SRINIVAS UNIVERSITY
INSTITUTE OF ENGINEERING & TECHNOLOGY

(SUBJECT: ARTIFICIAL NEURAL NETWORKS)

(SUBJECT CODE: 24SBT113)

AN INDIVIDUAL TASK REPORT ON

"Equations Off All Models"

Submitted in the partial fulfillment of the requirements for the First semester

BACHELOR OF TECHNOLOGY
IN
ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

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2025-26

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CERTIFICATE

This is to certify that, **NABHAN VP (01SU24AI061),** has satisfactorily completed the assessment in **ARTIFICIAL NEURAL NETWORKS (24SBT113)** prescribed by the Srinivas University for the 4th semester B. Tech course during the year **2025-26**.

MARKS AWARDED

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INTRODUCTION

Neural activation models are mathematical representations that explain how a neuron's activation level changes over time. In artificial neural networks—particularly continuous-time and biologically inspired systems—neurons are not simply binary units that switch on or off. Instead, their activation shifts gradually, influenced by internal dynamics, external signals, and interactions with other neurons. These models offer a structured and precise way to analyze such dynamic behavior.

A neuron's activation reflects its present state of responsiveness or excitation. This state is shaped by factors such as natural decay, incoming stimuli, signals from neighboring neurons, and inherent limits on activity. Typically, neural activation models are described using differential equations, which mathematically represent how activation evolves over time. These equations are valuable because they capture both short-term (transient) responses and long-term (steady-state) behavior.

One essential concept in neural activation modeling is decay. In biological neurons, when no input is present, the membrane potential gradually diminishes due to ionic leakage. This phenomenon is represented mathematically by including decay terms in the activation equations. The decay rate controls how quickly activation decreases. Without such a mechanism, activation levels could increase endlessly, which would be unrealistic in both biological and computational systems.

External input is another fundamental element of activation models. It refers to signals arriving from outside the neuron, such as sensory information or outputs from other layers within a network. Depending on their magnitude and direction, these inputs can either raise or lower the activation level. In most models, inputs are multiplied by weights to indicate their relative impact on the neuron's response.

Interactions among neurons are also incorporated into neural activation models. In network structures like autoassociative and heteroassociative systems, a neuron's activation depends on signals received from other neurons. These influences are typically represented through weighted summation terms. Feedback mechanisms enable networks to store information, retrieve patterns, and perform recognition tasks. Positive feedback strengthens activation, whereas negative feedback reduces or stabilizes it.

Saturation and boundedness are additional important features. Biological neurons cannot sustain unlimited activation; they operate within upper and sometimes lower limits. Shunting activation models explicitly include these constraints to keep activation within realistic bounds. This prevents instability and enhances biological plausibility.

Neural activation models can generally be divided into basic and advanced types. Basic models, such as passive decay or resting potential models, describe fundamental neuron behavior. More advanced models—like additive networks, inhibitory networks, shunting models, and heteroassociative networks—capture complex interactions across multiple neurons or layers.

Overall, neural activation models form a mathematical foundation for understanding how neurons behave over time. By integrating decay, external input, feedback interactions, and saturation effects, these models connect biological neural processes with artificial neural network design. A solid understanding of these models is crucial for studying neural dynamics and developing effective neural architectures.

Passive Decay Mode

The Passive Decay Model is one of the most basic and fundamental neural activation models used to describe the behavior of a neuron in the absence of any external input or interaction with other neurons. This model captures the natural tendency of a neuron's activation level to decrease over time due to internal leakage or loss of energy. It is inspired by biological neurons, where the membrane potential gradually decays if no stimulus is applied.

In this model, the neuron is considered to be isolated from its surroundings. There are no excitatory or inhibitory inputs acting on it, and no feedback from other neurons in a network. The only process affecting the neuron's activation is passive decay. This makes the model simple, yet very important, as it forms the foundation for more complex neural activation models.

Mathematically, the passive decay model is represented using a first-order differential equation. The rate of change of activation of neuron i with respect to time is proportional to the negative of its current activation. The equation is given by:

\frac{dx_i(t)}{dt} = -A_i x_i(t)

Here, represents the activation level of neuron i at time t, and is a positive constant known as the decay rate. The negative sign indicates that the activation decreases over time. The larger the value of , the faster the decay of activation.

