International Journal of Multidisciplinary Approach Research and Science
E-ISSN 2987-226X P-ISSN 2988-0076
Volume 3 Issue 02, May 2025, Pp. 561-568
DOI: https://doi.org/10.59653/ijmars.v3i02.1529
Copyright by Author

Forecasting of Biogas and Biomethane Outputs from Anaerobic Co-digestion Using Multilayer Perceptron Artificial Neural Networks (MLP-ANN)

D.A. Samuel[1], B.I. Eziefula[2], Gbushum Orkuma[3*], Abdulgafar Usman[4]
University of Suffolk, UK[1]
Chevron Nigeria, Nigeria[2]
Joseph Sarwuan Tarka University, Makurdi, Nigeria[3]
Joseph Sarwuan Tarka University, Makurdi, Nigeria[4]
Corresponding Email: orkuma.gbushum@uam.edu.ng*

Received: 09-03-2025   Reviewed: 12-04-2025   Accepted: 13-05-2025

Abstract

The intricate, nonlinear interactions between several process parameters make it difficult to accurately forecast biogas and methane (CH_4) yields in anaerobic digestion systems. Conventional kinetic models frequently do not capture these dynamics well, particularly in co-digestion systems with heterogeneous substrates. This was addressed by developing and testing a Multilayer Perceptron Artificial Neural Network (MLP-ANN) for predicting cumulative biogas and CH_4 production from the anaerobic co-digestion of soymilk dregs and cow manure. Different pH values, substrate mixing ratios, and hydraulic retention durations were used to operate batch-mode digesters. Three input parameters, one hidden layer with three neurons, and two output nodes that represented the yields of methane (CH_4) and biogas made up the feed-forward ANN architecture. The result showed negligible prediction errors and very high coefficients of determination (R^2) of 0.999 for both outputs, and the model exhibited exceptionally accurate predictive power. The average relative errors for the training and testing stages were 0.002 and 0.004, respectively, confirming the model's excellent generalization capabilities. These findings support the optimization of anaerobic digestion systems by validating the MLP-ANN as a reliable and efficient forecasting method. This MLP-ANN can be used for forecasting biogas and CH_4 outputs based on pH values, substrate mixing ratios, and hydraulic retention times.

Keywords: Anaerobic Co-digestion, Artificial Neural Networks, Biogas Output Prediction.

Introduction

The adverse effects of climate change, the depletion of fossil fuel resources, the associated anxiety over energy insecurity, and the quest for a sustainable energy transition have reawakened interest in the renewable energy technology of anaerobic digestion (AD). This technology is emerging as the top sustainable option due to its superiority in the sustainable energy ecosystem (Gustafsson et al., 2024). The AD process is simple, cheap, scalable, decentralised, and continuous at all times compared to solar and wind technologies. The AD technology is effective for harnessing methane (CH_4), a potent greenhouse gas (GHG), and thereby curtailing temperature inversion responsible for global warming (Itodo et al., 2021). It is also used for the remediation of organic waste while at the same time generating biogas with high energy content and high-nutrient byproducts that serve as an excellent organic fertilizer (Surra et al., 2019).

Biogas, with high CH_4 content, is produced in the AD system by the decomposition of organic matter in a hermetic environment that is devoid of oxygen. The gas majorly contains methane (CH_4 50-70%) and carbon dioxide (CO_2 30-50%), depending on the feedstock used to produce it and the operational conditions of the AD system (Kougias and Angelidaki, 2019). Factors such as the composition of the substrates (feedstock) and its carbon-to-nitrogen (C/N) ratio, temperature of operation, the pH, the Organic Loading Rates (OLR) and the Hydraulic Retention Time (HRT) are reported to influence the efficiency of an AD system (Orkuma et al., 2024). Thus, identifying the ideal interaction of factors needed for optimal biogas output is difficult to determine, as complex interactions between factors may result in unexpected outcomes. Traditional kinetic equation models such as the first-order model, cone model, modified Gompertz model, and logistic growth model, among others, have been widely applied and repeated in an oversimplified manner to forecast the interactions in AD systems without recourse to the complex nonlinear dynamics of these systems (Avinash and Mishra, 2024). The result of reviews, however, converges that machine learning models such as artificial neural networks (ANNs) perform better in modelling and forecasting the complex processes of AD than the traditional models (Ling et al., 2024; Avinash and Mishra, 2024).

