Applicability of ANN and MLR Models in Measuring the Impact of Environmental Parameters on the Body Temperature of Swine

Nibas Chandra Deb[1],* Jayanta Kumar Basak [2, 3] Na Eun Kim[1] Bolappa Gamage Kaushalya Madhavi[1] Hyeon Tae Kim[1]

[1]*Department of Bio-systems Engineering, Gyeongsang National University (Institute of Smart Farm), Jinju, 52828, Korea*
[2]*Institute of Smart Farm, Gyeongsang National University, Jinju, 52828, Korea*
[3]*Department of Environmental Science and Disaster Management, Noakhali Science and Technology University, Noakhali-3814, Bangladesh*
[*]*Correspondence author. Email: bioani@gnu.ac.kr; Tel.: +82-55-772-1896*

ABSTRACT
This study was conducted to identify key parameters such as temperature, humidity, carbon dioxide (CO2), and relative temperature-humidity index (RTHI) that affect the inside and outside environment of the Swine barn. Moreover, the climate of the Swine barn is always related to the Swine's body temperature (SBT). This study used three growth-related factors and eight environmental components as variables. Hidden layer neurons were performed in this experiment to determine the link between input and output parameters using an artificial neural network (ANNs) model. The model's accuracy was measured using three statistical performance metrics: regression coefficient (R^2), root mean square error (RMSE) and mean absolute error (MAE). The multiple linear regression (MLR) and ANN models were subjected to sensitivity tests to ascertain the input parameter's specific effects on the SBT. The predicted results were the same as the measured results in the ANNs model, while the predicted and measured results were different in the MLR model. Compared to different traits, trait F showed the best results such as an increase in RMSE (2.0 and 0.70%, respectively) and a decline in R^2 (2.10 and 1.40%, respectively). The ANNs model had higher efficiency compared to the MLR models. Furthermore, the RTHI, indoor temperature-humidity index (ITHI), relative temperature (RT), outdoor temperature-humidity index (OTHI), and outdoor temperature (OT) were positively associated and accounted for 81.2% and 70.8% of the SBT change, in the ANNs and MLR models, respectively. Overall, this study concludes that RTHI is an important indirect indicator for determining the body temperature of Swine (BTS).

Keywords: *Relative temperature-humidity index, swine body temperature, ANNs model, MLR model.*

1. INTRODUCTION

All biological activities of animals are dependent on body temperature [1]. Temperature boosts the rate of metabolic processes; however, if it rises above a particular point, biological functions may fail [1]. As a result, there is a growing interest in estimating the thermal comfort zone of an animal barn by assessing the animal's body surface temperature as well as the ambient environment within and outside the animal barn. The most important environmental parameters, likely the concentration of ammonia, carbon dioxide, temperature, and relative humidity, influence animal performance and fitness [2].

Swine's are homoeothermic animals, which indicates their body temperature is relatively constant throughout a wide range of ambient ammonia, carbon dioxide, temperature, relative humidity concentration, and other influential variables. Some studies reported that the environmental parameters affect the changes in swine's biological activity. Moreover, when swine are

A. D. Saputro et al. (Eds.): ICOSEAT 2022, ABSR 26, pp. 651–657, 2023.
https://doi.org/10.2991/978-94-6463-086-2_86

stressed by heat, Wilson and Crandall [3] found that they raise their respiratory frequency, peripheral blood flow, and heart rate to enhance heat loss and decrease voluntary feed intake times to reduce heat production within their bodies. To address these subjects, ambient environment and growth-related variables can be used to predict swine body surface temperature. Until now, most swine body temperature prediction modeling research has concentrated on linear regression, simple heat map, principal component analysis, and stepwise regression.

Consequently, these methods are insufficient to show the interactions between the body temperature of swine and difficulties in the environment [4-8]. When complex relationships exist among the studied variables, nonlinear models such as genetic expression (GE) and artificial neural networks (ANNs) would be acceptable. Some studies show that the ANNs model accurately predicts output variables and provides minor errors than other methods like the MLR model [9].

Now, ANNs have been widely used to process nonlinear data [10]. However, small research in animal science has used ANN models to predict the body temperature of swine's using ambient environmental variables within and outside the swine barn. As a result, the goal of this research was to create ANN models that could predict the body temperature of swine based on the input values. In addition, the sensitivity of the input variables was used to analyse the most and least influential parameters on swine body temperature.

