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Neural Network Visualization of Stochastic Dependence of Weight Gain Processes on Dairy Productivity of Cows

Nikolay Vorobyov*, Marina Selina and Anna Guselnikova

Moscow State Academy of Veterinary Medicine and Biotechnology – MVA named after K.I. Skryabin, Moscow, Russian Federation
*Corresponding author's e-mail: ni.vorobyov@mail.ru

The study aimed to determine the optimal dose of a humic feed additive that balances weight gain and milk-forming processes in cows using neural network analysis. The productivity of cows can be increased by regulating the nutritional diet. It is possible to disrupt the balance of weight gain and milk-forming processes, which leads to an increase in the risks of susceptibility of cows to pathogenic infections. A novel computational system, NONN, was developed to calculate indices representing weight gain (CSImass) and milk production (CSImilk) based on blood parameters. As a result, it was possible to determine the maximum intensity of weight gain processes with a slight decrease in dairy productivity of cows when they were fed humic supplement No. 3 containing 70% humic acid. Thus, the proposed NONN computing system allows monitoring the effect of feed additives on the balance of weight gain, milk-forming, and immune protective processes based on cow blood parameters, which can be applied in developing new technologies for keeping farm animals. This approach is adaptable to other feed additives and livestock species, providing a scalable solution for sustainable livestock management and improving resource efficiency in farming practices

Keywords: Milk-forming biochemical processes, humic acids, computational neural network, veterinary, food industry.

INTRODUCTION

Optimizing dairy cow productivity is a critical global challenge, driven by the growing demand for milk and meat and the need to ensure sustainable agricultural practices (Romanov *et al.*, 2015). Balancing weight gain and milk production in dairy cows is particularly complex, as nutritional interventions aimed at enhancing one often adversely affect the other (Dong *et al.*, 2020; Kharitonov, 2010; Ryadchikov, 2012). This trade-off underscores the necessity of innovative approaches to maintain productivity while safeguarding animal health and welfare (Aliev, 1997; Bogolyubova *et al.*, 2014; Bogolyubova and Romanov, 2019).Previous research has highlighted the role of feed additives, particularly humic and mineral-based supplements, in improving biochemical processes that influence growth, milk yield, and immune functions in livestock (Chaudhary *et al.*, 2024; Kochish *et al.*, 2023). Dairy productivity of cows is influenced by many external factors, including probiotic and mineral feed additives in the diet (Korotkiy *et al.*, 2024; Truong and Thu 2023; Zhaxalykov *et al.*, 2024). These studies collectively suggest that feed additives enhance nutrient digestibility, metabolic efficiency, and the adaptive capacity of dairy cows to varying environmental and dietary conditions. (Tkeshelashvili and Bobozhonova, 2024; Zaitsev *et al.*, 2023). However, the mechanisms by which these additives influence the balance between weight gain and milk production remain underexplored. Among mineral feed additives, one can distinguish feed additives with humic and fulvic acids, minerals, vitamins, amino acids, polysaccharides, and sterols necessary for full and healthy development (Kuznetsov, 2018; Nikulin and Ratnykh, 2017; Smirnova *et al.*, 2022; Vorobyov *et al.*, 2023a; Vasiliev *et al.*, 2018; Wayu *et al.*, 2019). Humic feed additives increase the intensity of biochemical processes, accelerate adaptation to keeping conditions, create conditions for the complete digestibility of plant-based feeds, and stimulate the destructive activity of the intestinal microbiota.To quantify the effect of humic feed additives on biochemical processes, we applied a fundamentally new information technology based on a computational neural network (Gafarov and Galimyanov, 2018; Kruglov and Borisov, 2002; Zaikina *et*

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al., 2022), which was intentionally prescribed to convert digital blood data into two indices of cognitive significance (indices CSImass, CSImilk =1...10 b/r;) (Sutrop, 2001; Vorobyov *et al.,* 2023a), quantitatively representing the intensity of weight gain and milk-forming processes. The calculated values of the CSImass and CSImilk indices transfer the analysis of the corresponding processes from the qualitative domain to the domain of quantitative ratios, which allows us to visualize the implicit, difficult-to-formalize dependence of weight gain biochemical processes on the level of dairy productivity (Vorobyov *et al.,* 2023b; Vorobyov *et al.,* 2023).

