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Survey Paper

SURVEYING ARTIFICIAL GLANDS IN ENDOCRINE NEURAL NETWORKS APPLIED IN CONTROL SYSTEMS

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Abstract. *In this paper, an effort would be made to provide a review of current state of the development of artificial glands within endocrine neural networks. The main goal is to systematize the approaches of building the glands, to offer mathematical apparatus behind them, and to describe control logics enabling smooth work and efficient synergy between the glands and traditional neural networks. In the final phase, this work will offer recommendations for selecting optimal gland profile in accordance with a specific use case.*

Key words: *Endocrine neural network, artificial gland, control systems, environmental stimulus, disturbance processing.*

1. INTRODUCTION

Artificial Neural Networks (ANNs) find extensive applications in control systems [1,2,3,4]. They emulate the functionality of the human nervous system, comprising interconnected neurons, hence their name. ANNs serve as nonlinear models for data generalization pertinent to specific processes, effectively tackling the complexity and nonlinearity inherent in systems. Consequently, they are employed to delineate intricate relationships between inputs and outputs, as well as for pattern recognition. ANNs exhibit

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rapid and high-quality data processing capabilities, and once trained, these networks can predict potential states or answer queries regarding 'What if?' scenarios. While various types of ANNs and their iterations are utilized in control systems, the following are frequently considered the most prevalent.

A Feedforward Neural Network (FNN) [5] is a commonly employed type of ANN, frequently utilized for regression problems. It operates with information flowing through the network in a unidirectional manner, lacking feedback connections within the network. There exist two primary types of feedforward networks: single-layer networks comprising only one hidden layer, and multilayer networks capable of having multiple hidden layers. In [6], an overview of the utilization of these neural networks for control purposes is presented. This overview highlights the distinctions, as well as the advantages and disadvantages, between variations of feedforward neural networks. A Cascade Forward Neural Network (CFNN) [7], unlike the basic FFNN, has feedback connections that link the input and output layers. It is often used for analyzing time series data and provides feedback about the current state of the system. Recurrent Neural Networks (RNNs) [8] use information from the previous time step, allowing them to remember a sequence of data. RNNs have an additional recurrent layer, enabling the use of the output from the previous time step when processing the current input. This type can be viewed as adding a memory cell to the neural network. RNNs are suitable for speech recognition, applications predicting the next word a user might type, translation, etc [9,10].

Convolutional neural networks (CNNs) are analogous to traditional neural networks in that they self-optimize during operation through learning [11, 12]. A CNN typically consists of three layers: a convolutional layer, a pooling layer, and a fully-connected layer. This type of neural network is primarily used for image classification and pattern recognition, finding applications in facial recognition systems, autonomous vehicles, and various intelligent systems [13,14]. The most significant advantage of convolutional neural networks is the reduction in the number of parameters required for model training. Unlike traditional neural networks, which often require a large number of parameters for image classification tasks, CNNs excel in extracting features from data with a convolutional structure, thereby mitigating two common problems: limited computing power and duration of model training, as well as overfitting. The distinguishing characteristics of CNNs include: (i) neurons in a CNN are not necessarily connected to all neurons from the previous layer, but only to certain neurons, and (ii) multiple connections can share the same weight [15].

Forecasting using neural networks essentially involves processing a specific dataset, training a model, and expecting the network to perform well in predicting the output. However, during the learning process, the network is typically trained on a limited dataset comprising both training and test data, which may not encompass the full diversity of inputs and scenarios encountered by the neural network in a real-world environment [16]. This lack of diversity in the dataset means that the input database may not encompass all disturbances that could arise during the operation of the neural network. Disturbances to the network can arise from external environmental influences, such as external stimuli, or from changes in the internal state of the system itself, such as parameter variations due to system aging. A common challenge faced by ANNs is their inability to always respond adequately and adaptively to sudden disturbances and external influences. ANNs can be characterized by the following limitations: (i) they may not perform effectively at the border of chaos, operating more reliably in an ordered domain; (ii) they have limited memory storage for potentially useful data; and (iii) they may be inefficient when confronted with dominant external influences.

Mathematically speaking, the general influence of other neurons (*h*) on a specific neuron *i*, due to external influences, can be represented as follows:

$$h_i = signal + noise + external\_stimulus \tag{1}$$

where *signal* represents a useful signal transmitted between neurons, *noise* represents internal disturbances originating from other neurons in the network, and the *external_stimulus* is an external influence. A neural network that adequately responds to external stimuli is characterized by the ability to recognize an occurring pattern and react accordingly when the external stimulus outweighs the noise, allowing the useful signal to prevail.