2. MATERIALS AND METHODS

2.1 Swine barn and experimental design

The study was carried out at Gyeongsang National University (smart farm systems lab), Jinju, Republic of Korea, in an experimental Swine barn. The walls of the experimental Swine barn were built with galvanized steel, while the roof was constructed with Styrofoam. These materials were chosen for their high thermal insulation capacity and use in maintaining a comfortable atmosphere within the experimental Swine barn [11]. Two experiments were performed on Six 50 days of Swine (initial weight = 28.5 ± 0.6 kilograms) over a period of 84 days from 2020 to 2021. In this Swine barn, the feed for Swine was supplied two times a day, at 9 a.m. and 5 p.m. The feed consumption, daily amounts of feed provided, and residues of each Swine were recorded. In addition, at the start of the trial, body weight was calculated by averaging weights taken twice a day. At the same time, the body surface temperature of the Swine was measured by the infrared sensors (IR sensor, model-MI3, Raytek Corporation, California, United States of America), which were perpendicular to the body of the Swine at four different body locations: forehead, backside, left side, and right side of each Swine at a fixed distance (25 cm). The IR sensor recorded the data every hour, From 10.00 a.m. to 6.00 p.m., and the computer collected body temperature data directly. Carbon dioxide (CO_2), humidity (%), temperature (^0C), and wind speed (ms^{-1}) data were recorded every ten-minute interims within and beyond the Swine barn using weather sensors and livestock environment management systems (LEMS).

2.2 Development of Multiple linear regression (MLR) and Artificial neural networks (ANNs) models and data analysis

ANNs are composed of linked artificial neurons that are connected and separated into three layers: input, hidden, and output (Figure 1). Multiple input-output vectors are used to assess the performance of a neural network to determine its dependability [12]. Hydrology [13] reported the output of the ANN network as given in Equation (1).

$$y_a = \alpha_0 + \sum_{l=1}^{n} \alpha_l \, f\left(\sum_{k=1}^{m} \beta_{kl} \, y_{t-1} + \beta_{0l}\right) + \varepsilon_t \qquad (1)$$

Where y_a is the body temperature of Swine, m is the number of input nodes, n is the number of hidden nodes, f is the transfer function, β_{kl} {k=1, 2,…, m; l=0, 1,…, n} are the weights from the input to hidden nodes, α_l {l=0, 1, …, n} are the vectors of weights from the hidden to the output nodes, and α_0 and β_{0l} denote the weights of arcs leading from the bias terms.

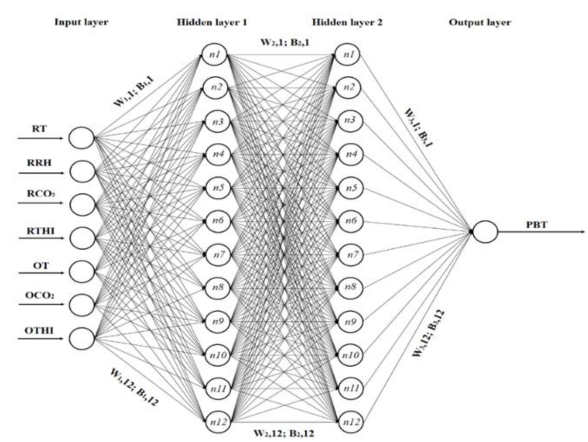


Figure 1 Feed Forward Back-propagation (FFBP) neural network model for predicting Swine's body temperature.

In this study, Matlab software (R2022a) was used to perform Feed Forward Back-propagation (FFBP) in an ANN model with the training function, as well as Bias (Learngdm) adaptive learning function and Gradient Descent with Momentum Weight. There are two hidden layers, and neurons were performed; in each hidden layer (4-20) neurons were investigated through trial and error to identify the ideal topology for the FFBP neural network. For the testing, training, and validation of the ANN and MLR, the dataset was divided into three sections: 20%, 65%, and 15% [9]. In this study, Equation (2) was used to create the MLR model [14].

$$y_a = a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n + \varepsilon_i \quad (2)$$

Where, y_a is the Swine body surface temperature (SBST), $x_1 - x_n$ is the input variables, $a_1 - a_n$ is the regression coefficient, a_0 is the intercept and ε_i is the error.