The Multilayer Perceptron (MLP) ANN, which is a class of Feedforward Artificial Neural Networks (FFANN), has been found to be effective in learning from previous data and making credible forecasts (Montesinos-Lopez, 2022). They are composed of three layers: the input layer comes first, followed by the hidden layer, which may include one or more neuro-nodes, as well as the output layer, where learning is achieved through forward-feed propagation and weight refinements based on precision enhancement (Sarma et al., 2014). The ANNs, particularly the MLP models, are designed to render a comprehensive solution for modelling complex, nonlinear systems, such as the AD process (Ibrahim et al., 2022). The MPL is also known to possess the ability to gain insights from experimental data, uncover intricate motifs, and make precise predictions without the need for explicit mathematical functions, as is characteristic of the kinetic models (Ling et al., 2024).

This study aims to develop and validate an MLP-ANN model to predict cumulative biogas and bioCH_4 surveyed volumes from the anaerobic co-digestion of Cm and soymilk dregs. The study focuses on using key operational parameters such as the cow manure with SMd ratio (Cm:SMd), hydraulic retention time (HRT), and initial pH as input variables. The model's performance will be evaluated using statistical metrics such as root mean square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2) to establish a reliable predictive tool for AD process optimization.

Literature Review

Studies have been conducted to assess the potential of ANN models in various bioenergy applications, including forecasting biogas production from different substrates, estimation of CH_4 contents, and process control. Jang et al. (2018) utilized ANN to predict methane potential from sewage sludge and food waste. Olatunji et al. (2023) modelled biogas and methane yield from anaerobic co-digestion of *Arachis hypogea* shells with combined pretreatment techniques using machine learning approaches. Their study showed that FCM-clustered ANFIS can predict biogas yield of pretreated *Arachis hypogea* shells satisfactorily, and they recommended the use of machine learning approaches in similar studies. Similarly, Mohd-Ali et al. (2015) reviewed various ANN applications in bioenergy systems and concluded that ANN models often outperform traditional regression-based methods. However, there seem to be few insights on the application of ANN for predicting biogas and bioCH_4 outputs, specifically, from an AD codigestion system using cow manure (Cm) and soymilk dregs (SMd), a mixture rich in nitrogen and carbohydrates, respectively. Comprehending the synergetic effects of these substrates through forecasting can support operational decision-making and strengthen the AD process performance.

Research Method

Anaerobic batch digestion experiments were conducted as described by Orkuma et al. (2025) using eight 2 L polyethylene biodigesters with a working volume of 1.8 L. The digesters were operated under mesophilic conditions at a constant temperature of 33 ± 1 °C for 30 days. The co-digestion substrates consisted of Cm and SMd mixed at different ratios: 2:1 (A), 3:1 (B), and 4:1 (C) and the control with only Cm. The organic loading rate (OLR) was maintained at 4 g VS/L in all treatments. Each digester received 144 mL and 1.65 L of inoculum and water, respectively, to initiate anaerobic microbial activity.

Biogas and bioCH_4 volumes were measured daily for 30 days, and the cumulative yields were computed. The dataset used for modelling comprised 63 instances of four treatments and sixteen observations, each representing a unique combination of process conditions using statistical block replicates. The input variables for the ANN model included the substrate (Cm:SMd) ratio, HRT and initial pH, while the output variables (targets) were cumulative biogas yield (mL/g VS) and cumulative BioCH_4 (mL/g VS).

An MLP architecture based on the unidirectional feedforward networks was used to construct the ANN model with the aid of the Statistical Program for Social Science ([IBM SPSS], 2021; Ver.28) software. The FF-ANN was composed of three neurons, representing the three input variables (Cm:SMd ratio, HRT and pH), with unknown neurons for the hidden layer and two neurons for the output layer (Biogas and BioCH_4). The operational sequence used for rescaling the training data in the input layers was standardized because this architecture computes the best number of units in the hidden layer (Komarysta *et al*., 2023). The batch training modes were adopted, and the optimization algorithm was the scaled conjugate gradient (SCG) on 70% and 30% of the training and testing data, respectively. The SCG is a secondorder optimization method that has been found to be faster and more memory-efficient than the basic backpropagation models with gradient descent optimization algorithms (Farizawani et al., 2020), and it is well suited for biogas optimization processes. The hyperbolic activation function was used in the hidden layer to predict outputs. The rescaling method for the output layer was standardized using the identity function, and the loss function was based the mean squared error for 200 epochs. The model's predictive performance was evaluated using RMSE, MAE and R^2, which were computed separately for biogas and methane yield predictions. Also, residual error distribution and actual vs. predicted plots were generated to visually assess prediction accuracy and bias.