Focusing on networks that are efficient in dealing with environmental disturbances and noises, in [17,18], the authors proposed a stimulus-dependent neural network (SDNN) that recognizes patterns, with its operation being dominantly influenced by external factors. Their idea was to adapt a neural network and form a model inspired by the way animals in nature react to environmental stimuli. They introduced SDNN with an external pattern serving as a fundamental element in the pattern recognition process. The research was conducted using a standard Hopfield model as a foundation. It was demonstrated that this modified model adequately responds to changes in the external environment, effectively recognizing new external patterns.

The remainder of the paper is organized as follows: Section 2 provides a brief review of endocrine neural networks predominantly used for controlling dynamical systems. Section 3 offers a detailed overview of various types of artificial glands, while Section 4 summarizes the findings and presents recommendations for selecting an optimal gland type and appropriate network structure.

2. A Brief Overview of Endocrine Neural Networks

Given that artificial neural networks are inspired by human beings, it is logical to once again look at how humans react to external stimuli. When external influences act upon living beings, the nervous, endocrine, and immune systems come into play. Living beings receive various stimuli from the external environment, and the nervous system, as the central unit, detects and reacts to them. Considering the wide spectrum of stimuli from the external environment, the nervous system must be capable of detecting, processing, and reacting to them appropriately. After detecting the stimuli, the endocrine system plays a role in secreting hormones depending on the type of stimulus. Hormone secretion actually alters the current state within the system, and based on these hormones, specific cells in the body are activated to recognize that change. It is clear that not all cells in the body respond to all secreted hormones; rather, there is a cause-and-effect relationship between certain cells and hormones. Lastly, the immune system's reaction aims to restore the organism to its normal or original state before the external stimuli were induced.

This approach, concerning the system's response to changes in external conditions, served as the starting idea for the development of Endocrine Neural Networks (ENNs). In this type of neural network, gland cells that simulate cells of the endocrine system are implemented and responsible for secreting hormones depending on the influences from the external environment. In recent years, ENNs have attracted the attention of many researchers, demonstrating their ability to adequately and effectively react in systems operating under variable conditions and their capacity to provide the system's response to external environmental influences.

The primary objective of this review paper is to offer readers a comprehensive understanding of the evolutionary trajectory of ENNs, elucidating their underlying structures and mathematical foundations. Through this exploration, we aim to underscore their profound relevance and efficacy within the domain of intelligent control for dynamic systems. Additionally, our focus extends to providing actionable recommendations for the selection of ENNs, tailored to environmental stimuli, disturbances, and specific application contexts. These insights will intend to empower researchers in strategically navigating the selection process, thereby optimizing the alignment between endocrine structures and the intricacies of their research problems within the domain of control systems.

3. An Overview of Artificial Glands

The application of artificial gland cells is directly linked to adjusting neural network signals in response to environmental stimuli. In most cases, these stimuli are utilized to activate the appropriate artificial glands. The simplest and most common function of these glands is to produce specific hormone concentrations and influence the weight coefficients of the neural network. This approach has been observed in various works [6,19-21]. All other implementations of gland cells are partially based on these established principles, with certain modifications and upgrades.

Specifically, the utilization of artificial gland cells in [6,19] involves altering the default structure of neural networks to create endocrine neural networks. The gland cells are assigned the task of producing specific hormone concentrations that affect network weights by multiplying their values with unique endocrine factors generated for each gland. The concentration of hormones depends on environmental stimuli $\delta_1, \delta_2, ..., \delta_i$ representing external inputs corresponding to environmental conditions, disturbances, or noise. The hormone concentration of a single gland (C_g) is expressed in [6,19] as:

$$C_g(t+1) = \beta_g C_g + R_g(t+1) \tag{2}$$

where R_g and β_g are the stimulation parameter and decay constant, respectively. In continuation, index g represents the number of gland in question. Stimulation parameter R_g can be calculated as follows:

$$R_g(t) = \frac{\alpha_g}{1 + C_g(t-1)} \sum_j \omega_{ij}(t) X_{ij} , \tag{3}$$

where α_g is the stimulation rate, ω_{ij} is ij-th weight coefficient and X_{ij} represents a proper input value. Index i presents the current network input, while index j presents the current hormone.

The neuron's output value (before applying the chosen activation function) can be presented as:

$$u = \sum_{i=1}^{n} \omega_i X_i C_g S_j . \tag{4}$$

In (4), S_j signifies a hormone sensitivity parameter within the range of 0 to 1, and n represents the number of inputs for the specified neuron. Neurons with lower sensitivity S_j might produce a negligible impact to the network, whereas those with a sensitivity parameter close to 1 will greatly influence network performance.

The difference between the approaches of implementing artificial glands in [6] and [20] lies in the application of gland structures within different neural networks. In [6] is realized Orthogonal Endocrine Neural Network (OENN) merged with Orthogonal Endocrine Adaptive Neuro-Fuzzy Interface System (OEANFIS), both enhanced with endocrine factors. Such an intelligent hybrid solution was used for control purposes and showed improved performances after processing environmental stimuli. On the other hand, in [20] the same mathematical apparatus for realization of endocrine component was used in order to design a new type of endocrine neural network which is based on the gland implementation inside the traditional Nonlinear-autoregressive model with the exogenous inputs neural network (NARX). Graphical representation of implementing gland cells within the NARX network is presented in Fig. 1. The figure [20] represents a role model and most common way of implementing artificial glands within ANNs.