Although there are several parameters that might be chosen as input variables, the correlation method was used to guide the input variable selection process. This method has two advantages: (i) it can be used to identify variables that are highly correlated, and (ii) it is used to deduce simple correlations between variables [15]. In this study, Statistical Package for the Social Sciences (IBM SPSS Statistics 22.0.0.0, New York, USA) was used for all statistical analyses, and the Origin Pro 9.5.5 (OriginLab, Northampton, Massachusetts, USA) was used for graphical representation.

3. RESULTS AND DISCUSSION

3.1 ANNS (FFBP) and MLR model performance

Environmental data, namely CO_2, temperature, relative humidity, and temperature-humidity index in and out of the swine barn, and three growth-related characteristics, such as feed intake, age of swine, and body weights, were taken into account to establish the suitable model structure in both FFBP and MLR models. The environmental parameters such as ITHI, OTHI IT, RTHI, and OT all showed a positive correlation with BTS. On the other hand, indoor relative humidity (IRH), indoor CO_2 concentration (ICO_2), and outdoor CO_2 concentration (OCO_2) showed a negative correlation with BTS.

Table 1 input parameters (correlation coefficients) with Swine body temperature

Parameters	Correlation coefficient(r)
Age	-0.17
Bodyweight	-0.11
Outside Carbon dioxide	-0.56
Inside room temperature-humidity index	0.80
Inside Room Relative humidity	-0.49
Feed Intake	-0.13
Outside temperature	0.61
Inside Room Temperature	0.79
Inside Room Carbon Dioxide	-0.60
Outside Relative Humidity	-0.12
Outside temperature-humidity index	0.62

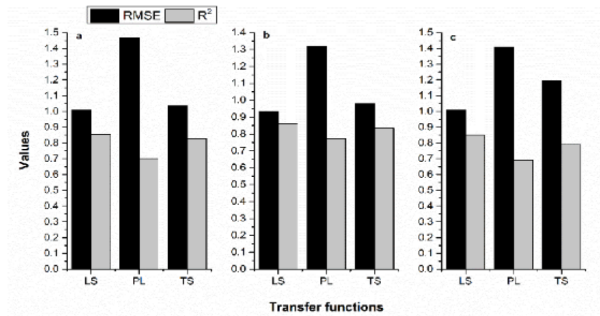


Figure 2 Bar graphs (a), (b), and (c) showed the efficacy of FFBP in the testing, validation, and training stage.

According to the correlation analysis, ITHI, OTHI, IT, OT, IRH, ICO[2], and OCO[2] ($r \geq 0.5$) were considered the input variables to simulate the model because they strongly correlate with the swine body temperature, which shows in (Table 1). Due to the highest R^2 and the least RMSE in the testing, validation, and training phases, the establishment of the FFBP model with log-sigmoid (LS) transfer function had the best performance, as shown in Figure (2). However, compared to all transfer functions, the linear transfer function performed the least performance. Furthermore, different numbers of neurons were evaluated in each hidden layer (4-20) to determine the optimal number of neurons in the hidden layers for the FFBP network with the log-sigmoid (LS) transfer function. The results demonstrated that the FFBP model with two hidden layers, and 20 neurons produced significant outputs in the training, validation, and testing stages (Figure 3). The efficiency of a regression-based model, like FFBP, is dependent on the existence of linear correlations between input and output variables [4].