The solution to this differential equation shows that the activation decays exponentially over time. The solution is:

x_i(t) = x_i(0)e^{-A_i t}

In this expression, is the initial activation of the neuron at time . As time increases, the exponential term decreases, causing the activation to approach zero. This demonstrates that, in the absence of input, the neuron eventually becomes inactive.

The passive decay model reflects an important biological property of neurons. In real neurons, the membrane potential decreases over time due to ion leakage across the membrane. Without continuous stimulation, the neuron cannot maintain its activation. The decay rate represents how quickly this leakage occurs. Neurons with a high decay rate lose activation rapidly, while neurons with a low decay rate retain activation for a longer period.Although the passive decay model is simple, it has several practical applications. It is often used as a baseline model to understand neuron dynamics. More complex models, such as those involving external input or feedback, typically include the passive decay term as a component. In this way, the passive decay model serves as a building block for advanced neural network models.In learning systems and signal processing applications, passive decay can be used to model forgetting

In conclusion, the Passive Decay Model describes the simplest form of neuron behavior, where activation decreases exponentially over time due to internal decay. Despite its simplicity, it plays a crucial role in neural modeling by providing insight into natural neuron behavior, ensuring system stability, and forming the foundation for more advanced activation models.

Modified Passive Decay Mode

The Modified Passive Decay Model is an extension of the basic passive decay model and is used to describe neuron activation more realistically by introducing the effect of capacitance. In biological neurons, the cell membrane does not behave like a simple resistor alone; it also has capacitive properties. This capacitance allows the neuron to store electrical charge, which affects how quickly the membrane potential changes over time. The modified passive decay model incorporates this important biological feature into the mathematical description of neuron behavior.In the basic passive decay model, neuron activation decreases exponentially at a rate determined only by the decay constant. However, in real neural systems, changes in activation do not occur instantaneously. Instead, they are influenced by the membrane's ability to accumulate and release charge. The modified passive decay model accounts for this by scaling the decay rate using a capacitance parameter. This results in a more accurate representation of neuron dynamics, especially in continuous-time neural networks.

The mathematical form of the modified passive decay model is expressed as:

\frac{dx_i(t)}{dt} = -\frac{A_i}{C_i} x_i(t)

Here, represents the activation of neuron i at time t. The parameter is the decay constant, and is the capacitance associated with the neuron. Both and are positive constants. The presence of in the denominator shows that capacitance directly influences the rate at which activation decays.

The solution to this differential equation is:

x_i(t) = x_i(0)e^{-\frac{A_i}{C_i}t}

From this solution, it is clear that the decay of activation is still exponential, but the effective decay rate is now . This means that capacitance acts as a moderating factor. If the capacitance is large, the decay rate becomes smaller, and the neuron retains its activation for a longer time. Conversely, if the capacitance is small, the decay rate increases, and activation decreases more rapidly.

Biologically, this behavior is significant. Neurons with higher membrane capacitance can store more charge, allowing them to maintain their membrane potential for longer periods. This results in slower changes in activation, providing a smoothing effect on neural responses. Neurons with lower capacitance respond more quickly but also lose activation faster. Thus, the modified passive decay model captures differences in neuron responsiveness and memory characteristics.

In practical applications, this model is useful in areas such as signal processing, control systems, and neural simulations. It helps in modeling temporal behavior, where the timing of activation changes is critical. The concept of capacitance also relates to short-term memory in neurons, as higher capacitance allows information to persist briefly even after the input is removed.

In conclusion, the Modified Passive Decay Model enhances the basic passive decay model by introducing capacitance, making it more biologically and computationally realistic. It explains how neurons store and release activation over time and how this storage affects the rate of decay. By incorporating capacitance, the model provides a smoother, more accurate description of neuron dynamics and serves as an essential building block for advanced neural network models.