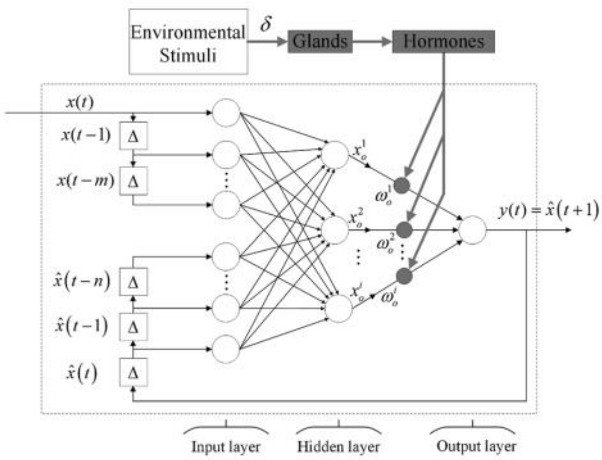

Fig. 1 Implementation of Gland cells within the NARX network [20]

In article [22], once again, the parameter δ, analogous to stimuli, embodies variations in system components and dynamics caused by changes in the environment or working conditions. In the paper, Generalized Quasi-Orthogonal Endocrine Adaptive Neuro-Fuzzy Inference System (GQOEANFIS) is designed with the OEANFIS once again as the core component. By injecting stimuli-like variations directly into the neurons of the fourth layer, the network becomes more adaptable to environmental changes even after the training process, enhancing its ability to respond to dynamic conditions while modeling complex mechatronic systems. In [22], a significant distinction in the implementation of the artificial gland cell is evident compared to the described scenarios in [6][20], where external stimuli influence hormone production. In this study, the stimuli directly affect the fourth layer of the neural network.

In article [19], the authors suggest a design approach for an orthogonal endocrine intelligent controller (OEI controller) applicable for the control of nonlinear dynamical systems. Artificial glands are incorporated into two conventional soft computing substructures (OENN and OEANFIS). These artificial glands serve to stimulate neural network weights in response to external disturbances, changes in the environment, or data from various sensors. In this research attempt, the OENN network's output forms an online stimulus signal (OLS), subsequently introduced to the fourth OEANFIS layer, as an artificially made stimulus. Here, the main contribution was made by proposing rhe OENN's output signal $\hat{y}(t)$ which will be computed using the following equation:

$$\hat{y}(t) = \sum_{i=1}^{n} (\omega_i(t) C_g(t) S_j(t)) \varphi_i(X) + R(X, m, C_g(t), S_j(t)) \,, \tag{5}$$

where φ_i is an orthogonal function and $R(X, m, C_g(t), S_j(t))$ represents an expansion error, which is decreasing when the number of expansion terms m increases. OLS is directly introduced to the forth OEANFIS layer, which generates control signal $x(t)$. Finally, the limiter is introduced to restrict the control signal in a specified range.

In the article [23], the authors proposed a new approach to tuning and optimizing the sensitivity parameter S_j. The adaptation of the parameter relies on mimicking the biological mechanisms of excitation and inhibition. Inhibitory signals act as synaptic potentials that prevent a neuron from initiating a pulse (action potential), thereby halting its transmission through the network. Conversely, excitation serves to trigger a neuron to produce a pulse, facilitating the transmission of information across the network by engaging other neurons. Using these principles, the input value of each neuron in the output layer is calculated in [23] according to the following equation:

$$X * P_p = \sum_{i=1}^{n} \begin{bmatrix} YN_i W_{pi} C_{GEX}^{p,a} S(G_{EX}^{p,a}; \delta, N_{EX}) \\ + YN_i W_{pi} C_{GIN}^{p,b} S(G_{IN}^{p,b}; \delta, N_{IN}) \end{bmatrix}, \tag{6}$$

where $S(G_{EX}^{p,a}; \delta, N_{EX})$ generates the sensitivity of the a_{th} excitatory gland, $S(G_{IN}^{p,b}; \delta, N_{IN})$ calculates the sensitivity of the b_{th} inhibitory gland for the p_{th} output neuron. $G_{EX}^{p,a}$ represents the number of excitatory glands influencing p_{th} neuron weights. Similarly, the number of inhibitory glands influencing p_{th} neuron weights is labeled as b in $G_{IN}^{p,b}$. Finally, W_{pi} is the output weight, d - the adaptive factor, $C_{GEX}^{p,a}$ represents the hormone concentration of the a_{th} excitatory gland of the p_{th} output layer neuron, and $C_{GIN}^{p,b}$ is the hormone concentration of the b_{th} inhibitory gland of the p_{th} output layer neuron.