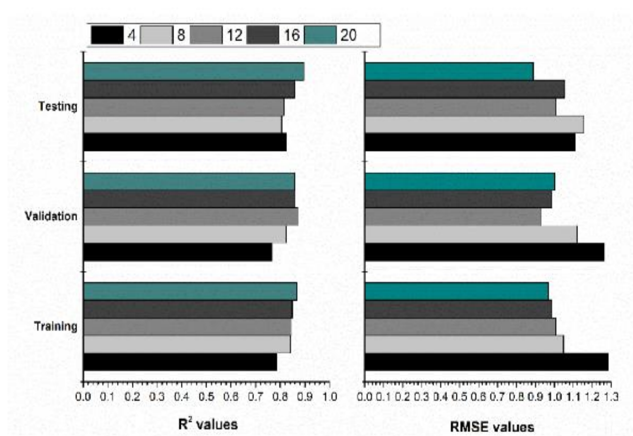
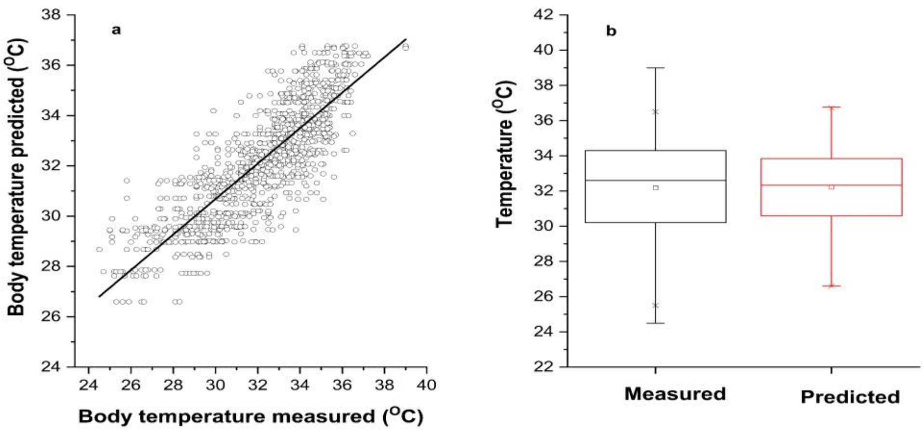


Figure 3 Feed Forward Back-propagation (FFBP) neural network model for predicting Swine's body temperature in the testing, validation, and training stage.

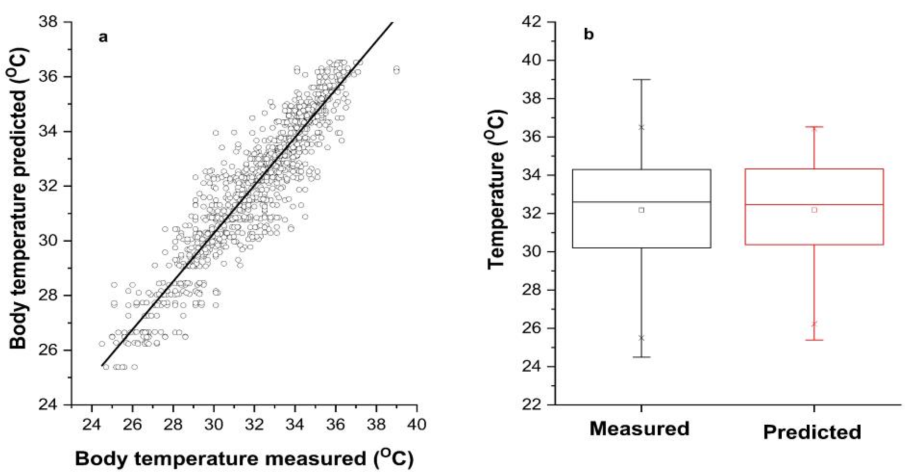
The regression model's efficacy was tested using the same inputs and output data as the FFBP to predict the



Figures 4 Scatter plot (a), and box plot (b) are represents the actual and expected Swine body temperature by using the MLR model.

most influential factors that affect the Swine's body temperature (SBT) to predict BTS, using equation (3).

$$BPT=20.48+0.219RT-0.037RRH-0.002RCO_2 + 0.04RTHI - 0.257OT - 0.01OCO_2 + 0.259OTHI \quad (3)$$



Figures 5 Scatter plot (a), and box plot (b) are represents the actual and expected Swine body temperature by using the FFBP model.

Table 2 Traits and inputs variables for sensitivity analysis

Trait	Input variables
A	RRH+RCO_2+RTHI+OT+OCO_2+OTHI
B	RCO_2 +OT+OCO_2+OTHI+RT+RRH
C	RTHI+RRH+ +OT+OTHI+RT+OCO_2
D	RCO_2+RT+RTHI+OCO_2+OTHI+RRH
E	RT+RCO_2+RTHI+OT+OCO_2+OTH
F	RRH+RTHI+ RT +OT+OTHI+RCO_2
G	RCO_2+RT +RTHI+OCO_2+RRH+OT

When SBT and the independent variables in Equation (3) have a linear relationship, this model can accurately predict SBT. Compared to the FFBP model, the MLR model was less capable of estimating SBT during training, validation, and testing.

