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Abstract- In this research, EEG signals were used to simulate and monitor the brain's electrical activity, especially focusing on detecting epileptic seizures. The study uses the Active Disturbance Rejection Control (ADRC) method as a control strategy, known for itsability to control complex and uncertain systems. This approach excels at estimating and mitigating perturbations in the brain's electrical activity and offers a robust solution for seizure control. A comparative analysis with the traditional proportional integration (PI) method revealed that the ADRC exhibits superior performance. This conclusion is underlined by the significantly lower values of key error metrics such as mean absolute error (MAE) and root mean square error (RMSE) obtainedwith ADRC. These findings confirm the enhanced efficacy and accuracy of ADRC in stabilizing brain activity during epilepticepisodes and mark it as a promising avenue for advanced neurological applications.

Index Terms: EEG signals, Active Disturbance Rejection Control (ADRC), Neural Mass Model (NMM), Comparison with PIcontrol

I. Introduction

Electroencephalogram (EEG) signals from the human brain have long been the subject of extensive research and medical interest due to their ability to reveal important information about the brain. These EEG signals, commonly called brain waves, provide a window into the complex neural processes underlying cognition, emotion, and motor control. Cognitive function is preserved when there is a balance between excitatory and inhibitory nerve signals in the brain. However, disturbances in this balance, such as increased activity, canlead to diseases such as epilepsy [1,2].

EEG signals are caused by synchronized electrical activity produced by many neurons. These signals can be divided into different frequencies, including delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-100 Hz). Each isassociated with a specific brain and activity. Delta waves often occur during sleep, while theta waves are associated with memory and spatial navigation. Alpha waves are important in theresting state of sleep, while beta and gamma waves are associatedwith cognitive activity. The brain works best when there is a balance between excitatory and inhibitory signals. Excitatory signals are often mediated by neurotransmitters such as glutamate, which promote the firing of neurons; Inhibitory signalsare generally associated with gamma-aminobutyric acid (GABA),which suppresses further neural activity. This balance is important for information processing, memory consolidation, and general cognitive development. However, deficiency in this small interaction can affect brain function and lead to seizures. Epileptic seizures are caused by sudden and abnormal electrical activity in the brain. The causes of epilepsy can be diverse and multi-factorial abnormal brain function, infections, or head trauma [1,2]. However, the main point of these differences is the disruption of the fine balance between permissive and inhibitory nerve signals. For example, genetic changes can cause excitatory neurons to become overactive, while brain damage can disrupt inhibitory pathways, both of which can ultimately lead to seizures. constantly interacts with the external environment through sensory and cognitive processes. External inputs can modulate neural activity and play an important role in controlling or disrupting the balance between excitatory and inhibitory signals [4]. For example, exposure to certain visual or auditory cues can cause seizures in the right individuals, demonstrating the influence of external inputs on neural dynamics.

Recent years have seen significant advances in our ability to record,analyze, and interpret EEG signals. These technological advances allow Machine learning algorithms, including deep neural networks, to be used to identify subtle patterns in EEG data that precede seizures. Additionally, wearable EEG devices enable continuous monitoring, allowing for early intervention and personalized treatment strategies [1,4]. A particularly promising approach to seizure control is the implementation of Active Disturbance Rejection Control (ADRC) [1]. ADRC is an advanced control method that uses real-time EEG data to predict and prevent interference from neural activity. ADRCworks to restore the balance required for brain function by altering perceptual and inhibitory signals. Comparative studies of ADRC and conventional controls such as proportional interval (PI) control have shown that ADRC has the best efficacy in reducing seizures.

To measure the performance and accuracy of the control method, the mean absolute error (MAE) and the root mean square error (RMSE) are the essential measurement parameters [1]. These parameters measure the difference between expected neural activity and the actual recorded EEG signal. The lower MAE and RMSE values indicate that there is a good relationship between the requirements and the results, that is, the control method is better. Constant comparison analysis shows that ADRC outperforms PI control and reduces MAE and RMSE values [1].