Result and Discussion

Figure 1 depicts the MLP-FFN design for biogas and CH_4 yield prediction, while Table 1 provides a summary of the network architecture. The network was fed three AD process parameters (pH, HRT, and Cm:SMd ratio), which were then processed by three hidden neurones in a single hidden layer to provide cumulative biogas and CH_4 yields. This MLP architecture is a 3-3-2 array with 20 weighted synaptic connections and five bias constants—three in the hidden layer and two in the output layer—. The feedforward operation of the ANN model resulted in precise output predictions of biogas and CH_4 quantities as each input moved through the layers via the activated weighted synapses.

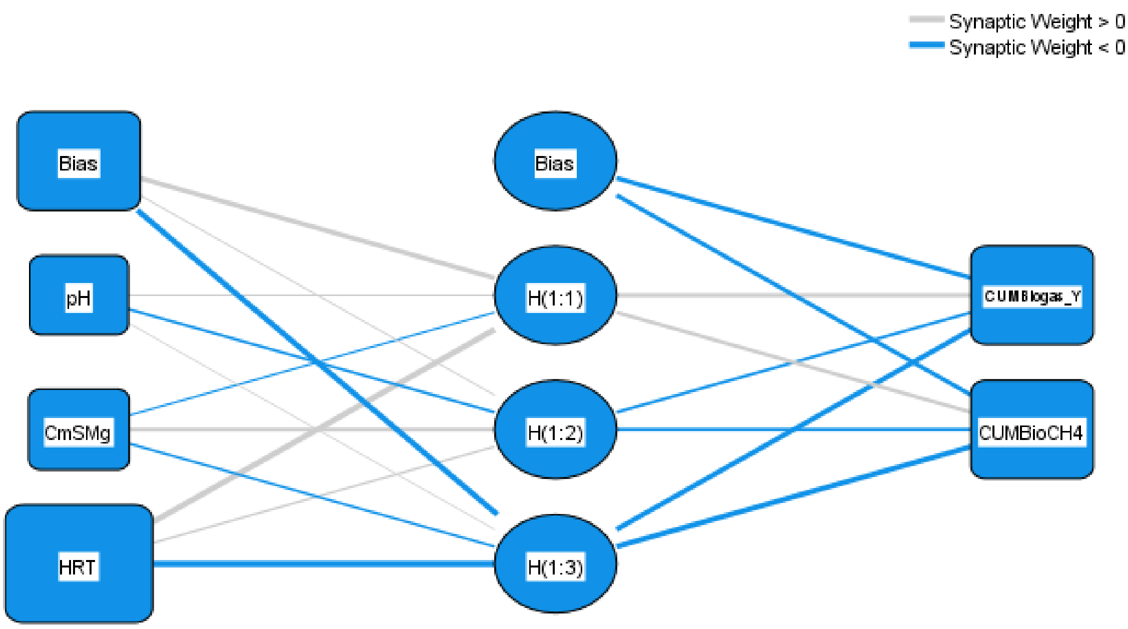

Figure 1: Multilayer Perceptron Network Architecture

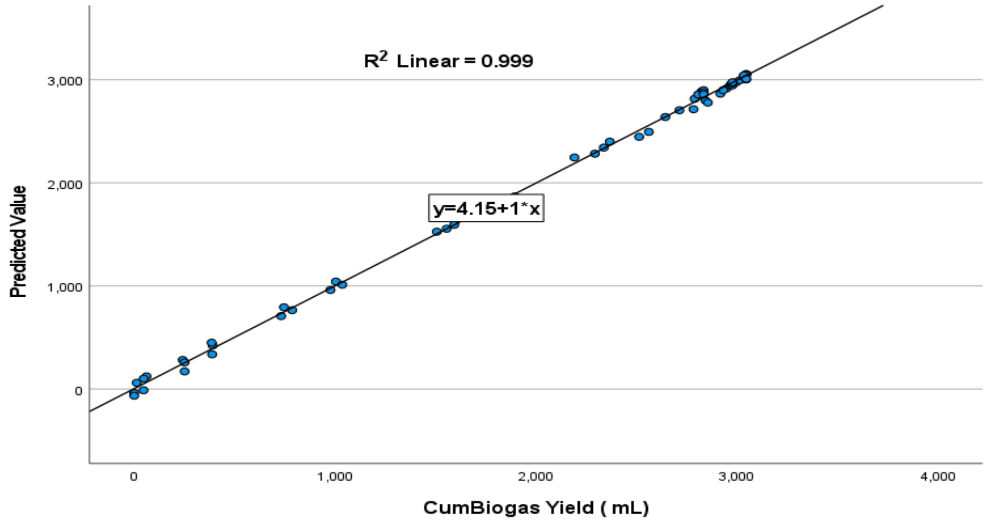

Figure 2: ANN Plot of Predicted vs Experimental Values of CumBiogas Yield

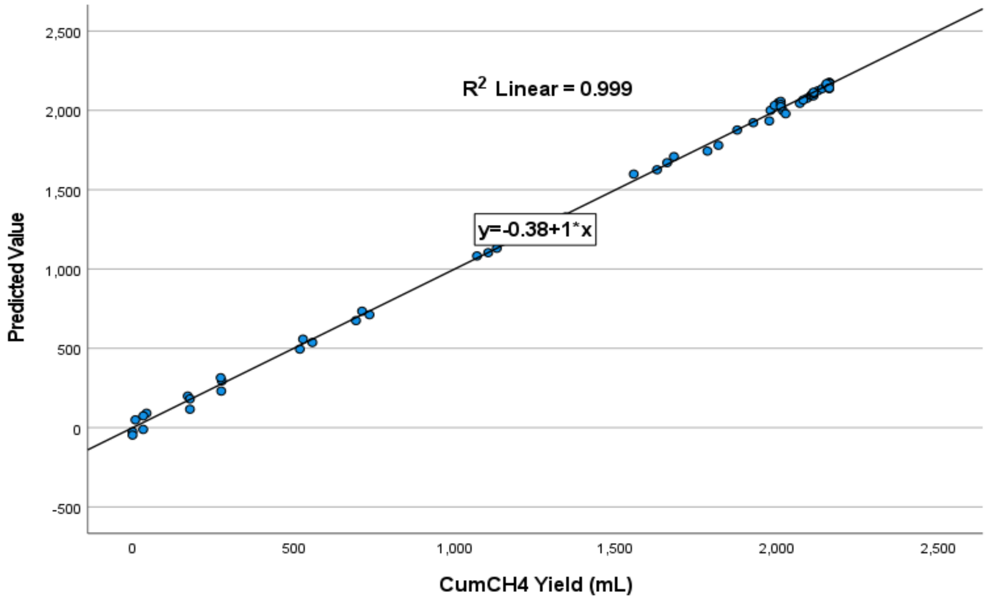

Figure 3: ANN Plot of Predicted vs Experimental Values of $CumCH_4$ Yield

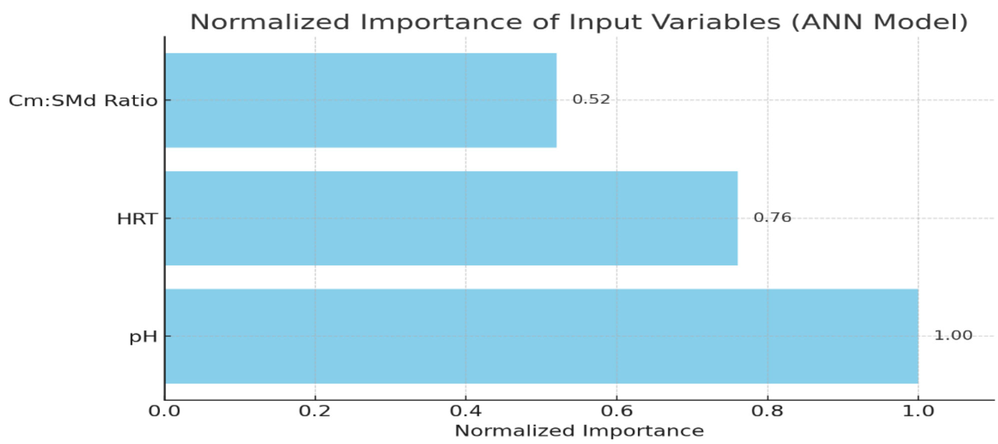

Figure 4: Independent Variable Importance Graph

Table 1: Summary of the MLP ANN Information

		Predicted				
		Hidden Layer 1			Output Layer	
Predictor		**H(1:1)**	**H(1:2)**	**H(1:3)**	**CumBiogas**	**CumBioCH4**
Input Layer	(Bias)	0.886	0.016	-1.077		
	pH	0.020	-0.066	0.015		
	Cm:SMg	-0.029	0.358	-0.046		
	HRT	1.232	0.034	-1.907		
Hidden Layer 1	(Bias)				-0.468	-0.459
	H(1:1)				0.438	0.374
	H(1:2)				-0.163	-0.178
	H(1:3)				-0.932	-0.989

Table 2: Summary Performance of the MLP-ANN

Statistics	**SSE**	**Average Overall RE**	**RE for Scale Dependents**	**RMSE**	**RMSE**	**R^2**
Testing (70%)	0.021					