Figure 4 and 5 illustrate a graphical representation of the actual and expected values by the MLR and FFBP models, which can aid in a better understanding of the two models' abilities.

3.2 Sensitivity analysis of ambient environmental variables

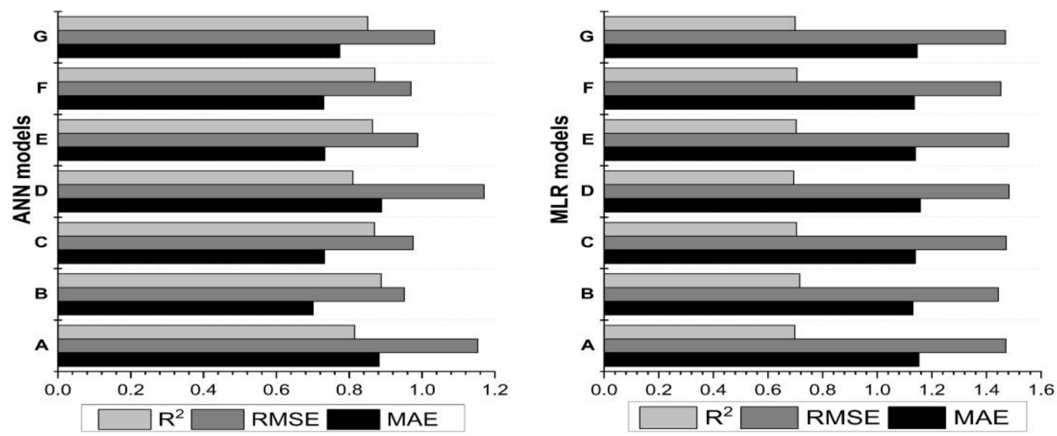


Figure 6 Sensitivity testing of the swine body temperature input variables by using MLR and ANN models.

For both the MLR and FFBP models, examined each input variable's sensitivity tests to determine the input variables' effect on the predicted SBT value. This present study was seven different traits, which are exhibited in Table 2. Their ability to predict SBT drastically dropped when running the MLR and FFBP models without RTHI, as seen in Figure (6). Compared to the two different models, the predicted results were the same as the measured results in the ANNs model, while the predicted and measured results were different in the MLR model. The FFBP and MLR model's selected trait without RTHI could predict SBT with increases of 22.02 and 2.60% in RMSE and reductions of 8.70 and 3.12% in R^2, respectively. For trait A, the FFBP and MLR models indicated a 20.35 and 1.92% increase in RMSE, respectively, and a decrease of 8.52 and 2.41% in R^2. The FFBP and MLR models showed an 8.53 and 1.89% rise in RMSE and a 4.27 and 2.57% decrease in R^2 for trait G, respectively.

Both models showed an increase in RMSE and a reduction in R^2, respectively. Compared to different traits, trait F showed the best results, such as an increase in RMSE (2.0 and 0.70%, respectively) and a decline in R^2 (2.10 and 1.40%, respectively). Furthermore, the RTHI, ITHI, RT, outdoor temperature-humidity index OTHI, and outdoor temperature OT were positively associated and accounted for 81.2% and 70.8% of the SBT change, respectively, in the ANNs and MLR models. Overall, this study concluded that RTHI is an essential indirect indicator for determining the swine's body temperature in the livestock barn.

4. CONCLUSION

The MLR and FFBP models were used in the current study to determine the parameters that influence Swine body temperature. According to the findings, the FFBP model with a log-sigmoid transfer function, two hidden layers, and 20 neurons performed better than the MLR model in predicting SBT. The sensitivity analysis showed that the RTHI is the most influential factor in predicting the body temperature of Swine. In addition, the results also showed that if the RTHI value increase or decreases, then the body temperature of Swine also rises or drop. In conclusion, RTHI is an important useful indirect indication for estimating Swine body temperature.