As an additional contribution in [23], given that the default output of a single neuron is (4), and in order to avoid a possibility of that u could become 0 (for sensitivity S_j equal to zero), the equation 4 is transformed in [23] to:

$$u = \sum_{i=1}^{n} \omega_i X_i (1 + C_g S_j) \,. \tag{7}$$

Now, when hormone sensitivity S_j is equal to zero in (7), an endocrine neural network will function as a traditional network without any gland influence, producing neuron output as: $u = \sum_{i=1}^{n} \omega_i X_i$.

Differing from previous papers where each gland was treated as an independent unit, in [17], the authors proposed an approach for improving the performance of the endocrine neural network by establishing mutual connections between glands, thereby enabling comprehensive interactions among them. The role of each gland remains the same as described in papers [6] and [19]; however, in this approach, the concentration of hormones from one gland will depend on the others. For example, if a gland secretes a large concentration of a hormone that is important for other glands, that hormone will have a significant impact on them. This relationship is represented by the following equations:

$$AF_i = \frac{K}{1+e^{-MO^i}} . \tag{8}$$

$$MO_i = \Pi_{h=1,h\neq i}^{n_g} c_h . \tag{9}$$

where AF_i is the interaction coefficient of i-th gland with the value between 0 and 1, and c_h is the concentration of hormone of h-th gland which is determined by accounting the concentrations of other hormones. Based on (8, 9) the cell output can be represented as follows:

$$u = \sum_{i=1}^{n_x} w_i x_i \Pi_{j=1}^{n_g} C_j S_{ij} M_{ij} AF_j - b , \tag{10}$$

where n_x is the number of inputs, n_g is the number of glands in the system, while b is the threshold of the cell.

The paper [18] introduces an Artificial Endocrine Neural Network (AES) as a part of the Artificial Homeostatic System (EAHS), which is inspired by the self-regulation principles in the human organism. AES consists of a module for Hormonal Level (*HL*), Hormone production controller (HPC) and endocrine gland (*EG*). HL is responsible for remembering the level of hormones in the system, the controller has the task of controlling the release of hormones based on the environmental conditions and the internal state of the system. The controller sends information to the endocrine gland, which is responsible for secreting and producing hormones when needed. The hormone production (HP_i) of the i-th hormone is updated as follows:

$$HP_i(t+1) = \begin{cases} 0 \, if \; IS_i < \theta_i \\ (100 - \%ES_i)\, x\, \alpha_i \,(Max(HL_i) - HL_i(t)) , \\ \quad otherwise \end{cases} \tag{11}$$

$$IS_i(t+1) = \begin{cases} 0 \, if \, (ES_i \geq \lambda_i) \; and \; (HL_i \geq \omega_i) \\ IS_i(t) + \beta(Max(IS_i) - IS_i(t)) \; , \\ \quad otherwise \end{cases} \tag{12}$$

$$HL_i(t+1) = HL_i(t)\, x\, e^{-1/T_i} + HP_i(t) , \tag{13}$$

In (11), IS_i represents the internal state, ES_i represents the external stimulus and HL_i represents the hormone level. Further, θ_i represents the target threshold for the *IS*, while α_i is the scaling factor. In Eq (12), λ_i is a threshold associated with *ES* and ω_i is a threshold associated with *HL* while β represents the gain value for the rate of change on the internal state. It is also considered that the variable *T* represents the half-life variable.

In the paper [24], an Artificial Hormone Network (AHN) was introduced to enable the robot to respond to changes in the external environment and the internal state of the system. This hormone network comprises hormone channels, sensory channels, hormone receptors (HR), and hormone glands (HG). A Hormonal Gland (Fig. 2) is tasked with secreting hormones whose concentration is influenced by information from the external environment and the system's state.

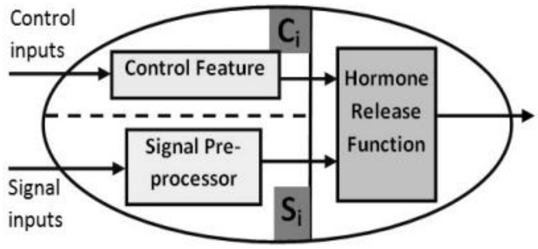

Fig. 2 The hormonal gland mechanism from [24]

There are two types of input signals on each gland: Signal input (*Si*) and Control input (*Ci*). These signals enter the Signal Pre-processor and Control Feature blocks, respectively. The pre-processing block receives the signal input and determines how the gland responds to other hormones and external influences, while the Control Feature unit processes the control input to define the effect of each signal input on hormone secretion.