The CSImass and CSImilk indices are dimensionless quantitative characteristics of blood parameters, with an assigned cognitive function to quantify the intensity of weight gain and milk-forming processes. Due to the lack of dimensionality of these indices, it is problematic to formulate classical regression mathematical expressions with their participation. Therefore, it was decided to use the multidimensional scaling method (Tolstova, 2006) to present an approximate visual image of the desired dependence with a two-dimensional Scale scaling matrix. After filling in the cells of the Scale matrix using the scaling method, an image of the dependence of weight gain processes on milk-forming processes is visualized.With varying amounts of feed and feed additives, one can see a redistribution of energy and nutritional resources. As a result, dairy productivity may increase and weight gain and protective immune processes may decrease, which entails an increase in the risks of morbidity and a reduction in the dairy productivity period (Kamalieva *et al.,* 2020; Nikulin and Ratnykh, 2017; Ratnykh, 2018). By examining the features of this process, it is possible to determine the optimal dose of the humic feed additive, which ensures a balance of weight gain and milk-forming processes.

The paper aimed to determine the optimal dose of the humic feed additive that balanced weight gain and milk-forming processes in cows.

MATERIALS AND METHODS

***Research Design and Methodology*:** To achieve the purpose of the study, the latest neural network information technology was used, which calculates the CSImass and CSImilk indices based on blood parameters to visualize implicit dependence $CSImass = f(CSImilk)$.

To solve the task and test the neural network algorithm we experimented with giving humic feed additives with different concentrations of humic acid to cows on March 1-31, 2023 in Nadezhda LLC (Russia, Ryazan region, Alexander Nevsky district, Blagiye village).

***Experimental Design*:** The cows were divided into five groups (10 specimens each). All animals received the same diet, balanced in nutrient content and considering the needs of highly productive cows. Humic feed additives (No. 1-3) (Table 1) were given to all cows of the experimental groups individually and daily in the amount of 40 g (Table 2).

Table 1. Chemical composition of three humic feed additives.

Chemical composition	Humic feed additives		
	No. 1	No. 2	No. 3
Humic acid, %	50	60	70
Crude ash, %	27	22	19
Magnesium, %	3.5	0.17	0.18
Iron, mg/kg	22,000	11,500	12,090
Manganese, mg/kg	760	70	119
Zinc, mg/kg	22.3	18	16
pH	6.4	8	7.6

***Control Group*:** Two groups of cows (No. 1 and No. 4) were designated as control groups, which did not receive the humic feed additive. These groups served as a baseline for comparing the effects of the additive on weight gain and milk production (Table 2).

***Experimental Group*:** Cow groups No. 2, 3, and 5 were the experimental groups (Table 2). These groups received humic feed additives No. 1, 2, and 3, respectively (Table 1).

***Data collection*:** Blood samples were collected from all groups at the conclusion of the experiment. The selected blood parameters included erythrocyte count, calcium, albumins, and total protein levels (Table 2). These were

Table 2. Blood parameters and weight gain of cows, CSImass and CSImilk indices by experiment variants.

Blood parameters and CSImass and CSImilk indices	Cow groups				
	No. 1	No. 2	No. 3	No. 4	No. 5
Erythrocytes, 10^{12}/l	12.3±0.7	11.3±0.6	12.0±0.4	5.3±0.2	5.4±0.2
Calcium, mM/l	2.8±0.02	2.8±0.08	2.8±0.08	2.90±0.03	3.31±0.04
Albumins, g/l	31.4±0.3	32.5±0.7	31.6±0.7	34.9±0.5	37.5±0.7
Total protein, g/l	71.5±2.5	71.5±1.5	71.8±2.1	91.0±1.7	84.7±1.4
Weight gain, %	0.0	7.9	1.9	0.0	40
Gross milk yield, kg	1,808±54	1,845±87	1,864±77	1,808±45	1,889±40
CSImass, $SE = \pm 0.1$	3.7	6.1	3.7	3.3	8.2
CSImilk, $SE = \pm 0.1$	1.9	6.3	6.8	3.8	6.2

chosen based on their relevance to weight gain and milk-forming processes, as well as their ability to act as indicators of the metabolic and immune status of the animals.

***Dosage Range*:** Three experimental groups were provided with humic feed additives containing varying concentrations of humic acid (50%, 60%, and 70%) to explore the effects of a dosage range. This approach aimed to identify the optimal dose for maximizing both weight gain and milk production.

***Replication*:** Each experimental condition was replicated across five groups, each containing 10 cows, to ensure statistical reliability and minimize variability due to random factors.