CumBiogas		0.002				
$CumBioCH_4$			0.002			
Training (30%)	0.021					
CumBiogas		0.002				
$CumBioCH_4$			0.002			
Validation						
CumBiogas				6.71	5.27	0.999
$CumBioCH_4$				3.69	3.88	0.999

SSE- sum of square error, RE- relative error, RMSE- Root Mean Squared Error, MAE- Mean Absolute Error, R^2- Coefficient of Determination

The training and testing performance of the MLP-ANN model was assessed using the sum of squares error (SSE) and average relative error (ARE). The results are in Table 2. It reveals that during training, the model exhibited an SSE of 0.090 and an overall ARE of 0.002. Whereas, on the testing set, the SSE was 0.072 with an overall ARE of 0.004. These low error values indicate minimal overfitting and strong generalization capability of the model. Further evaluation of the forecasting metrics revealed an RMSE value of 6.71 mL/g VS for biogas and 5.27 mL/g VS for $BioCH_4$, while the MAE values were 3.69 and 3.88 mL/g VS, respectively. Additionally, the ANN models' predictive performance for predicting the cumulative biogas and $BioCH_4$ Countries yields was evaluated using regression analysis between the experimental and predicted values. Figures 2 and 3 display the linear regression plots for both responses. For the CumBiogas and CumBiogas yields, the relationships are captured in Equations 1 and 2.

$$\boldsymbol{y = 4.15 + x} \quad (1)$$

$$\boldsymbol{y = -0.38 + x} \quad (2)$$