There are two ways to manage hormone secretion: Inhibitory/Stimulatory control and Negative/Positive feedback control. The first method allows for preventing or stimulating hormone secretion based on the switch principle, depending on the presence of external signals or hormones (the presence of a signal is defined by a given threshold). The feedback control enables reduced or increased hormone secretion as a fine adjustment.

The final block is a hormone release mechanism, which identifies the required hormone concentration and instructs the gland to secrete the given hormone. The concentration of the hormone secreted by the gland at each time step depends on the processed input signal, subject to the influence of the stimulation rate (α_g), and the concentration of the hormone in the previous time step, subject to the decay rate (β_g). Below is the definition of the hormone concentration value at time step t:

$$C_g(t) = (\alpha_g F(S_i)) + (\beta_g C_g(t-1)), \tag{14}$$

where $C_g(t)$ represents the hormone concentration in the time step t, and $F(S_i)$ represents the output from the Signal Pre-processor block. It is important to note that the values for C_g, α_g and β_g should be between 0 and 1.

In [25], a hormone feedback mechanism was proposed to protect the system from overflow. The negative feedback cell (Fig. 3) is very similar to an ordinary endocrine gland introduced in previous papers. It is affected only by the concentration of the main hormone and undergoes determined deterioration according to the established dynamics of the gland. Utilizing this mechanism limits the rapid growth of hormone concentration and prevents overflow.

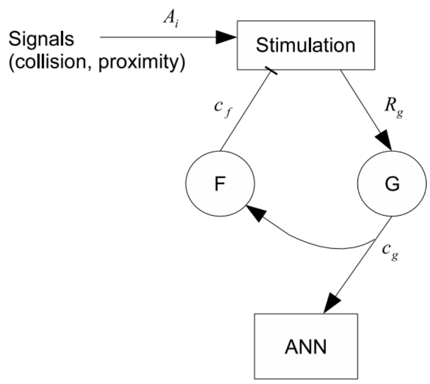

Fig. 3 An artificial neuroendocrine architecture with negative feedback proposed in [25]

The following equation presents the formula for the concentration of the feedback hormone as proposed in [25]:

$$c_f(t) = \beta_f c_f(t-1) + \alpha_f c_g(t) \tag{15}$$

Authors in [26] based their work on developing Artificial Orthogonal Gland (AOG) mechanism. Earlier presented studies focused mostly on acquiring environmental stimuli, converting them into suitable input signals, and delivering them to the glands. Subsequently, hormone concentrations within each gland were computed based on the stimuli level and these calculated values were fed into a neural network to update the values of proper network weight coefficients. Each gland in these papers primarily operated independently of the other involved glands, responding to distinct environmental stimuli. The authors in [26] made a progress in a different direction, proposing a mechanism (Fig. 4) that would enable dependent mutual operations of glands and mutual interactions between different hormones. The structure is designed to accommodate two types of input signals. The Control Input (CI) regulates hormone production, enabling interaction between glands and linking hormones within the hormone network. The Signal Input (SI) determines the hormone stimulation level within a gland and defines its influence on the neural network. As a final remark, it is important to highlight that this mechanism comprises three distinct types or substructures – hormonal, signal, and control mechanisms.

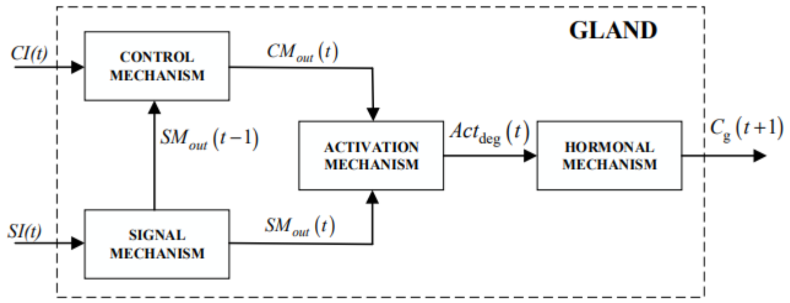

Fig. 4 AOG mechanism from [26]

Finally, in [27], the authors introduced a simplified hormone decay function derived from the Neal/Timmis system. In the original version of the system, the hormone is released and decays according to a geometric function as described by the following equations:

$$r_g = \alpha_g \sum_{i=0}^{nx} x_i \tag{16}$$

$$C_g(t+1) = C_g(t)\beta \tag{17}$$

where r_g represents the rate of hormone release, α_g represents the stimulation rate for gland g, x_i represents the input to the gland and n is the number of inputs. $C_g(t)$ and $C_g(t+1)$ represent the hormone concentration in time step t and the following time step $t+1$, while β is the decay constant. However, the authors decided to simplify this process to reduce the number of variables in the system. To achieve this, the hormone decay function was redesigned to use a single variable for both release and decay. This means that the same variable is used to determine the rate of hormone release as well as the rate of hormone decay. In this way, instead of using two separate variables for hormone release and decay, only one variable is used, which simplifies the model and reduces the number of variables to keep track of. The modified equation for determining hormone concentration at time step $t+1$ is below:

$$C_g(t+1) = C_g(t) - r(C_g(t) - q) \tag{18}$$

where r represents the amount of hormone secreted, and q represents the decay/release rate.