In summary, this research article provides an overview of EEG signals and their pathology and roles in the brain. It is an important study in understanding the brain and its dysfunction. The balance between excitatory and inhibitory nerve signals is essential for maintaining brain function, and imbalances can lead to seizures. External inputs, including sensory and cognitive processes, play an important role in regulating neural activity [2,4].

Advances in EEG-based epilepsy diagnosis and neuromodulation technology have opened new areas in epilepsy treatment [2]. Among these technologies, Active Disturbance Rejection Control (ADRC) has emerged as an excellent method that gives better results compared to traditional controls such as PI. Error measures such as MAE and RMSE consistently show that ADRC is effective in reducing seizure frequency.

This research paper lays the foundation for an in-depth investigation of the interaction between neural signals, external feedback, and interruption. Limbic control pathways in the context of epilepsy. By leveraging the power of EEG signals and innovative control strategies, we aim to contribute to ongoing studies of effective, personalized, and timely interventions for the treatment of epilepsy.

II. METHODS

The Neural Mass Model (NMM) is a critical mathematical framework employed to elucidate epileptiform activities arising from an imbalance between excitation and inhibition within neural networks [1,6]. To comprehend the significance of NMM, it is essential to grasp that it’s fundamentally a mathematical abstraction of brain dynamics. The human brain consists of a vast network of neurons, and these neurons communicate through synapses, which are connections that allow information to flow from one neuron to another. In a healthy brain, there’s a delicate balance between excitatory and inhibitory signals. However, when this balance is disrupted, it can lead to various neurological disorders, including epilepsy [3].

NMM serves as a tool to model these disruptions and study their effects [6]. The model is divided into three subpopulations, each representing different types of neurons and their interactions. This abstraction enables scientists and researchers to simulate and understand how abnormal neural activity, such as epileptic seizures, emerges from deviations in the normal balance between excitation and inhibition. By examining NMM, scientists can explore potential mechanisms underlying seizures and develop strategies for their control and treatment [4,6]. The structure of the Neural Mass Model is the foundation upon which its predictive power and utility rest. This model is essentially a network of interconnected neuron subpopulations that mimic the real neural circuitry within the brain. It comprises three primary subpopulations: the main subpopulation, the excitatory feedback sub-population, and the inhibitory feedback subpopulation. These sub-populations represent distinct groups of neurons that play essential roles in neural communication. To simulate this model, we deployed EEG signals as brain neuron activity input, integrated with their pe- periods of action. Although they cannot simulate the neuron activity in discrete terms, they can nearly resemble the random neuron activity [3,6]. Now, while referring to other research papers we observed that a lot

$$\begin{cases} h_e(t) = H_e t e^{-t/\tau_e} / \tau_e \\ h_i(t) = H_i t e^{-t/\tau_i} / \tau_i \end{cases} \tag{1}$$

$$\begin{cases} \ddot{y}_e(t) + 2\dfrac{\dot{y}_e(t)}{\tau_e} + \dfrac{y_e(t)}{\tau_e^2} = \dfrac{H_e i_e(t)}{\tau_e} \\ \ddot{y}_i(t) + 2\dfrac{\dot{y}_i(t)}{\tau_i} + \dfrac{y_i(t)}{\tau_i^2} = \dfrac{H_i i_i(t)}{\tau_i} \end{cases} \tag{2}$$

of them have used time domain conferences to execute the NMM and ADRC modulation. But we were stuck with 2 issues in this:

(i) Without a data set available to us we couldn’t determine the accuracy of the ADRC or PI methods if graphs stood simulated in continuous terms.

(ii) As we conceded the observations through discrete terms, it became more readable and comprehensive for the readers to directly understand the concept and simulations.

So, taking less than 1, impulse response and the input signal of the excitatory and inhibitory subpopulation we can obtain the output signal of the respective populations which we can use in our NMM mode, obtaining the other constant values from the given table. For obtaining the equivalent structure of a closed-loop system by ADRC, the plant block is nothing but the NMM model on which the system is applied. While yr=0 is the ideal condition to suppress the epileptic activity, the signal variation can be observed with the varying yr which is the desired output [1]. we opted for discrete values for each of the blocks in their defined ranges from the web. The main subpopulation consists of principal cells that receive inputs from the excitatory and inhibitory feedback subpopulations. These inputs are essential for modeling the synaptic interactions that occur in neural networks. The excitatory feedback subpopulation mimics excitatory neurons, while the inhibitory feedback subpopulation represents inhibitory neurons. In real neural circuits, these neurons release neurotransmitters that either enhance or inhibit the firing of other neurons.

