion products, prediction.

1. Introduction

To succeed in production and business, businesses need to deeply understand the challenge of producing and sell the right products. Theoretical and practical issues about customers and fashion products have been studied extensively.

Nguyen Thi Mai Hoa *et al*. have studied the characteristics of women's consumption of office fashion products in Hanoi city [1, 2]. Duong Thi Hanh *et al*. studied personal factors such as age, occupation, lifestyle, income, and family status, ... They influence the level of spending on fashion products of women aged 25-55 in Hanoi city [3]. This study grouped the audience based on the influencing factors and the expense of fashion. Women's fashion expense in Hanoi city is divided into 3 groups and is significantly affected by women's income, age, and occupation. In recent years, artificial intelligence has become more and more applied in the fashion apparel industry and shows outstanding advantages, especially, when retailers are trying to use computer algorithms to predict consumers' emotions and thoughts, from there to better meet customer needs and tastes as well as sales prediction. Sztandera forecast women's apparel sales using fuzzy models based on historical sales data, color trends, and size quantities [4]. In this study, univariate and multivariate models were established to predict clothing sales. The multivariable fuzzy logic model has better predictive ability than other models. Performance, R^2 and actual sales and predicted sales of the models were compared. R^2 of the 3 variables models applying fuzzy logic, artificial neural network, and linear model are 0.93, 0.82, and 0.75, respectively. Thomassey *et al.* designed an ANN to predict apparel sales [5]. Thomassey and Fiordaliso predicted the mid-sales of new products based on group and classification techniques [6]. The authors have proposed apparel sales predicting systems based on soft computational techniques, such as fuzzy logic, neural networks, and evolutionary processes, permitting the processing of uncertain data. They have evaluated the performances of these models on actual sales data of an important French textile distributor. Sun *et al.* applied ANN to predict sales based on important attributes of fashion products, including color, size, and price [7]. Asli Aksoy established an adaptive network-based translucent inference system to predict demand in the garment industry [8]. Wong and Guo studied medium-term sales predicted based on the fact of retailing fashion goods using the ANN model [9]. The authors used ANFIS to predict the demand for apparel manufacturers. The designed model combines the learning ability of neural networks and the generalization capability of fuzzy logic. The inputs and outputs of the predicting system are determined based on the apparel manufacturer's requirements and the predicting horizon is approximately one month.

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Predicting the fashion product expense of a person is very important for product strategy planning and prices in the production and trading of garments, but is very limited, especially not mentioned to consumers in Vietnam.

This study aims to establish a model to predict the fashion product expense of women aged 25 to 55 in Hanoi city applying the Bayesion Model Average technique and artificial neural network. The results contribute to building the basis of strategic planning of products and prices in the production and trading of garments.

2. Methods

This study was conducted with survey data from March 2022 to May 2022 among women aged 25-55 years in Hanoi city. These were selected for this study because most of them are of working age and have income, so they make up a large proportion of customers buying fashion products. The qualitative method is applied to preliminarily identify factors belonging to the object that affect the level of spending on women's fashion through an in-depth interview with 10 experts in production and business in the garment and fashion industry who understand the Hanoi market.