The coefficient of determination of both biogas and $BioCH_4$ yields was similar (R^2 = 0.999), indicating a near-perfect fit. The slope of 1 and a minimal intercept value suggest that the ANN model was highly accurate with negligible bias across the dataset, except for the very small negative intercept of Equation 1 for the $CumBioCH_4$, which signifies a slight underprediction at lower methane yields but overall exhibits a highly reliable prediction. The mean percentage deviation (PMD) of predicted values from measured biogas yield was 4.88%, and from measured CH_4 yield was 3.06%. These low deviations suggest that the model is well-calibrated and exhibits minimal bias, with a slight tendency to underpredict yields. The high R^2 values in the plots also lend support to the robustness of the ANN model in simulating the biogas and methane production process from cow manure and soymilk dregs codigestion, making it a powerful tool for forecasting system behaviour.

Regarding the variable importance among the input variables, pH showed the highest normalised importance, followed by HRT and Cm:SMd ratio (Figure 4). This aligns with literature indicating pH as a critical parameter influencing microbial activity and methanogenesis. Compared to Modified Gompertz, cone, and first-order models previously applied to the same dataset, the MLP-ANN model demonstrated superior predictive power and flexibility. Traditional models often struggled with multi-variable interactions, which the ANN more effectively handled.

Conclusion

This study confirms the potential of MLP-ANN to accurately predict cumulative biogas and $bioCH_4$ yields from anaerobic co-digestion processes as a function of pH, HRT, and substrate ratios. The model outperformed traditional kinetic models and identified pH as the most critical predictor. The findings support the use of ANNs as decision-support tools in bioenergy systems.