Non-Zero Resting Potential Model

4. Non-Zero Resting Potential Model

The Non-Zero Resting Potential Model is an important neural activation model that extends the basic passive decay concept by introducing the idea of a resting potential that is not equal to zero. In biological neurons, even when no external stimulus is applied, the membrane potential does not fall to zero. Instead, it stabilizes at a constant negative value known as the resting potential. This model captures that realistic behavior in mathematical form and is widely used in continuous-time neural network analysis.In the simple passive decay model, neuron activation always decays exponentially to zero. While this is mathematically convenient, it is not biologically accurate. Real neurons maintain a baseline level of electrical potential due to ionic concentration differences across the cell membrane. The non-zero resting potential model accounts for this by adding a constant input term that counteracts the decay and shifts the steady-state activation to a non-zero value.

The mathematical equation for the non-zero resting potential model is given by:

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) + P_i$$

Here, represents the activation of neuron i at time t. The parameter is the decay constant, and is a constant term representing a persistent internal input or bias. This bias term is responsible for maintaining the neuron's activation at a non-zero level even when no external stimulus is present.

The solution of this differential equation is:

$$x_i(t) = \left(x_i(0) - \frac{P_i}{A_i}\right)e^{-A_i t} + \frac{P_i}{A_i}$$

The steady-state value is the non-zero resting potential of the neuron. Its magnitude depends on both the bias input and the decay rate . A larger bias results in a higher resting potential, while a higher decay rate reduces the resting potential. This relationship provides insight into how neurons balance internal excitation and leakage to maintain stability.Biologically, this model reflects the fact that neurons are never completely inactive. Ion pumps and channels continuously work to maintain a baseline membrane potential. Even in the absence of sensory input, the neuron remains at this resting state, ready to respond quickly to incoming signals. The non-zero resting potential model captures this readiness in mathematical terms.

From a computational viewpoint, the non-zero resting potential model is very useful. It allows neurons to have a baseline activity level, which can improve the responsiveness of neural networks. Instead of starting from zero, neurons can respond more rapidly to small inputs. This is particularly beneficial in associative memory models and pattern recognition systems, where small changes in activation can carry meaningful information.

In conclusion, the Non-Zero Resting Potential Model describes neuron activation that stabilizes at a constant non-zero value rather than decaying to zero. By introducing a constant bias term, the model closely resembles biological neuron behavior and enhances the realism, stability, and responsiveness of artificial neural networks.

Zero Resting Potential with External Input

5. Zero Resting Potential with External Input

The Zero Resting Potential with External Input model is an important neural activation model that explains how a neuron behaves when it has no inherent resting potential but is influenced by an external stimulus. In this model, the neuron's activation naturally tends to decay to zero in the absence of input, but when an external input is applied, the activation increases and eventually stabilizes at a non-zero value determined by the input strength. This model bridges the gap between simple decay models and more complex input-driven neural systems.

In the basic passive decay model, neuron activation always decreases over time and approaches zero. While this represents natural leakage, it does not explain how neurons respond to stimuli. The zero resting potential with external input model improves this by introducing an external input term. However, unlike the non-zero resting potential model, this model assumes that without input, the neuron has no baseline activity. Zero is the natural resting state, and any activation arises solely due to external influence.

The mathematical representation of this model is:

\frac{dx_i(t)}{dt} = -A_i x_i(t) + B_i I_i

Here, denotes the activation of neuron i at time t. The parameter is the decay constant, which determines how fast activation decreases. represents the external input applied to the neuron, and is a scaling factor or weight that controls the influence of the input on the neuron's activation.

The solution to this differential equation is:

x_i(t) = x_i(0)e^{-A_i t} + \frac{B_i I_i}{A_i}\left(1 - e^{-A_i t}\right)

This solution consists of two parts. The first term represents the effect of the initial activation, which decays exponentially over time. The second term represents the contribution of the external input. As time increases, the exponential term approaches zero, and the activation converges to a steady-state value of .

This steady-state value is crucial because it shows how the neuron responds to sustained input. A stronger external input or a higher input weight results in a higher final activation. On the other hand, a larger decay constant reduces the steady-state activation. This relationship clearly illustrates the balance between excitation due to input and decay due to leakage.