Understanding the structure of NMM is crucial because it provides a framework for modeling and simulating how neural networks function under different conditions [1,6]. By altering the parameters and connections within this model, researchers can gain insights into how changes in neural activity can lead to pathological conditions like epilepsy.

The Neural Mass Model relies on a set of mathematical equations to describe the dynamics of neural interactions within the three subpopulations. These equations are the key to translating complex neural behaviors into a quantifiable form that can be analyzed and manipulated for research and clinical purposes.

Equation (1) is particularly noteworthy as it describes the impulse response functions for both the excitatory and inhibitory subpopulations. These functions are essential because they capture how synaptic inputs are transformed into changes in membrane potential in the neurons. The parameters in these equations, such as synaptic gains (He and Hi) and synaptic time constants (te and ti), define the characteristics of these transformations.

In essence, these equations provide a mathematical basis for understanding how neurons process incoming signals and how these processes contribute to the overall behavior of the neural network. They serve as the building blocks for simulating and studying the dynamics of the NMM and its application in modeling and understanding neural disorders like epilepsy [6].

$$S(v) = \frac{2e_0}{1 + e^{r(v_0 - v)}} \quad (3)$$

The dynamics of the Mass Models are further elucidated through the use of second-order ordinary differential equations (ODEs), as outlined in equation (2). These ODEs play a pivotal role in connecting the input and output signals of the excitatory and inhibitory subpopulations, thus contributing to the overall behavior of the neural network1 [1,6].

The ODEs describe how changes in the membrane potential and firing rates of neurons within the model are influenced by various factors, including synaptic inputs and feedback mechanisms [1]. By solving these differential equations, researchers can gain insights into how neural activity evolves and how it responds to different patterns of inputs and interactions.

It's important to emphasize that these equations provide a dynamic framework for understanding the behavior of the neural network, allowing researchers to simulate and analyze how alterations in neural dynamics can lead to different outcomes, including pathological conditions like epileptiform activities [8]. This mathematical representation is a fundamental tool in the study of neural mass models and their applications in neuroscience research. A crucial aspect of the Neural Mass Model is its inclusion of nonlinear transformations to mimic the behavior of real neurons. We introduced equations(1) and (2) that describe impulse response functions and synaptic interactions [7]. However, the process of transforming membrane potentials into firing rates is inherently nonlinear, and this nonlinearity is essential for accurately modeling neural behavior. Equation (3) introduces a sigmoidal function that performs this nonlinear transformation. In this equation, the sigmoid function S takes the average membrane potential as its input and yields the average firing rate as output. The parameters e0, v0, and r influence the shape and characteristics of this sigmoidal function [1,6].

The sigmoid function is crucial because it captures the thresholding behavior of neurons, where they remain quiescent untila certain level of excitation is reached, at which point they rapidly fire.Without this nonlinearity, the model would fail to replicate essential neural behaviors.

Researchers use these nonlinear transformations to ensure that the Neural Mass Model faithfully represents the firing properties of real neurons [1]. This inclusion of nonlinearity allows the model to capture the intricacies of neural dynamics, making it a valuable tool for understanding and studying neurological disorders like epilepsy. The Neural Mass Model introduces the concept of connectivity constants to characterize the interactions among different neuronal populations within the model. These constants denoted as C1, C2, C3, and C4, are fundamental components that define the strength and nature of synaptic connections between the subpopulations.

C1 and C2 represent the number of synapses established by the inhibitory feedback subpopulation onto the main subpopulation and itself, respectively. Conversely, C3 and C4 denote the number of synapses formed by the excitatory feedback subpopulation onto the main subpopulation and the inhibitory feedback subpopulation [1,6]. These connectivity constants are critical because they determine the extent to which one subpopulation influences another. In essence, they quantify the strength of the connections between different types of neurons in the model. By adjusting these constants, researchers can explore how changes in synaptic connectivity impact the overall behavior of the neural network.