Table 1. Scale and encode classification variables

Factors/ variables	**Options**	**Scale**		**Options**	**Scale**
1. Education level (lev)	High school and lower	1	***2. Family (fam)***	Living alone	1
	Intermediate, college	2		With husband/child	2
	University	3		With parents	3
	Graduate school	4		With parents, husband/child	4
3. Occupation (occ)	Trading, free-flowing ponds	1	***4. Children (child)***	No children yet	0
	Workers, similarly.	2		1 with	1
	State administrative staff	3		2 with	2
	Office workers, teachers	4		3 or more children	3
	Manager, business owner	5			
5. Stylelife (stl)	Survivors: the lowest income, the least potential, the oldest of all segments, the customer loyal to the brand.	1	Markers: low potency, practicality, value independence, focus on family, work, entertainment and little interest in the outside world. Appreciate practical and useful products.		2
	Believers: low potency, modest income, conservative consumption, advocacy of reputable products and brands, a life focused on family, religion, community, and country.	3	Strives: successful group-like values, low potential, limited economic, social and psychological potential, style is important for competing with those they admire.		4
	Achievers: High potential, success at work, job and family satisfaction, political conservatism, respect for authority and rank, and support for reputable products and services that help show success to colleagues.	5	Thinkers: High potential, driven by ideas, maturity, responsibility, well-trained, home entertainment, up-to-date, open to changes, high income, practical and reasonable consumption.		6
	Experiencers: High potency, young, high energy, physical and social activities, eager for consumption (clothing, fast food, music...), especially new products and services.	7	Innovators: Value yourself, abundant potential, feel comfortable to express your potential, need to build an image - the expression of independence and personality, the highest income, towards the better in life.		8
6. ***Age (age)***	The age of the person surveyed.		**7.** ***Income (inc)***	One-year income of the surveyed person (million VND).	
8. ***Outcome (outc)***	The level of spending on personal fashion a year of the person surveyed (million VND).		**9.** ***Attractiveness (attr)***	The attractiveness of the individual is surveyed, self-rated on a scale from 0 to 10 (0 corresponds to Completely Unattractive; 10 corresponds to Completely Attractive).	

The results of qualitative research show that factors belonging to the survey subjects are believed to affect the fashion product expense and recommendations to collect information including age, occupation, education level, family status, number of children, lifestyle, the level of income for a year and the person's self-attractiveness [3]. The selection of 8 input variables of predicted model based on previous research results [2, 3] has identified factors (belonging to individual customers) affecting the level of spending on fashion products. Categorical variables (*lev, farm, occ, child, stl, attr*) are coded and using corresponding scales appropriate to the possible levels. Continuous variables (*age, inc, outc*) are determined directly by survey. This technique is commonly used in research related to the economic and social fields.

Based on this result and the overall study [2, 3], the questionnaire is set up to survey in detail the level of spending on the fashion of the subjects and the influencing factors. We proposed variables scale as in Table 1.

These scales were tested and calibrated after surveying over 20 questionnaires with a group of subjects suitable for the study. The survey sample size is determined by [3]:

$$n = \frac{N}{1 + N(e)^2} \quad (1)$$

where, n is the number of people to survey, N is the estimated number of women aged 25 to 55 in Hanoi city 2021) [10]; e is the standard deviation, select $e = 0.1$.

$$n = \frac{N}{1 + Ne^2} = \frac{1803665}{1 + 1803665(0,1)^2} = 99,99 \quad (2)$$

Choose to survey 156 women aged 25 to 55 years old in Hanoi city with the same number as Table 2.

Table 2. Units, locations, and number of surveyors

	Unit	Location	Amount
1	Hanoi University of Industry	No. 298 Cau Dien Street - Bac Tu Liem District - Hanoi city	35
2	Discovery Complex Shopping Mall	No. 302 Cau Giay Street, Cau Giay District, Hanoi city	30
3	Vincom Ba Trieu Shopping Mall	191 Ba Trieu, Le Dai Hanh, Hai Ba Trung, Hanoi city	28
4	Bao Linh Monalisa Import and Export Co., Ltd.	Le Trong Tan, Duong Noi Ward, Ha Dong District, Hanoi city	33
5	Vincom Center Metropolis	29 P. Lieu Giai, Ngoc Khanh, Ba Dinh, Hanoi city	30
	Sum		**156**

After the survey, all questionnaires were collected, checked and entered on excel software. Eliminating the questionnaires with missing data, 150 valid questionnaires were obtained.

2.1. Define the Optimal Multivariate Model Using the BMA Technique

The optimal linear multivariate model represents the relationship between *outc* and *age*, income (*inc*), *child, fam*, lifestyle (*stl*), occupation (*occ*) and *attr* of the surveyed women as determined by the *BMA* technique on R software, a widely used and useful software for statistical analysis and machine learning and artificial intelligence models [11].