In conclusion, the Zero Resting Potential with External Input model describes neuron activation that arises purely from external stimulation and decays to zero in its absence. By combining decay and input terms, the model effectively captures stimulus-driven neuron behavior and serves as a foundation for more complex network models involving feedback and interactions.

Additive Autoassociative Network Model

6. Additive Autoassociative Network Model

The Additive Autoassociative Network Model is an important neural activation model used to describe how neurons interact with each other through feedback connections. Unlike earlier models that consider only decay and external input, this model includes the influence of other neurons in the network. It is called autoassociative because the network associates patterns with themselves, meaning it can store patterns and recall them even when presented with partial or noisy versions of the same patterns.

In an autoassociative network, each neuron receives input not only from external sources but also from other neurons within the same network. The activation of a neuron is therefore determined by three main factors: natural decay, external input, and the weighted sum of outputs from other neurons. This interaction allows the network to exhibit collective behavior, which is essential for memory storage and pattern completion.

The mathematical equation of the additive autoassociative network model is given by:

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) + B_i I_i + \sum_{j=1}^{n} w_{ij}\,\phi_j(x_j(t))$$

Here, represents the activation of neuron i at time t. The parameter is the decay constant, which ensures that activation does not grow without bound. is the external input, and is the weight associated with that input. The term represents the synaptic weight from neuron j to neuron i, and is the output or activation function of neuron j.

The additive nature of the model comes from the summation term, where contributions from all connected neurons are added together. Each connected neuron influences neuron i based on its current activation and the strength of the synaptic connection. Positive weights correspond to excitatory connections, increasing activation, while negative weights correspond to inhibitory connections, reducing activation.

One of the key features of this model is feedback. Because neurons are connected to each other, changes in one neuron's activation can influence others, which in turn can influence the original neuron. This feedback loop allows the network to settle into stable activation patterns known as attractor states. These attractor states correspond to stored memories or learned patterns.

Biologically, the additive autoassociative model resembles recurrent neural circuits found in the brain, where neurons are highly interconnected. Such circuits are believed to play a crucial role in memory and cognition. The feedback connections help reinforce consistent patterns of activity and suppress inconsistent ones, leading to robust information storage.

In conclusion, the Additive Autoassociative Network Model extends simple neuron models by incorporating feedback from other neurons. Through additive interactions and recurrent connections, it enables memory storage, pattern recall, and robust associative behavior. This model forms the theoretical foundation for many classic neural networks used in cognitive modeling and artificial intelligence.

Inhibitory Feedback Model

7. Inhibitory Feedback Model

The Inhibitory Feedback Model is a neural activation model that focuses on the role of inhibition in regulating neuron activity within a network. While excitatory connections increase neuron activation,

inhibitory connections reduce or suppress activation. In biological neural systems, inhibition is just as important as excitation, as it helps control signal flow, prevent overactivation, and maintain balance within neural circuits. The inhibitory feedback model captures this essential behavior using mathematical equations.

In earlier models such as the additive autoassociative network, feedback from other neurons can be both excitatory and inhibitory. However, the inhibitory feedback model emphasizes the suppressive influence of feedback and external input. This type of model is especially useful in explaining competitive interactions among neurons, where only certain neurons remain active while others are suppressed.

The mathematical equation of the inhibitory feedback model is expressed as:

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) - B_i I_i - \sum_{j=1}^{n} w_{ij}\,\phi_j(x_j(t))$$

Here, denotes the activation of neuron i at time t. The term represents passive decay, ensuring that activation decreases over time in the absence of other influences. The term represents inhibitory external input, and the summation term represents inhibitory feedback from other neurons in the network. The weights are assumed to be positive, so the negative sign ensures an overall inhibitory effect.

The key characteristic of this model is that all feedback and input terms reduce the neuron's activation. As a result, the neuron's activity is tightly controlled. When inhibitory input increases, the activation decreases more rapidly. This behavior reflects biological processes such as lateral inhibition, where the activation of one neuron suppresses the activity of neighboring neurons.

The choice of activation function also affects the network's behavior. Nonlinear activation functions can introduce thresholds, ensuring that neurons are completely shut off when inhibition exceeds a certain level. This leads to sparse activation patterns, which are efficient for information processing and memory storage.