Neural Network Model

***Stages of computing and training the NONN neural network*:** To calculate the CSImass and CSImilk indices based on cow blood parameters, we created the NONN computational neural network (Visual Basic for Application (VBA) code) in an Excel environment (Fig. 1).

***Stage 1*:** The L1 neuron layer normalizes the digital data of cow blood (Blood, Table 1, Fig. 1) using the standard normalization function for numerical data *Normalization()* (Mascarenhas, 2018) and writes the normalization results to the FNorm matrix.

$$FNorm = Normalization(Blood) \quad (1)$$

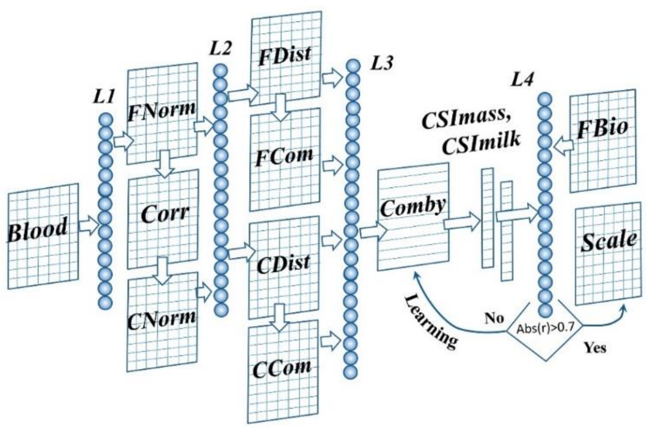

Figure 1. NONN computational neural network that converts cow blood data into CSImass and CSImilk indices = 0...10 b/r. Learning is a cyclic neural network software service that implements cyclic modification and testing of the algorithm for calculating the CSImass and CSImilk indices. Comby is a database of neural network algorithms. Blood and FBio are two-dimensional matrices containing blood parameters, weight gain, and dairy productivity of cows (Table 2). Scale is a two-dimensional scaling matrix that visualizes an implicit dependency $\boldsymbol{CSImass = f(CSImilk)}$.

***Stage 2*:** The L1 neuron layer calculates the correlation matrix Corr using FNorm matrix data and the standard *Correlation()* procedure (Nikolić *et al*., 2012).

$$Corr = Correlation(FNorm) \quad (2)$$

***Stage 3*:** The L1 neuron layer calculates the product of FNorm×Corr matrices, performs line-by-line normalization of the received digital data using the standard *Normalization()* procedure, and writes the normalization results to the CNorm matrix.

$$CNorm = Normalization(FNorm \times Corr) \quad (3)$$

***Stage 4*:** The L2 neuron layer calculates the FDist and CDist Euclidean distance matrices using digital data located in the columns of the FNorm and CNorm matrices and the standard computational procedure *EuclidDistance()* (Everitt *et al*., 2011).

$$FDist_{kl} = EuclidDistance\,(FNorm_{1k}, \dots, FNorm_{Nk}; FNorm_{1l}, \dots, FNorm_{Nl}) \quad (4)$$

$$CDist_{kl} = EuclidDistance\,(CNorm_{1k}, \dots, CNorm_{Nk}; CNorm_{1l}, \dots, CNorm_{Nl}) \quad (5)$$

where *k*, *l* = 1,...,M are the ordinal numbers of columns in the FNorm and CNorm matrices; M=5, N=4 are the number of cow groups and the number of measured blood parameters; the number of columns and rows in the FNorm and CNorm matrices; *EuclidDistance()* is the standard procedure for calculating Euclidean distances between columns of FNorm and CNorm matrices.

***Stage 5*:** The L2 neuron layer calculates the FCom and CCom matrices using data from the diagonal symmetric matrices FDist, CDist, and the standard procedure for calculating the eigenvectors of symmetric matrices *EigenVectors()* (Markova and Korchevskaya, 2011).

$$FCom = EigenVectors(DFist) \quad (6)$$

$$CCom = EigenVectors(CDist) \quad (7)$$

***Stage 6*:** The L3 neuron layer calculates the values of the CSImass and CSImilk indices using computational algorithms of the NONN neural network presented in the Comby algorithm database. Computational algorithms convert digital data from FNorm, CNorm, FDist, CDist, FCom, and CCom matrices into CSImass and CSImilk indexes. When creating the database of Comby algorithms, we used algebraic expressions where mathematical operands were used in a combined form concerning the data of the FNorm, CNorm, FDist, CDist, FCom, and CCom matrices.