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \varepsilon \quad (3)$$

where, Y is the dependent variable (level of spending on fashion), $X_1, X_2, \ldots X_p$ is an independent variable (*age, income, occ, child*, etc.); $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$ are regression coefficients determined from experimental data; ε is random error. *BIC* (Bayesian Information Criterion) is used to select the optimal model that represents the linear relationship between input and output variables and is recommended by statisticians [11]. This is a measure for balancing complexity (number of variables) and model optimization (via *RSS* - Residual Square Sum). The optimal model was selected as the model with the smallest *BIC* [11].

$$BIC = n \log(RSS_p) + p \log n \quad (4)$$

where, RSS_p is the defined value of the model with p variable input, n is the total number of variables.

2.2. Setting up an Artificial Neural Network for Prediction of Fashion Product Expence

Structure of ANN

The neural network that has been established to predict fashion expense is a 3-layer feed-forward network, using only one hidden layer. For simplicity, the network to which the input sumer is applied is the *Net* function:

$$Net = \sum_{i=1}^{m} \mathrm{w_i} * s_i + b \tag{5}$$

where S_i is the input signal and the corresponding weight is w_i; b is the bias threshold parameter.

Since the network is set up with a not-too-large number of neurons, it is recommended to choose to use the input function at a moderate level without the use of complex functions, such as integrated functions and polynomial functions. The output signal can be calculated $Y = f(Net)$ with $f(.)$ being the neuron's activation function.

Input layer

The input layer of the expenditure predicting network has 8 parameters related to the survey object, including: income level (*inc*), occupation (*occ*), number of children (*child*), family status (*fam*), qualifications (*lev*), lifestyle (*stl*) and attraction (*attr*). The input neurons x_i with $i = 1 \div 8$. These inputs will be tested for correlation coefficients pairwise to remove one of the two input variables with a correlation coefficient greater than 0.95 because they reflect the same effect on the model output. The input layer is added with a bias neuron equal to 1 to increase the convergence of the network [12-14].

Hidden layer

The hidden layer comprises neurons in the middle of y_j. This layer receives signals from the input layer neurons through the weights u_{ij}.

$$y_j = f(Net_j) = f(\sum_{i=1}^{8} x_i u_{ij} + b_j \tag{6}$$

where x_i (i = 1, 2,…, 8) are input layer neurons;

y_j are the hidden layer neurons; j is determined by trial-and-error method;

u_{ij} are the weights between input layer neuron i and hidden layer neuron j;

b_j is the bias neuron.

The maximum number of neurons of the hidden layer is determined by the Kolmogrov formula:

$$N_{hide} < 2 * N_{input} + 1 = 2*8 + 1 = 17 \tag{7}$$

where N_{hide} is the number of hidden layer neurons, N_{input} is the number of neurons of input layer [12, 13].

Output layer

The output z output is the fashion product expense (*out*).

$$\begin{aligned} z_k &= f\left(Net_k\right) = f\left(\sum_j y_j w_{kj} + c_k\right) \\ &= f\left(\sum_j w_{kj}\left(\sum_i x_i u_{ji} + b_j\right) + c_k\right) \end{aligned} \tag{8}$$

where z_k (k = 1) is output layer neuron;

w_{kj} are the weights between output layer neuron k and hidden layer neuron j;

c_k is the bias neuron.

8 input layer neurons were received from the survey results. The layered neuron recognizes signals from hidden layer neurons through the weights w_{kj} and signals from bias c_k neuron. The design network adds neural bias equal to 1 to increase the network's ability to learn to adapt.