In learning systems, inhibitory feedback helps improve generalization and prevent overfitting. By suppressing irrelevant or weakly activated neurons, the network focuses on the most important features of the input. This principle is widely used in modern neural architectures through techniques such as normalization and regularization, which are inspired by biological inhibition.

In conclusion, the Inhibitory Feedback Model highlights the importance of inhibition in neural systems. By incorporating inhibitory external input and feedback, the model explains how neural activity is controlled, stabilized, and made selective. It provides valuable insight into competitive neural behavior and forms the basis for many practical neural network designs.

Classical Neural Circuit Model (Perkel Model)

8. Classical Neural Circuit Model (Perkel Model)

The Classical Neural Circuit Model, commonly known as the Perkel Model, is a biologically inspired

neural activation model that represents neurons and their interconnections using concepts from electrical circuit theory. This model was proposed to better understand how signals propagate and interact in real neural circuits by drawing an analogy between neurons and electrical components such as resistors. The Perkel model provides a simple yet powerful framework for analyzing continuous-time neural dynamics.

In biological neurons, electrical signals travel through dendrites and axons, encountering resistance along the way. Similarly, in the Perkel model, neuron activation is influenced by resistive pathways that connect neurons. Each neuron is modeled as a node in an electrical circuit, and synaptic connections are modeled as resistors. This approach allows the application of well-known electrical principles to neural modeling.

The mathematical equation of the Perkel model is given by:

\frac{dx_i(t)}{dt} = -\frac{1}{R_i} x_i(t) + \sum_{j=1}^{n} \frac{1}{R_{ij}} \, \phi_j(x_j(t))

Here, represents the activation (analogous to voltage) of neuron i at time t. The term is the resistance associated with neuron i, representing leakage or loss within the neuron. The term represents the resistance of the connection between neuron j and neuron i. The function is the output or firing response of neuron j.

The first term, , represents passive decay of activation due to internal resistance. A smaller resistance value means higher leakage and faster decay, while a larger resistance results in slower decay. This term ensures that the neuron does not maintain activation indefinitely and contributes to the stability of the system.

Biologically, the Perkel model reflects how neurons integrate inputs from multiple sources. Each incoming signal contributes to the neuron's activation based on the strength of the connection. At the same time, internal leakage ensures that old signals gradually fade away. This balance between input integration and decay is a fundamental property of real neurons.

In learning applications, adjusting resistances is equivalent to modifying synaptic weights. Lowering resistance strengthens connections, while increasing resistance weakens them. This provides a natural way to model synaptic plasticity within the circuit framework.

In conclusion, the Classical Neural Circuit Model (Perkel Model) uses electrical resistance concepts to describe neuron activation and interaction. By modeling neurons as circuit elements, it provides a biologically meaningful and mathematically elegant way to study continuous-time neural dynamics, stability, and associative behavior, making it a foundational model in neural network theory.

Heteroassociative Network Model

9. Heteroassociative Network Model

The Heteroassociative Network Model is a neural network model designed to associate patterns from one set with patterns from another set. Unlike autoassociative networks, which recall the same pattern that was

stored, heteroassociative networks map an input pattern to a different output pattern. This type of association is fundamental in many cognitive processes such as translation, pattern mapping, and stimulus–response learning. The model is widely used in neural network theory to explain how information is transformed across different layers.

In a heteroassociative network, neurons are typically organized into two distinct layers: an input layer and an output layer. Neurons in the input layer influence neurons in the output layer through weighted connections, and in some models, feedback connections also exist from the output layer back to the input layer. The key idea is that activity in one layer produces a corresponding activity pattern in the other layer.

The mathematical formulation of the heteroassociative network model consists of two coupled differential equations, one for each layer. The equations are given by:

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) + \sum_{j=1}^{N} f_j(y_j(t))\, v_{ij} + I_i$$

$$\frac{dy_j(t)}{dt} = -B_j y_j(t) + \sum_{i=1}^{M} g_i(x_i(t))\, w_{ji} + J_j$$

Here, represents the activation of the ith neuron in the first layer, and represents the activation of the jth neuron in the second layer. The constants and are decay rates for neurons in the respective layers. The terms and represent external inputs or bias terms.