***Stage 7*:** The L4 neuron layer in the Learning testing and learning cycles of the NONN neural network iterates through algorithms from the Comby algorithm database and calculates the CSImass and CSImilk indices and the correlation and regression coefficients of the indices with the data of the FBio matrix (weight gain, gross milk yield) (Table 1, Fig. 2). The exit from the Learning cycle was carried out using the Comby44 algorithm at $r(CSImass, FBio) > 0.9$ and the Comby76 algorithm at $r(CSImilk, FBio) > 0.8$.

***Stage 8*:** Using the calculated values of the CSmass and CSImilk indexes (Table 2) the Scale matrix was built (Fig. 2). The cells of the Scale matrix were filled with the ordinal numbers of the experiment variants (cow group numbers,

Table 1) considering the values of the CSImass and CSImilk indices in the corresponding cow groups. As a result, the filled cells of the Scale matrix presented a visual image of an implicit dependence $CSImass = f(CSImilk)$, which has the character of an extreme dependence with a single maximum.

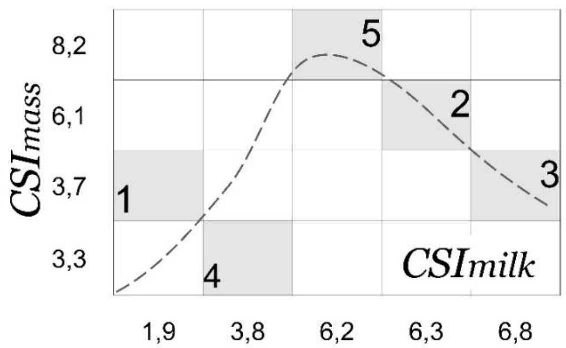

Figure 2. A Scale matrix that visualizes a mathematically implicit dependence $CSImass = f(CSImilk)$, where CSImass and CSImilk are indices representing the intensities of weight gain and milk-forming processes in cow organisms. The dotted line represents the average extreme trend of this dependence.

***Training and Validation*:** A fundamental feature of neural network programs is the presence of the DeepLearning configuration and learning service which provides access to the program code of the computational algorithm of the neural network and the ability to change the algorithm code (Kulakov and Dimitrov, 2018; Pogodaev *et al*., 2021; Schmidhuber, 2015; Widrow *et al*., 2013) in the cycles of testing and validation of the computational algorithm of the neural network. In the search for a correct computational algorithm for the neural network, it is proposed to use computational basic procedures for statistical analysis of multidimensional digital data, namely, regression, correlation, cluster, and discriminant analyses.

***Feature Engineering*:** Feature engineering techniques, such as normalization and correlation analysis, were used to preprocess the blood parameter data. Matrices such as FNorm and CNorm were developed to standardize and scale the input features for effective computational analysis. Advanced methods like multidimensional scaling were applied to visualize implicit dependencies.

RESULTS

In this study, we used cow blood parameters to control weight gain and milk-forming processes and, based on the results of neural network calculations, the intensity of weight gain and milk-forming processes. The amount of erythrocytes, calcium, albumins, and protein in the blood was determined. The number of measured blood parameters can reach several dozen. Regardless of the number of blood parameters, it is necessary to calculate only two dimensionless indices CSImass and CSImilk = 0...10 b/r, which quantitatively characterize the intensity of weight gain and milk-forming processes.

A deterministic mathematical relationship can be set between blood parameters and CSImass and CSImilk indices, which represent a single value of the CSImass and CSImilk indices for one set of blood parameters. When the blood parameters change, other index values are calculated. The representation of dependence $CSImass = f(CSImilk)$ is characterized by a stochastic correlation, which guarantees with a given probability only the fact of an increase/decrease in the intensity of weight gain processes with an increase/decrease in the intensity of milk-forming processes, focusing on the values of the CSImass and CSImilk indices in the experimental variants.

A new information technology based on the use of artificial intelligence in the form of a NONN neural network allowed us to correctly calculate the CSImass and CSImilk indices in experimental variants based on blood parameters and determine the humic additives that resulted in the maximum intensity of weight gain processes with a slight decrease in the intensity of milk-forming processes. The trained and configured NONN neural network presented a stochastic relationship of the CSImass and CSImilk indices at a confidence level of 80-90%.