Highly correlated parameters will communicate the same information to the neural network. So, these 8 inputs will be tested in pairs to consider removing 1 of 2 values if there is a correlation greater than 0.95. The exclusion of these parameters from the input has little effect on ANN's generalization ability (the number of epochs and the total error are not changed significantly) [13, 14]. When two parameters have a correlation coefficient greater than or equal to 0.95, only 1 of 2 parameters is used in the network. The activation function used for the predicted network is the monopolar Sigmoid function:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{9}$$

This is the most commonly used function in straight-forward neural network applications, the derivative of the Sigmoid function can be calculated easily, simply, and can be represented into the number of categories of the Sigmoid function.

Learning algorithm

The learning algorithm applied to the predicted neural network is error-back propagation. The ability to learn parameters and learn the structure of the neural network is very effective, so the parameters included will be learned and applied to adjust the weights to suit the samples. This is a strategy that adjusts the weights clearly and accurately. Error-back-propagation algorithm is the most commonly used in the training of the neural networks.

The error value of the network for the *(m+1)*-th sample that generates the error function E and the error signals for the output δ_k and hidden layers δ_j are determined by the formula:

$$E_{m+1} = \frac{1}{2}(d - z)^2 + E_m \tag{9}$$

where E_m is the error of the network with the m-th learning sample;

E_{m+1} is the error of the network with the (m+1)-th learning sample;

d is the desired output of the (m+1)-th learning sample;

z is the output of the neural network with the $(m+1)$-th learning sample.

$$\delta_k = (d_k - z_k)z'_k = (d_k - z_k)f'(Net_k) \tag{10}$$

$$\delta_j = f'(Net_j) \sum_k \delta_k \; w_{kj} \tag{11}$$

where, δ_k is the error signal for the output;

δ_k is the error signal for the hidden layer.

The network propagates errors in the opposite direction of the original signal propagation direction to update the values of the weights.

Correction w_{kj}:

$$\Delta w_{kj} = \eta(d_k - z_k)f'(Net_k)y_j = \eta\delta_k y_j \tag{12}$$

where, η is learning rate;

Correction c_k:

$$\Delta c_k = \eta\delta_k \tag{13}$$

Correction u_{ji}:

$$\Delta u_{ji} = \eta \sum_k \delta_k w_{kj} \; f'(Net_j)x_i = \eta\delta_j x_i \tag{14}$$

Correction b_j:

$$\Delta b_j = \eta\delta_j \tag{15}$$

During each epoch, E is compared with Emax (The maximum value of the error function of the model was selected when training). If $E \leq Emax$ then terminate the learning process and give the final resulting weights. If $E > Emax$ then reset the value $E = 0$, $m = 1$, initiate a new learning epoch by going back to the first step.

Neural networks use error-back-propagation algorithms when the design has an important advantage. It doesn't have to know the exact type of function, the number, or the location of the parameters in that function. So, this algorithm provides a trick that helps the network adjust the value of the numbers on the basis of the Gradient-descent method [12, 13]. The process of dividing learning and testing sample sets for the *ANN* model is performed on *R* software.

3. Results and Discussion

3.1 The Relationship Between Input Variables

The linear correlation between the input variables of the predicted model is considered using the *pair.panel* function on the *R* software to remove one of the two variables with a correlation coefficient $r \geq 0.95$ because the information their impact on the output are similar.

The results of the pairwise correlations of the input values in Fig. 1 show that some r correlation coefficients have significant values. r achieves the greatest value equal to 0.78 when considering the relationship between the number of children (*child*) and family status (*fam*). This was followed by a correlation between *age* and *child* of 0.67. There is no value of r when considering the pairwise correlation of inputs greater than or equal to 0.95. Therefore, it is possible to use the 8 parameters surveyed above as inputs for the predicted model.