The weights and represent the strength of connections between the two layers. The functions and are activation or output functions that determine how neuron activations are transformed before being transmitted. These functions can be linear or nonlinear, depending on the desired network behavior.

A key feature of the heteroassociative network model is cross-layer interaction. Neurons in one layer do not interact directly with neurons in the same layer; instead, all interactions occur between layers. This structure makes the model suitable for tasks where input and output spaces are different. For example, mapping letters to sounds, images to labels, or sensor readings to control actions can all be modeled using heteroassociative networks.

Biologically, heteroassociative networks resemble neural pathways that connect different regions of the brain. Sensory areas are connected to motor or associative areas, allowing sensory input to produce appropriate responses. The bidirectional nature of some heteroassociative models reflects feedback mechanisms found in the brain, where higher-level areas influence lower-level processing.

In conclusion, the Heteroassociative Network Model provides a powerful framework for mapping one pattern to another. By using two interacting layers with weighted connections, the model explains how neural systems perform associative mapping, transformation, and stimulus–response learning, making it essential in both biological and artificial neural network studies.

Shunting Activation Model

10. Shunting Activation Model

The Shunting Activation Model is an advanced neural activation model that introduces bounded neuron activity, ensuring that neuron activation remains within a fixed range. Unlike earlier models where activation could grow without limit or become excessively negative, the shunting model incorporates

saturation effects that closely resemble real biological neurons. This makes the model highly stable and biologically realistic, especially for continuous-time neural networks.

In biological neurons, activation cannot increase indefinitely. There are natural upper and lower limits imposed by membrane properties and ion channel dynamics. The shunting activation model captures this behavior by modifying how external input affects the neuron. Instead of adding input directly to the activation, the input is multiplied by a term that depends on the current activation level. This mechanism naturally limits the growth of activation as it approaches its maximum value.

The mathematical equation of the basic shunting activation model is:

$$\frac{dx_i(t)}{dt} = -A_i x_i(t) + (B_i - x_i(t)) I_i$$

Here, represents the activation of neuron i at time t. The parameter is the decay constant, which causes activation to decrease over time. is the external input applied to the neuron, and represents the upper bound or saturation level of activation.

The key feature of this equation is the term . When the activation is small, this term is large, allowing the input to significantly increase activation. As the activation approaches the upper bound , the term becomes small, reducing the effect of the input. Eventually, when , the input has no effect, and the activation stops increasing. This ensures that activation never exceeds the maximum limit.

Biologically, this behavior reflects the saturation of neuron firing rates. A neuron can only fire at a certain maximum rate, no matter how strong the input is. The shunting model captures this limitation naturally, without requiring artificial clipping or thresholding.

From a computational perspective, the shunting activation model is highly stable. Because activation is bounded, the risk of instability due to excessive excitation is greatly reduced. This makes the model suitable for large recurrent networks, where uncontrolled activation could otherwise lead to divergence or oscillations.

The shunting model is also effective in representing gain control. Neurons adjust their sensitivity based on current activation levels. When activation is low, neurons are highly sensitive to input. When activation is high, sensitivity decreases. This adaptive behavior is important in sensory processing systems, where neurons must respond to a wide range of input intensities.

In many extensions of the shunting activation model, inhibitory inputs and lower bounds are also included. These extensions allow activation to be constrained between a minimum and maximum value. Such models are used to explain on-center off-surround behavior in vision, where central neurons are excited while surrounding neurons are inhibited.

The shunting activation model is widely used in image processing, pattern recognition, and normalization tasks. It helps networks emphasize relative differences in input rather than absolute magnitudes. This improves robustness to noise and variations in input scale.

In learning systems, shunting dynamics help maintain balanced activation across neurons, preventing

dominance by a few highly active units. This leads to more distributed and efficient representations.

In conclusion, the Shunting Activation Model provides a biologically realistic and mathematically stable way to model neuron activation. By introducing bounded activation and adaptive input scaling, it overcomes limitations of simpler models and plays a crucial role in advanced neural network architectures.