References

Avinash, L. S., & Mishra, A. (2024). Comparative evaluation of Artificial Intelligence-based Models and Kinetic Studies in the Prediction of Biogas from Anaerobic Digestion of MSW. *Fuel*, *367*, 131545.

Farizawani, A. G., Puteh, M., Marina, Y., & Rivaie, A. (2020). A review of artificial neural network learning rule based on multiple variants of conjugate gradient approaches. In *Journal of Physics: Conference Series,* 529(2) p. 022040. IOP Publishing.

Gustafsson, M., Meneghetti, R., Souza Marques, F., Trim, H., Dong, R., Al Saedi, T., Rasi, S., Thual, J., Kornatz, P., Wall, D., Berntsen, C., Saxegaard, S., Lyng, K.A., Nägele, H.J., Heaven, S., Bywater, A. (2024). A perspective on the state of the biogas industry from selected member countries. Gustafsson, M., Liebetrau, J. (Ed.) *IEA Bioenergy Task* 37, 2024:2

IBM SPSS (2021). *Statistics for Windows*, Version 28.0. Armonk, NY: IBM Corp.

Ibrahim, M., Haider, A., Lim, J. W., Mainali, B., Aslam, M., Kumar, M., & Shahid, M. K. (2024). Artificial neural network modelling for the prediction, estimation, and treatment of diverse wastewaters: A comprehensive review and future perspective. *Chemosphere*, 142860.

Itodo, I. N., Bala, E. J., & Sambo, A. S. (2021). *Biogas technology in Nigeria*. CRC Press.

Jang, H. M., et al. (2018). Prediction of methane production potential of anaerobic co-digestion of sewage sludge and food waste using artificial neural networks. *Bioresource Technology*, 248, 179–187.

Komarysta, B., Dzhygyrey, I., Bendiuh, V., Yavorovska, O., Andreeva, A., Berezenko, K., ... & Maidanskyi, I. (2023). Optimizing biogas production using artificial neural network. *Eastern-European Journal of Enterprise Technologies*, *122*(8).

Kougias, P. G., & Angelidaki, I. (2018). Biogas and its opportunities—A review. *Frontiers of Environmental Science & Engineering*, *12*, 1-12.

Ling, J. Y. X., Chan, Y. J., Chen, J. W., Chong, D. J. S., Tan, A. L. L., Arumugasamy, S. K., & Lau, P. L. (2024). Machine learning methods for the modelling and optimisation of biogas production from anaerobic digestion: a review. *Environmental Science and Pollution Research*, *31*(13), 19085-19104.

Mohd-Ali, J., Hussain, M. A., Tade, M. O., & Zhang, J. (2015). Artificial Intelligence techniques applied as estimator in chemical process systems – A literature survey. *Expert Systems with Applications*, 42(14), 5915–5931. https://doi.org/10.1016/j.eswa.2015.03.023

Montesinos-Lopez, O. A., Montesinos López, A., & Crossa, J. (2022). *Multivariate statistical machine learning methods for genomic prediction* (p. 691). Springer Nature.

Olatunji, K. O., Madyira, D. M., Ahmed, N. A., Adeleke, O., & Ogunkunle, O. (2023). Modelling the biogas and methane yield from anaerobic digestion of Arachis hypogea shells with combined pretreatment techniques using machine learning approaches. *Waste and Biomass Valorization*, *14*(4), 1123-1141.

Orkuma, J. G., Samuel, D. A., Eziefula, B. I., & Kantiok, D. Y. (2025). Assessment of Biogas potential of Codigested Cow Manure with Soymilk Dreg. *International Journal of Innovative Science and Research Technology*, 10 (3).

Sarma, M., Sarma, K. K., Sarma, M., & Sarma, K. K. (2014). Fundamental considerations of ANN. *Phoneme-Based Speech Segmentation using Hybrid Soft Computing Framework*, 47-75.

Surra, E., Bernardo, M., Lapa, N., Esteves, I., Fonseca, I., Mota, J.P., (2019). Biomethane production through anaerobic co-digestion with Maize Cob Waste based on a biorefinery concept: A review. *Journal of Environmental Management,* 249: 1-21. https://doi.org/10.1016/j.jenvman.2019. 109351