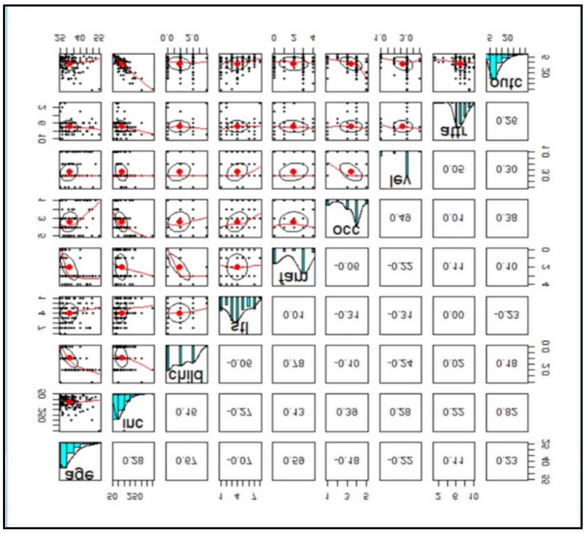

Fig. 1. The pairwise linear correlations of the inputs

3.2. Predicting the Fashion Products Expense Using a Linear Multivariate Model Using BMA

The data was processed using the *BMA* technique on *R* software to look for the optimal linear multivariate model between survey values that applied to women aged 25-55 and the fashion product expense. 11 models have been found. The most optimal model selected is:

$$outc = -3{,}09148 + 0{,}09604*inc + 0{,}34012*attr \tag{8}$$

and $R^2 = 0{,}683$; $BIC = -162{,}198$.

where *outc* is the fashion products, *inc* is the income of one-year, *attr* is the level of self-assessment attraction of that person. The *BMA* chart shows the models obtained in Fig. 2.

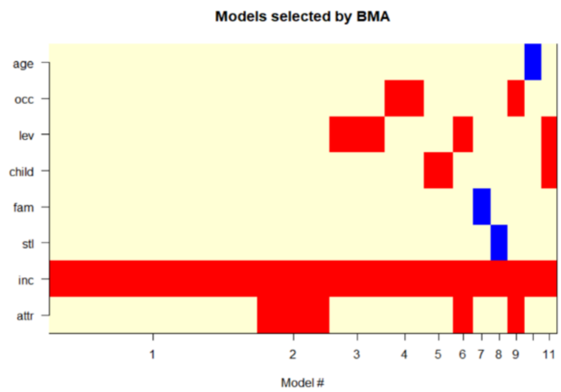

Fig. 2. Models that show the relationship between input variables and the level of expenditure Fashion defined by the *BMA* technique

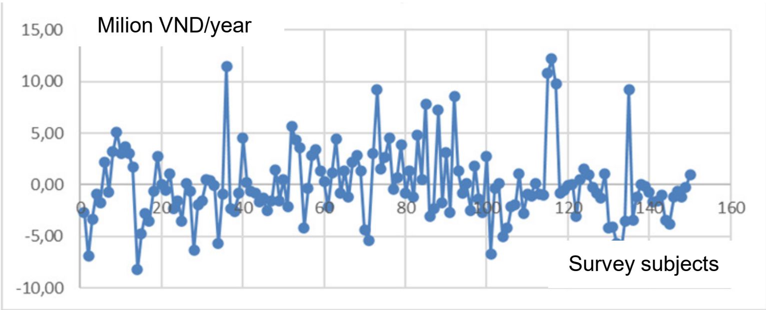

Fig. 3. The errors of predicted expenses by the multi-linear model using BMA

The results showed that *inc* (the one-year income of the surveyed women) were present in all models (Fig. 2), meaning that income always affected the fashion product expense of the surveyed women. Next is the level of self-assessment attraction (*attr*) and other variables. The fashion product expense tends to be proportional to income levels (*inc*), levels of self-assessment attraction (*attr*), occupation (*occ*), qualifications (*lev*), number of children (*child*), and inverse proportions to age (*age*) and lifestyle (*stl*). The multi-linear model showed that the variability of *inc* and *attr* input values could explain 68.3 percent of the variation in fashion product expense with survey subjects. The errors in the prediction by this model is shown in Fig. 3.

The average error between the actual and predicted expense value of this model is VND 2.59 million per year and the biggest error of VND 12.2 million per year is quite important.