4. Recommendations

In this section, the findings acquired during the review of endocrine networks in the previous part of the paper will be summarized through two perspectives for selecting the optimal type of endocrine network. The first perspective focuses on selecting the right network in accordance with the principles of addressing environmental stimuli and disturbances within the gland mechanisms. The second perspective is based on potential use cases and recommendations on how to select a proper network in accordance with the experimental setup and specific task.

4.1. Gland type selection approach

For control applications requiring adaptive responses to environmental stimuli, the OENN and OEANFIS prove effective. These networks demonstrate suitability in handling variable conditions and disturbances, showing improved performance after processing environmental stimuli. In scenarios where endocrine components need to be integrated into traditional neural network structures, the NARX is a good solution. This type of network is suitable for modeling dynamic systems with input-output relationships, making it a valuable tool in various applications.

For systems requiring a high-level adaptability to dynamic conditions and changes in the environment, the GQOEANFIS is recommended. This mechanism enhances the network's response to environmental variations, thereby improving adaptability while modeling complex systems. In applications where mutual interactions between glands are desired, the AOG mechanism offers good application potential. This mechanism enables dependent mutual operations of glands and interactions between different hormones, facilitating comprehensive interactions among mathematical units. These networks are effective in scenarios where the concentration of hormones from one gland depends on others, enhancing network performance through comprehensive interactions. Finally, for systems requiring protection against overflow due to a rapid growth of hormone concentration, the Hormone Feedback Mechanism is recommended. This mechanism ensures the stability and reliability of the system in volatile conditions.

4.2. Network selection depending on the use case

Based on the diverse approaches and implementations of endocrine neural networks (ENNs) presented in the previous section, the choice of which type of ENN to use depends on the specific technical requirements of the application and the desired behavior of the control system. From simpler applications such as ENARX for data analysis purposes, to complex hybrid intelligent structures such as OENN-OEANFIS capable of performing complex system control, ENNs have proved as competent models for resolving a variety of control problems. For example, time-series forecasting has a wide range of applications in control systems, especially in the model predictive control since it provides useful information about the potential behavior of a variable in the future. ENNs specially tailored for time-series forecasting are ENARX, Improved Neuro-Endocrine Model (INEM) with gland interaction and OENNPP. All of these networks have proven to perform time-series forecasting and prediction tasks successfully.

Beside the ENN application in data analysis and prediction, these structures have found their purpose as control components of high applicability in control systems. For instance, the structure combining OENN and OEANFIS (OENN-OEANFIS) proved as an effective tool to be utilized for online PID controller tuning, providing the means to design an adaptive system control, sensitive to the varying environmental stimuli. The implementation of this structure is particularly recommended when there is a need to reduce the influence of disturbances and improve the control of highly nonlinear systems. Concretely, the effectiveness of the OENN-OEANFIS model is proved by successfully applying it for 3D crane tracking control. Moreover, the OENN-OEANFIS structure also finds its purpose as an intelligent controller itself, not solely as a PID tuner. As the control structure, it is especially suitable for nonlinear MIMO systems, such as two rotor aerodynamic systems. Another structure suitable to be employed as an intelligent controller in dynamical systems is OENN structure combined with Artificial Orthogonal Glands, or OENN + AOG structure. This structure can be successfully applied in the control of complex nonlinear systems such as magnetic levitation systems.

Further, ENN networks can be utilized in system modeling as well. GQOEANFIS, a structure carefully developed based on the regular ANFIS model with the aim to solve the issues of large computation time and to implement an adaptive mechanism, was designed with the main purpose of modeling complex and highly nonlinear mechatronic systems such as ABS systems. The strengths of this approach are even more emphasized when utilized alongside with a GQOENN model, a structure specialized in predicting the modeling error. This structure is highly recommended for nonlinear system modeling and as a part of complex control algorithms such as quasi-sliding mode control.

Finally, there is a wide range of ENN applications in robotics. For example an artificial endocrine controller has demonstrated promise as a means of solving the issue of the power management in robotic systems. Also, EAHS proved to be an effective structure for behavior coordination in autonomous mobile robots, while AHN network can be used to ensure the robot's high resilience to the changes in the dynamic surroundings. AAES-ANN structure can also be applied to incorporate online adaptation to faults and disturbance in robotic systems, while ANN-AES is successfully applied to enable collaboration in robotic swarm systems.

5. Conclusion

This survey paper represents an attempt to summarize the main insights, operational approaches, and applicability values of ENNs. To the best of the authors' knowledge, this is the first attempt to systematize the base of knowledge of ENNs, aiming to provide other researchers in this field with a helpful foundation for further work.