Visualization of the implicit dependence $CSImass = f(CSImilk)$ in the Scale matrix (Fig. 2) allowed us to determine the dose of humic acid at which the maximum intensity of weight gain processes was achieved. The maximum was found in the blood parameters in group No. 5 which received humic feed additive No. 3 containing 70% humic acid (Table 1).

This can be explained by the fact that humic acids have a narrowly directed effect on weight gain biochemical processes and do not affect milk-forming processes. As a result, the distribution of nutritional and energy resources becomes more balanced. Weight gain, milk-forming, and immune defense processes are equally supported.

DISCUSSION

Dairy productivity of cows depends on the intensity of biochemical processes occurring in their organisms. Dairy productivity can be artificially overestimated by regulating the volume and quality of the nutritional diet and feed additives administered with the diet (Kholif *et al*., 2021). By stimulating dairy productivity, it is possible to reduce the intensity of weight gain biochemical processes and the activity of protective immune processes. As a result, the risks of premature morbidity increase, and the time of dairy productivity is shortened (Silvi *et al*., 2024).

Previous studies have extensively documented the role of humic substances in enhancing nutrient absorption, metabolic efficiency, and immune functions in cattle. For example, Malyugina Horky (2024) demonstrated that humic acids improve feed digestibility and promote better adaptation to environmental conditions, findings that align with the weight gain benefits observed in this study. However, unlike these studies, the current research offers a detailed quantitative analysis of the balance between weight gain and milk productivity using advanced neural network tools.

Comparatively, other research efforts, such as those by Placha *et al*. (2022) and Onomu, Okuthe (2024), have focused on specific biochemical or metabolic improvements attributed to feed additives. While these studies reported significant enhancements in animal health and productivity, they primarily relied on traditional statistical approaches. The application of a neural network in this study provides a unique contribution by visualizing the implicit stochastic dependencies between weight gain and milk production, an aspect not addressed in earlier works.

Moreover, the findings of this research complement the work of El-Baz and Khidr (2024), who employed neural networks to analyze the effects of feed macroalgae on poultry intestinal microbiota. Both studies emphasize the potential of artificial intelligence in livestock research.

Future studies should explore the long-term effects of humic feed additives on overall animal health, reproductive performance, and milk quality. Large-scale field trials are essential to validate the practical applicability of these findings under diverse farming conditions. Additionally, investigating potential synergistic effects of combining humic feed additives with other supplements, such as probiotics and prebiotics, could further enhance livestock productivity and sustainability.

***Conclusion*:** The study demonstrated the efficacy of the NONN computational neural network in quantifying and visualizing the relationship between weight gain and milk-forming processes in dairy cows. By integrating cutting-edge neural network technology, the study established a robust framework to analyze the effects of humic feed additives on critical biochemical processes. The ability to calculate and interpret dimensionless indices, CSImass and CSImilk, from blood parameters marks a significant advancement in monitoring and optimizing livestock management practices. These indices provide a quantitative basis for assessing the biochemical and metabolic impacts of dietary interventions. Moreover, the visualization of implicit stochastic dependencies using scaling matrices offers an innovative tool for understanding complex biological interactions. The insights gained can guide future research in optimizing livestock productivity while ensuring animal welfare and sustainability in farm management practices.

***Authors' contribution statement*:** Conceptualization, N.V. and A.G.; Methodology, M.S.; Software, M.S.; Validation, N.V., A.G. and M.S.; Formal Analysis, N.S.; Investigation, N.V.; Resources, A.G.; Data Curation, A.G; Writing – Original Draft Preparation, M.S.; Writing – Review & Editing, N.V.; Visualization, A.G.; Supervision, N.V.; Project Administration, N.S.; Funding Acquisition, N.V.

Conflict of interest: The authors declare that there is no conflict of interest.

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Ethical statement: The study adhered to the principles outlined in the European Convention for the Protection of Vertebrate Animals used for Experimental and Other Scientific Purposes (2005), ensuring humane treatment of animals through ethical research practices, minimizing pain and distress, and implementing rigorous welfare standards throughout the experimental process.

Availability of data and material: The datasets generated and analyzed during the study are available from the corresponding author upon reasonable request.

***Code Availability*:** not applicable

***Consent to participate*:** Consent to participate was obtained from all stakeholders involved in the study, including farm owners and relevant supervisory bodies

Consent for publication: Consent for publication was obtained from all authors

***SDGs addressed*:** Responsible Consumption and Production – The study promotes sustainable livestock management practices by optimizing feed additive usage to enhance resource efficiency and minimize environmental impact

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