3.3. Results of Fashion Product Expense Prediction Using the ANN Model

After training the network on *R* software, the *ANN* structure for predicting has been established as follows (Fig. 4):

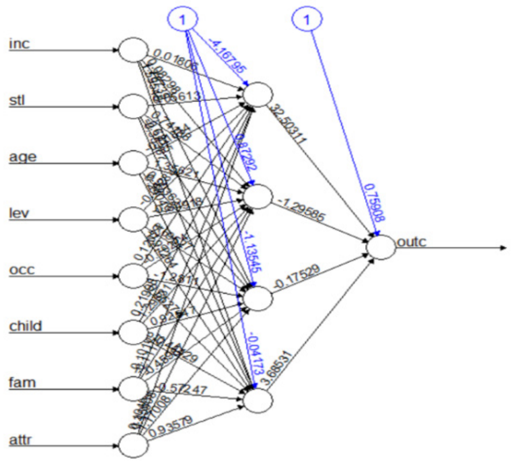

Fig. 4. Structure of fashion product expense predicting ANN

The expense predicting network is set up as a 3-layer feed-forward with the structure 8, 4 (+1), 1 in which the hidden layer is supplemented with a bias neuron equal to 1 to increase the adaptive learning capacity of the network. The input layer consists of 8 neurons that receive input variables x_i, corresponding to the values of 8 surveyed parameters related to the survey object (*inc, occ, lev, fam, stl, attr, child, age*). The hidden layer consists of 4 neurons y_j and a bias neuron with a value of 1. The number of neurons in the hidden layer $j = 4$ is determined by the "*trial-error*" method. The activation function of the predictive ANN is the unipolar Sigmoid function. The output layer of the network set includes 1 neuron z_k ($k = 1$) which is the expense (*out*). The weight matrices U_{ji}, W_{kj}, b_j, and c_k between layers are obtained after finishing training the network at the 88750 epochs.

3.4. Learning and Testing Samples of the Predictive Network

The learning sample set includes 104 samples {*x(l), d(l)*} was randomly selected on *R* software (at the rate of 70% of the learning sample and 30% of the testing sample) with $l = 1 \div 104$, *x(l)* is the input vector, *d(l)* is the desired output vector. The testing set consists of 46 samples {*x(t), d(t)*} is the remaining samples after randomly selecting the learning samples with $t = 1 \div 46$, *x(t)* is the input vector, *d(t)* is the actual output vector. These two subsets are completely independent and do not overlap.

The number of learning and testing samples is determined by the command *ind <- sample(2, nrow(MC), replace = TRUE, prob=c(0.7, 0.3))* on *R* software to ensure coverage of the possible input space of survey samples [11]. The data is in text file format from (1+8) survey results that match the Sigmoid activation function and generate the appropriate input matrices for the learning process of the network. The testing sample is in the form of a 1x8 matrix without the desired output value of the expenses.

3.5. Predictability of the Established Network

The observation errors on the learning samples

ANN was trained with 104 samples. The learning of the neural network was finished after 88750 epochs while *Emax* = 0.01.