Understanding these connectivity constants is essential for customizing the Neural Mass Model to simulate specific neural circuits accurately.

Table 1. Interpretation and values of the parameters in an NMM.

Parameters	Description	Values
H_e	Average excitatory synaptic gain	3.25 mV
H_i	Average inhibitory synaptic gain	22 mV
τ_e	Average synaptic time constant for excitatory population	0.0108 s
τ_i	Average synaptic time constant for inhibitory population	0.02 s
C_1, C_2	Average number of synaptic contacts in the excitatory feedback loop	$C_1 = 135$; $C_2 = 108$
C_3, C_4	Average number of synaptic contacts in the inhibitory feedback loop	$C_3 = 33.75$; $C_4 = 33.75$
v_0, e_0, r	Parameters of the nonlinear S function	$v_0 = 6$ mV; $e_0 = 2.5\ s^{-1}$; $r = 0.56\ mV^{-1}$

NMM: neural mass model.

Table 1 provides a set of nominal parameter values for various components of the Neural Mass Model. These values serve as a baseline or reference point for simulations and analyses. It's essential to recognize the significance of these nominal values in the context of the model's applications and research [1].

The parameters listed in Table 1 include average synaptic gains (He, Hi), average synaptic time constants (te, ti), and connectivity constants (C1, C2, C3, C4), among others. Each of these parameters plays a specific role in shaping the behavior of the model [1,6]. The nominal parameter values serve several crucial purposes: Baseline Comparison: They provide astarting point for simulations and experiments.

In practical terms, excitatory input reflects the synaptic activity originating from other regions of the brain. It can be thought of as the neural information flow coming into the modeled network from external sources. To capture the dynamic nature of these inputs, researchers often use white noise as a mathematical representation. The output of the Neural Mass Model denoted as y(t), corresponds to the average synaptic activities of the pyramidal cells within the main subpopulation. Importantly, this output can be interpreted as electroencephalography (EEG) signals. EEG is a valuable tool in neurosciences for recording and studying brain activity, making the modeling of y(t) particularly relevant for understanding the relationship between the model's behavior and real-world brain measurements.

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Dynamics of S depend on the slope at equilibrium, termed sigmoid gain Ks:

$$K_s = \dot{S}(v)\Big|_{v=v_0} = \frac{2e_0 r e^{(v_0-v)}}{[1+e^{r(v_0-v)}]^2}\Big|_{v=v_0} = \frac{e_0 r}{2} \quad (4)$$

We have used these values as a reference to compare how changes in parameters affect the model's behavior.
Realistic Modeling: These values are often based on empirical data and biological knowledge, making the model's behavior more realistic and biologically plausible.
Consistency: They ensure consistency and reproducibility in re-research. When multiple researchers work with the same model, having nominal values helps standardize experiments and analyses.
Insight Generation: By examining how the model behaves under these nominal conditions, researchers can gain insights into the underlying neural mechanisms and dynamics.
It's important to note that while these values are valuable as a starting point, the true power of the Neural Mass Model lies in its flexibility. We didn't change or make adjustments to these parameters to get a clear reference and prevent errors. But definitely, researchers can adjust these parameters to explore various scenarios and simulate different neurological conditions. This adaptability allows for the investigation of how changes in synaptic gains, time constants, and connectivity influence neural activity, making it a valuable tool for studying disorders like epilepsy.
To comprehend the Neural Mass Model's behavior under different conditions and perturbations, researchers often employ linearization techniques. Linearization simplifies complex nonlinear systems into more manageable linear models, which are amenable to mathematical analysis and control design. In the context of the NMM, this process involves approximating the nonlinear sigmoidal transformation function with a linear approximation, allowing researchers to explore the system's behavior in response to perturbations.
The sigmoidal transformation function (S) described by equation(3) introduces nonlinearity into the model, capturing the thresholding behavior of real neurons. However, analyzing nonlinear systems can be challenging. Linearization helps overcome this challenge by approximating the system's behavior around a specific operating point. The linearization process involves calculating the system's linear transfer function, which relates inputs to outputs in the frequency domain. This transfer function can then be used for various analyses, such as stability analysis, frequency response analysis, and control design. By linearizing the NMM, researchers can gain valuable insights into how it responds to different inputs and disturbances.
It's important to note that while linearization simplifies the analysis, it introduces limitations. The linearized model is only accurate within a certain range around the chosen operating point. Beyond this range, nonlinear effects become significant, and the linear model may no longer accurately represent the system's behavior. Nonetheless, linearization is a powerful tool for exploring the behavior of complex systems like the NMM and provides a basis for control design and stability analysis.