The paper begins by emphasizing the importance of properly addressing environmental stimuli and disturbances when working with dynamic control systems, offering various insights on overcoming these challenges. Subsequently, attention is directed towards a modern approach for efficiently addressing such issues, namely the application of ENNs to adapt systems to volatile conditions. Here, the paper provides basic operational principles of ENNs and introduces foundational components.

The third section constitutes the main part of this survey paper, presenting the primary variants of ENNs proposed thus far. Special attention has been paid to provide prospects for ENN application in robotics. The focus lies on showcasing the operational mechanisms of each endocrine structure, the development of artificial glands, and the integration of each proposed mechanism into a default ANN environment. Additionally, an emphasis is placed on comparing the analyzed solutions and identifying the differences that characterize them.

Finally, the fourth section aims to provide recommendations regarding the selection process of ENNs based on environmental stimuli and disturbances and/or specific use cases for which such networks should be utilized. These recommendations are intended to assist researchers in selecting an optimal endocrine structure for their specific research problem in the domain of control systems.

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References

[1] M. T. Hagan, H. B. Demuth, O. D. Jesús, "An introduction to the use of neural networks in control systems,", *International Journal of Robust and Nonlinear Control: IFAC-Affiliated Journal*, vol. 12 no 11, pp. 959-985, 2002, doi: 10.1002/rnc.727

[2] S. A. Emami, P. Castaldi, A. Banazadeh, "Neural network-based flight control systems: Present and future," *Annual Reviews in Control*, vol. 53, pp. 97-137, 2022, doi: 10.1016/j.arcontrol.2022.04.006

[3] I. Eski, A. Temürlenk, "Design of neural network-based control systems for active steering system", *Nonlinear dynamics*, vol. 73, pp. 1443-1454, 2013, doi: 10.1007/s11071-013-0875-y

[4] J. Dunfied, M. Tarbouchi, G. Labonte, "Neural network based control of a four rotor helicopter", In *2004 IEEE International Conference on Industrial Technology*, 2004. IEEE ICIT'04, Hammamet, Tunisia, vol. 3, pp. 1543-1548, 2004, doi: 10.1109/ICIT.2004.1490796

[5] V. K. Ojha, A. Abraham, V. Snášel, "Metaheuristic design of feedforward neural networks: A review of two decades of research," *Engineering Applications of Artificial Intelligence*, vol. 60, pp. 97-116, 2017, doi: 10.1016/j.engappai.2017.01.013

[6] M. B. Milovanović, D. S. Antić, M. T. Milojković, S. S. Nikolić, S. Lj. Perić, M. D. Spasić, "Adaptive PID Control Based on Orthogonal Endocrine Neural Networks," *Neural Networks*, vol. 84, pp. 80–90, Print ISSN: 0893-6080, Publisher: Elsevier, December 2016, doi: 10.1016/j.neunet.2016.08.012.

[7] B. Warsito, R. Santoso, R., Suparti, H. Yasin, "Cascade forward neural network for time series prediction," *Journal of Physics: Conference Series*, vol. 1025, p. 012097, IOP Publishing, May 2018,, doi: 10.1088/1742-6596/1025/1/012097

[8] R. Qamar, B. A. Zardari, "Artificial Neural Networks: An Overview," *Mesopotamian Journal of Computer Science*, pp. 130-139, 2023, doi: 10.58496/MJCSC/2023/014.

[9] K. K. Dutta, S. Poornima, R. Sharma, D. Nair, P.G. Ploeger, "Applications of recurrent neural network: Overview and case studies", *Recurrent Neural Networks*, pp. 23-41, CRC press, 2022, doi: 10.1201/9781003307822-3

[10] A. K. Tyagi, A. Abraham, *Recurrent neural networks: Concepts and applications*, CRC Press, 2022, doi: 10.1201/9781003307822

[11] K. O'shea, R. Nash, "An introduction to convolutional neural networks," arXiv preprint, 2015. [Online]. Available: https://arxiv.org/abs/1511.08458, doi: 10.48550/arXiv.1511.08458.

[12] S. Albawi, T. A. Mohammed, S. Al-Zawi, "Understanding of a convolutional neural network," *2017 international conference on engineering and technology (ICET)*, Antalya, Turkey, pp. 1-6, August 2017, doi: 10.1109/ICEngTechnol.2017.8308186

[13] A. Dhillon, G. K. Verma, "Convolutional neural network: a review of models, methodologies and applications to object detection," *Progress in Artificial Intelligence*, vol. 9 no. 2, pp. 85-112, 2020, doi: 10.1007/s13748-019-00203-0

[14] M. M. Taye, "Theoretical understanding of convolutional neural network: Concepts, architectures, applications, future directions," *Computation*, vol. 11 no. 3, p. 52, 2023, doi: 10.3390/computation11030052

[15] Z. Li, F. Liu, W. Yang, S. Peng, J. Zhou, "A survey of convolutional neural networks: analysis, applications, and prospects," *IEEE transactions on neural networks and learning systems*, vol. 33 no. 12, pp. 6999-7019, 2021, doi: 10.1109/TNNLS.2021.3084827.