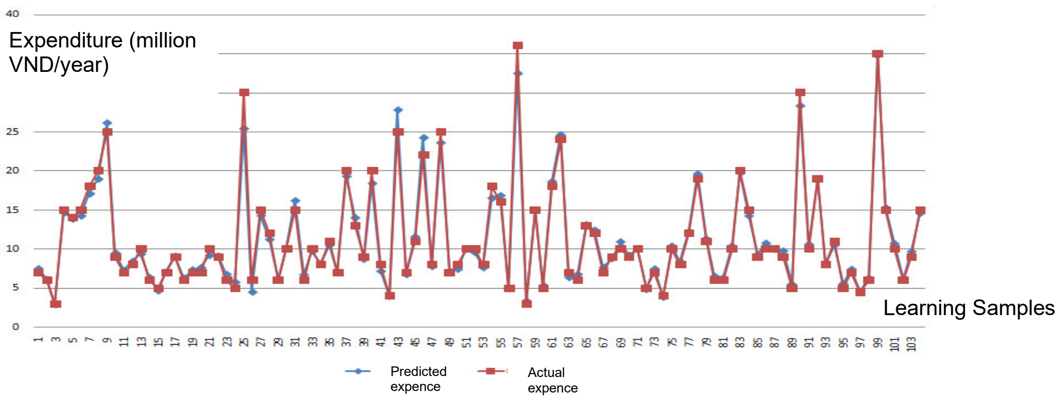

Fig. 5. Predicted and actual expenses on the learning sample set

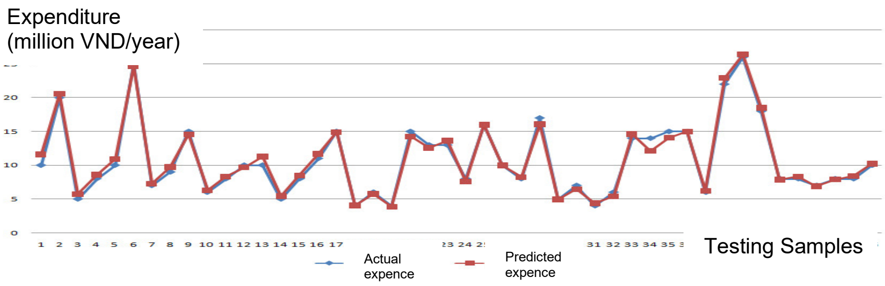

Fig. 6. Predicted and actual expenses on the testing sample set

The results of the network training show that the value of the *outc* output layer neuron is quite consistent with the output target on the sample set (Fig. 5). The average error of the predicted expenditure by ANN on samples is 0.59 million VND/year, the biggest error is 4.55 million VND/year when compared to the actual expense of the survey subjects on the sample set.

The observation errors on the testing samples

To evaluate the network's ability to predict expense, the predicted results were reviewed on a testing sample set of 46 samples. Fig. 6 shows that the network's predicted results have been consistently established with the actual expenses surveyed on the testing set.

The average error of the predicted expenditure by ANN on 46 testing samples was VND 0.48 million per year, the biggest error was VND 1.87 million per year when compared with the actual expenditure of the survey subjects. The correlation coefficient achieved between the predicted and actual expenses is R^2 = 0.987 (Fig. 7). The results of the variance analysis when comparing the predicted and actual values of the expenses on the 46 testing samples showed no statistically meaningful differences. The 95% confidence interval of the difference is -0.13(-2.38; 2.11) million VND/year and *p-value* = 0.907.

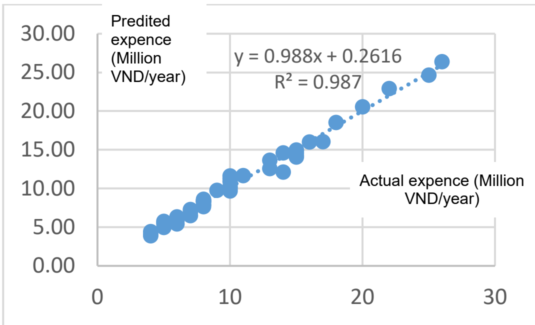

Fig. 7. The relationship between the predicted and actual expenses on the testing set

Thus, artificial neural network has established a more accurate expenditure level forecast than the multivariate linear model defined by the BMA technique. Therefore, the established ANN can predict accurately and can be applied. The predicted results will be even more accurate and effective if the network training process is carried out with more data.

4. Conclusion

The 3-layer feed-forward network model with 8-layer neurons in, 4 (+1) hidden layer neurons, and 1 output neuron, Sigmoid activation function, trained by the error-back-propagation algorithm allows to specifically predict the value of the fashion product expense of women aged 25-55 in Hanoi city within the scope of the survey.