AUTHORS' CONTRIBUTIONS

" Nibas Chandra Deb' Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools, or data; Wrote the paper", " Jayanta Kumar Basak'supervision ", " Na Eun Kim and Bolappa Gamage Kaushalya Madhavi' analysis tools, "Hyeon Tae Kim' project administration and supervision"

ACKNOWLEDGMENTS

This research was supported by the Korea Institute of Planning and Evaluation for Technology in Food, Agriculture, Forestry and Fisheries (IPET) through the Agriculture, Food and Rural Affairs Convergence Technologies Program for Educating Creative Global Leaders, funded by the Ministry of Agriculture, Food and Rural Affairs (MAFRA) (717001-7).

REFERENCES

[1] L. Kessel, L. Johnson, H. Arvidsson, and M. Larsen, "The relationship between body and ambient temperature and corneal temperature", Invest Ophthalmol Vis Sci 51(12) (2010) 6593-6597.

[2] L.C. Rome, E.D. Stevens, H.B. and John-Alder, "The influence of temperature and thermal acclimation on physiological function. In: Feder ME, Burggren WW (Eds.), Environmental Physiology of the Amphibians. The University of Chicago Press, Chicago, 1992, pp. 183–205.

[3] T.E. Wilson and C.G. Crandall, "Effect of thermal stress on cardiac function", Exerc Sport Sci Rev. 39 (2011) 12-17.

[4] J.K. Basak, E. Arulmozhi, J. Park, F. Khan, F.G. Okyere, Y.J. Lee, D. Lee, and H.T. Kim, Monitoring predictive and informative indicators of body surface temperature of pigs in the context of the thermal comfort zone of livestock barn using an infrared sensor. Spring Joint Conference (Korean Society for Agricultural Machinery, the Korean Society for Bio-Environment Control, and the Korean Society of Animal Environmental Science and Technology), 9-10 May, 2019, Gyeongsang National University, South Korea.

[5] D.D. Soerensen and L.J. Pedersen, "Infrared skin temperature measurements for monitoring health in pigs: a review", Acta Vet Scand, 57(5) (2015) 1-11.

[6] J.C. Jang, M.H. Lee, J.Y. Lee, H.C. Choi, D.Y. Choi, H.J. Kim, and H.T. Kim, "Monitoring pig body temperature using infrared sensors", J Biosyst Eng. 40(4) (2015) 368-372.

[7] G.M. Mostaço, K.D. Miranda, I.D. Condotta, D. Salgado, "Determination of piglets' rectal temperature and respiratory rate through skin surface temperature under climatic chamber conditions", Eng Agríc Jaboticabal 35(6) (2015) 979-989.

[8] M.L. McClure, C.L. Burdett, M.L. Farnsworth, M.W. Lutman, D.M. Theobald, P.D. Riggs, D.A. Grear, and R.S. Miller, "Modeling and mapping the probability of occurrence of invasive wild pigs across the contiguous United States", PLoS ONE 10(8) (2015) 1-17.

[9] M. Abdipour, M.Y. Hmazekhanlu, S.H.R. Ramazani, and A.H. Omidi, "Artificial neural networks and multiple linear regression as potential methods for modeling the seed yield of safflower (*Carthamus tinctorius* L.)", Ind Crop Prod. 127 (2019) 185-194.

[10] H.W. Shin, E. Llobet, J.W. Gardner, E.L. Hines, and C.S. Dow CS, "Classification of the strain and growth phase of cyanobacteria in potable water using an electronic nose system", IEE P-Sci Meas Tech. 147(4) (2000) 158-164.

[11] B.E. Moon, H.T. Kim, J.G. Kim, Y.S. Ryou, and H.T. Kim, "A fundamental study for the development of an unglazed transpired collector control system in the windowless pig house", J Agric Life Sci. 50 (2) (2016) 175-185.

[12] Bishop CM. 1996. Neural Networks for Pattern Recognition. Published by Oxford University Press, USA, ISBN: 978-0198538646.

[13] Hydrology, ASCE Task Committee on Application of Artificial Neural Networks in Hydrology. 2000. Artificial neural networks in hydrology. I: Preliminary concepts. J Hydrol Eng. 5(2):115 123.

[14] Darlington RB, Hayes AF. 2016. Regression Analysis and Linear Models: Concepts, Applications, and Implementation. Guilford Publications.

[15] M.D.R. Amezcua, S. Walsh, P.H. Luimes, and R.M. Friendship, "Infrared thermography to evaluate lameness in pregnant sows" Can Vet J. 55(3) (2014) 268-272.