$$\begin{cases} G_e(s) = \dfrac{H_e\tau_e}{(\tau_e s+1)^2} \\ G_i(s) = \dfrac{H_i\tau_i}{(\tau_i s+1)^2} \end{cases} \quad (5)$$

Understanding the behavior of complex systems often involves translating their dynamics into the frequency domain using transfer functions. In the case of the Neural Mass Model, researchers use Laplace-transformed transfer functions to describe how inputs and disturbances affect the system's outputs.
The transfer functions are a fundamental tool in systems analysis and

the transfer function of the NMM is given by GNMM(s) where, Y(s) and P(s) are the Laplace transformation of y(t) and p(t), respectively:

$$G_{\mathrm{NMM}}(s) = \frac{Y(s)}{P(s)} = \frac{G_e(s)}{1+K_s^2 G_e(s)[C_3C_4G_i(s) - C_1C_2G_e(s)]} \quad (6)$$

control theory. They provide a concise representation of how the system responds to different frequencies of inputs.

Equation (5) presents the Laplace-transformed transfer functions for the NMM, providing a mathematical framework for studying the system's frequency response [1]. By analyzing these transfer functions, researchers can gain insights into the system's dynamics, stability, and sensitivity to different input frequencies. Some common analyses conducted using transfer functions in the context of the NMM include Frequency Response Analysis: Researchers examine how the model responds to different frequencies of excitatory inputs, helping understand how neural populations within the model react to various patterns of stimulation. Stability Analysis: Transfer functions are used to assess the stability of the system. Stability is a crucial consideration in understanding how the model behaves under different conditions and perturbations. Control Design: Transfer functions are instrumental in designing control strategies for the NMM. By manipulating the transfer functions, researchers can develop approaches to regulate and control the model's behavior, which can have implications for treating neurological disorders. In summary, transfer functions are a valuable mathematical tool for characterizing the behavior of the Neural Mass Model in the frequency domain. They provide a means for researchers to gain insights into how the model responds to various inputs and disturbances, contributing to a deeper understanding of neural dynamics and their applications in neuroscience research. Root locus analysis is a powerful method used to study the stability and behavior of linear systems, and it has significant applications in control theory and system design. In the context of the Neural Mass Model (NMM), root locus analysis provides insights into how changes in key parameters, specifically the excitatory and inhibitory gains, affect the system's stability.
Fig 1 and Fig 2 in the provided content display root locus diagrams specific to the NMM. These diagrams are graphical representations of how the system's poles, which are the roots of the characteristic equation, change concerning parameter variations. Eachpoint on a root locus represents a possible location of the poles as a specific parameter, such as the excitatory or inhibitory gain, varies. Here's how root locus analysis is relevant to the NMM: Stability Assessment: Root locus diagrams reveal regions of parameter space where the system is stable and where it becomes unstable. Stability is a crucial consideration when studying neural dynamics, as it determines whether a neural network's behavior remains controlled ordevolves into chaotic or epileptic activity.
Parameter Tuning: By examining root locus plots, we can identify optimal parameter values to maintain stability or achieve specific system behaviors. This is particularly relevant when designing control strategies to regulate neural network activity.
Sensitivity Analysis: Root locus analysis helps assess the sensitivity of the system to parameter variations.

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It's worth noting that root locus analysis is most applicable to linearized systems, as it relies on linear transfer functions. While the NMM is inherently nonlinear, the linearized version of the model can provide valuable insights into its behavior within certain operational ranges. Researchers can use this analysis to explore the relationship between parameter variations and neural stability, shedding light on how epilepsy and other neural disorders may be influenced by changes in neural mass parameters.