[16] H. Chen, J. Chen, J. Ding, "Data evaluation and enhancement for quality improvement of machine learning," *IEEE Transactions on Reliability*, vol. 70, no. 2, pp. 831-847, 2021, doi: 10.1109/TR.2021.3070863

[17] D. Chen, J. Wang, F. Zou, W. Yuan, W. Hou, "Time series prediction with improved neuro-endocrine model," *Neural Computing and Applications*, vol. 24, no. 6, pp. 1465-1475, 2014, doi: 10.1007/s00521-013-1373-3.

[18] R. C. Moioli, P. A. Vargas, P. Husbands, "A multiple hormone approach to the homeostatic control of conflicting behaviours in an autonomous mobile robot," *2009 IEEE Congress on Evolutionary Computation*, Trondheim, Norway, pp. 47-54, IEEE, May 2009, doi: 10.1109/CEC.2009.4982929.

[19] M. B. Milovanović, D. S. Antić, M. T. Milojković, M. D. Spasić, "Adaptive Control of Nonlinear MIMO System With Orthogonal Endocrine Intelligent Controller," *IEEE Transactions on Cybernetics*, vol. 52, no. 2, pp. 1221-1232, Feb. 2022, doi: 10.1109/TCYB.2020.2998505.

[20] M. Milovanović, D. Antić, M. Rajić, P. Milosavljević, A. Pavlović, C. Fragassa, "Wood Resource Management Using an Endocrine NARX Neural Network," *European Journal of Wood and Wood Products*, vol. 76, no. 2, pp. 687–697, Print ISSN: 0018-3768, Publisher: Springer Berlin Heidelberg, March 2018, doi: 10.1007/s00107-017-1223-6.

[21] C. Sauze, M. Neal, "Artificial endocrine controller for power management in robotic systems," *IEEE transactions on neural networks and learning systems*, vol. 24 no. 12, pp. 1973-1985, 2013, doi: 10.1109/TNNLS.2013.2271094.

[22] S. Lj. Perić, D. S. Antić, M. B. Milovanović, D. B. Mitić, M. T. Milojković, S. S. Nikolić, "Quasi-Sliding Mode Control with Orthogonal Endocrine Neural Network-Based Estimator Applied in Anti-Lock Braking System," *IEEE/ASME Transactions on Mechatronics*, vol. 21, no. 2, pp. 754–764, Print ISSN: 1083-4435, Publisher: IEEE, April 2016, doi: 10.1109/TMECH.2015.2492682.

[23] M. Milovanović, D. Antić, M. Milojković, S. S. Nikolić, M. Spasić, S. Perić, "Time Series Forecasting with Orthogonal Endocrine Neural Network Based on Postsynaptic Potentials," *Journal of Dynamic*

Systems, Measurement, and Control, vol. 139, no. 4, pp. 041006-1÷041006-9, DS-15-1656, Print ISSN: 0022-0434, Publisher: American Society of Mechanical Engineers, April 2017, doi: 10.1115/1.4035090.

[24] P. Teerakittikul, G. Tempesti, A. M. Tyrrell, "Artificial hormone network for adaptive robot in a dynamic environment," *In 2012 NASA/ESA Conference on Adaptive Hardware and Systems (AHS)*, Erlangen, Germany, pp. 129-136, IEEE, June 2012, doi: 10.1109/AHS.2012.6268640.

[25] J. Timmis, M. Neal, J. Thorniley, "An adaptive neuro-endocrine system for robotic systems," *2009 IEEE Workshop on Robotic Intelligence in Informationally Structured Space*, Nashville, TN, USA, pp. 129-136, IEEE, March 2009, doi: 10.1109/RIISS.2009.4937917.

[26] M. Milovanović, A. Oarcea, S. Nikolić, A. Djordjević, M. Spasić, "An approach to networking a new type of artificial orthogonal glands within orthogonal endocrine neural networks," *Applied Sciences*, vol. 12 no. 11, p. 5372, 2022, doi: 10.3390/app12115372.

[27] J. Timmis, L. Murray, M. Neal, "A Neural-Endocrine Architecture for Foraging in Swarm Robotic Systems," *González, J.R., Pelta, D.A., Cruz, C., Terrazas, G., Krasnogor, N. (eds) Nature Inspired Cooperative Strategies for Optimization (NICSO 2010), Studies in Computational Intelligence*, vol. 284, Springer, Berlin, Heidelberg, 2010, doi: 10.1007/978-3-642-12538-6_27