The predicted values on the testing set by *ANN* are highly correlated with the actual value ($R^2 = 0.987$). The average error of the predicted fashion expenditure by ANN on 46 testing samples was VND 0.48 million per year, the biggest error was VND 1.87 million per year when compared with the actual expenditure of the survey subjects. The established artificial neural network gives more accurate and reliable forecasting results than the linear multivariate model defined by the BMA technique.

The training and testing processes with 104 learning samples and 46 testing samples show that ANN has been designed for accurate, reliable, and useful results. ANN can be applied for the prediction of the fashion product expenses to support the strategic planning of the production and sale of fashion products.

While this study limitation concentrated on 150 women from 25 to 55 years old at 5 locations in 5 districts of Hanoi city, future research could examine and evaluate in the larger sample size and broader research scope.

References

[1] H. M. T. Nguyen, Study on fashion product consumption characteristics of workplace clothes at Hanoi City, M.S Thesis, Hung Yen University of Technology and Education., Hung Yen, Vietnam, 2017.

[2] H. M. T. Nguyen, Le. N. T., Study on fashion product consumption characteristics of workplace clothes at Hanoi City, Journal of Science and Technology - Hanoi University of Industry, 2017.

[3] Duong Thi Hanh, Research on some factors affecting the expenses on fashion products of women aged 25-55 in Hanoi city, Master thesis, Hanoi University of Industry, 2021.

[4] L. Sztandera, C. Frank, and B. Vemulapali, Prediction of women's apparel sales using soft computing methods, Lect Notes Artif Intell, 3215: 506-512, 2004. https://doi.org/10.1007/978-3-540-30134-9_68

[5] S. Thomassey, M. Happiette, and J. Castelain, A global forecasting support system adapted to textile distribution, Int J Prod Econ, 96: 81-95, 2005. https://doi.org/10.1016/j.ijpe.2004.03.001

[6] S. Thomassey, and A. Fiordaliso, A hybrid sales forecasting system based on clustering and decision trees, Decis Support Syst, 42: 408-421, 2006. https://doi.org/10.1016/j.dss.2005.01.008

[7] Z. Sun, T. Choi, K. Au, and Y. Yu, Sales forecasting using extreme learning machine with applications in fashion retailing, Decis Support Syst, 46: 411-419, 2008. https://doi.org/10.1016/j.dss.2008.07.009

[8] A. Aksoy, N. Öztürk, and E. Sucky, Demand forecasting for apparel manufacturers by using neuro-fuzzy techniques, Journal of Modelling in Management, vol. 9 Issue: 1, pp.18-35, 2014. https://doi.org/10.1108/JM2-10-2011-0045

[9] Z. X. Guo, W. K. Wong, S. Y. S. Leung, J. T. Fan, and S. F. Chan, A genetic-algorithm-based optimization model for solving the flexible assembly line balancing problem with work sharing and workstation revisiting, IEEE Trans Syst Man Cy C, 38: 218-228, 2008. https://doi.org/10.1109/TSMCC.2007.913912

[10] General Statistics Office of Vietnam, https://www.gso.gov.vn/so-lieu-thong-ke

[11] F. Dominici, J. J. Faraway, M. Tanner, and J. Zidek, Linear Models with R, CHAPMAN & HALL/CRC, CRC Press Taylor & Francis Group, 2014.

[12] Giuseppe Ciaburro, Balaji Venkateswaran, Neural Networks with R: Smart models using CNN, RNN, deep learning, and artificial intelligence principles, Published by Packt Publishing Ltd., Birmingham B3 2PB, UK, 2017.

[13] M. T. Hagan, H. B. Demuth, and M. H. Beale, Neural Network Design, PWS Publishing Company, 1996.

[14] Nguyen Thi Le, Ngo Chi Trung, Le Huu Chien, Seam pucker prediction based on fabric structure and mechanical properties using neural network, Journal of Science and Technology, No.65, 2008.