Impulse response analysis is a powerful technique for understanding how systems, including the Neural Mass Model (NMM), respond to sudden changes or perturbations in inputs. In the context of the NMM, impulse responses provide critical insights into the model's behavior and its ability to replicate real-world neural dynamics.

The NMM's impulse responses reveal how the model's neural populations react to abrupt changes in excitatory and inhibitory inputs.Key points related to impulse response analysis in the context of the NMM include:

Temporal dynamics are captured by impulse responses in Neural Mass Models (NMMs), revealing neural populations' speed and magnitude of response to sudden perturbations. Insights into synaptic interactions and feedback mechanisms are gleaned, aiding analysis of how changes in synaptic gains and time constants affect model output. Impulse responses also enable stability assessment, crucial for identifying pathological neural activity like epilepsy. Model validation against experimental data refines parameters and structure. Clinical insights gained shed light on neurological disorders and treatments. In summary, impulse response analysis is vital for exploring NMM dynamics, enhancing understanding of epilepsy and related conditions. The Neural Mass Model (NMM) has found significant applications in the field of epilepsy research. Its utility in modeling neural dynamics and understanding the mechanisms underlying epileptic seizures has made it a valuable tool for both researchers and clinicians. Here are some key ways in which the NMM is applied in epilepsy research:

Seizure Prediction and Control: Researchers use the NMM to simulate neural activity leading up to seizures. By analyzing the model's behavior, they aim to identify patterns or biomarkers that could predict impending seizures. Additionally, the NMM can be used to design control strategies to prevent or mitigate seizures in real time.

Furthermore, the NMM has practical applications in epilepsy researchand beyond. It aids in seizure prediction, drug development, patient-specific modeling, and understanding comorbidities associated with epilepsy. The model also serves as an educational tool for trainingclinicians and researchers in neural dynamics and disease mechanisms

$$\ddot{y} = f(\cdot) + bu \tag{7}$$

$$u = \frac{u_0 - z_3}{b_0} = \frac{k_p(y_r - z_1) - k_d z_2 - z_3}{b_0} \tag{8}$$

$$\begin{cases} \dot{z}_1 = z_2 + \beta_1(y - z_1) \\ \dot{z}_2 = z_3 + \beta_2(y - z_1) + b_0 u \\ \dot{z}_3 = \beta_3(y - z_1) \end{cases} \tag{9}$$

$$\ddot{y} = \bar{f}(\cdot) + k_p(y_r - z_1) - k_d z_2 - z_3 \tag{10}$$

Understanding Seizure Onset: The NMM helps researchers investigate the onset of seizures at the network level. By altering parameters related to excitatory and inhibitory interactions, they can gain insights into the conditions that lead to abnormal synchronized neural activity.

Patient-Specific Modeling: Personalized medicine is a growing trend in epilepsy treatment. The NMM can be customized to simulate the neural dynamics of individual patients based on their clinical data, enabling tailored treatment strategies.

Research into Comorbidities: Epilepsy often co-occurs with other neurological conditions. The NMM provides a platform to study the interactions between epilepsy and comorbidities, enhancing our understanding of complex patient presentations.

Education and Training: The NMM is used in educational settings to train clinicians and researchers in the principles of neural dynamics and epilepsy. Simulations with the model help individuals understand the underlying mechanisms of the disorder.

Hypothesis Testing: Epilepsy research often involves formulating hypotheses about neural mechanisms. The NMM allows researchers to test these hypotheses in a controlled computational environment, providing valuable insights.

In summary, the NMM has a wide range of applications in epilepsy research, from understanding the fundamental neural dynamics to developing clinical interventions. Its flexibility and ability to simulate complex neural interactions make it an indispensable tool for expanding our knowledge of epilepsy and improving patient care. Hence, the Neural Mass Model (NMM) is a powerful mathematical framework that plays a pivotal role in elucidating the neural dynamics underlying conditions like epilepsy. It offers a detailed representation of neural populations and their interactions, allowing researchers to simulate and analyze the emergence of abnormal neural activities. Through mathematical equations, linearization techniques, transfer functions, and various analyses such as root locus and impulse response, the NMM provides valuable insights into neural behavior and its response to perturbations.

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$$\ddot{y} = k_p(y_r - y) - k_d\dot{y} + k_p e_1 + k_d e_2 + e_3 \tag{11}$$

$$G_{\text{cld}}(s) = \frac{k_p}{s^2 + k_d s + k_p} \tag{12}$$

As we look to the future, there are several exciting directions for the continued development and application of the NMM. These include Enhanced Personalization: Advancements in data collection and computational power will enable even more precise patient-specific modeling, leading to tailored treatments for individuals with epilepsy. Integration with Advanced Imaging: Combining the NMM with advanced neuroimaging techniques like functional MRI and EEG can provide a more comprehensive understanding of neural dynamics and their relation to epilepsy.

Closed-Loop Therapies: The NMM can contribute to the development of closed-loop systems that detect and intervene in real-time to prevent seizures, improving the quality of life for epilepsy patients.

Multi-Scale Modeling: Future iterations of the NMM may incorporate multi-scale modeling, allowing researchers to explore interactions between neural populations at different levels of granularity. Collaboration with Experimental Research: The NMM will continue to complement experimental studies, helping bridge the gap between theoretical modeling and empirical data.

In summary, the Neural Mass Model stands as a valuable tool for understanding and addressing epilepsy and other neurological disorders. Its continued evolution and integration with cutting-edge research will undoubtedly contribute to advancements in neuroscience and clinical practice, ultimately benefiting patients and furthering our understanding of the human brain.

III. SIMULATIONS

Our simulation study aims to evaluate the effectiveness of the Active Disturbance Rejection Control (ADRC) approach, an active disturbance rejection control technology. ADRC is viewed favorably for its ability to resolve system problems and maintain operational efficiency without requiring extensive facility knowledge. It consists of three components: a control system (Facility), a predictive controller using the Extended Occasion Observer (ESO), and a signal control scheme.

This technology is useful in project management as it can manage disruptions effectively. Our simulations focus on using the ADRC method to control specific processes in circuits. The circuit includes the carefully designed ESO subsystem with specific equations and parameters such as b and w0. By solving these equations, we can determine the values of z1, z2, and z3 according to the input signals Y(s) and U(s). We use a Simulink model to estimate the internal state and then run the calculated results from realblocks capturing their maximum and minimum values.

By choosing proper kp and kd, desired closed-loop dynamics can be obtained. However, six parameters need tobe determined. To address it, let us say:

$$\begin{gathered} s^3 + \beta_1 s^2 + \beta_2 s + \beta_3 = (s + \omega_o)^3 \\ s^2 + k_d s + k_p = (s + \omega_o)^2 \end{gathered} \tag{13}$$

then the bandwidth-parameterization-based tuning approach can be obtained, that is:

$$\beta_1 = 3\omega_o, \beta_2 = 3\omega_o^2, \beta_3 = \omega_o^3, k_p = \omega_c^2, k_d = 2\omega_c \tag{14}$$

Therefore, tunable parameters become ω_c, ω_0 and b_0. From equations (8) and (13), we have:

$$u = \frac{\omega_c^2(y_r - z_1) - 2\omega_c z_2 - z_3}{b_0} \tag{15}$$

Taking Laplace transformation for both sides of equation (9), we have:

$$\begin{cases} z_1(s) = \dfrac{3\omega_o s^2 + 3\omega_o^2 s + \omega_o^3}{(s+\omega_o)^3} y(s) + \dfrac{b_0 s}{(s+\omega_o)^3} u(s) \\ z_2(s) = \dfrac{(3\omega_o^2 s + \omega_o^3) s}{(s+\omega_o)^3} y(s) + \dfrac{b_0(s + 3\omega_o)s}{(s+\omega_o)^3} u(s) \\ z_3(s) = \dfrac{\omega_o^3 s^2}{(s+\omega_o)^3} y(s) - \dfrac{b\omega_o^3}{(s+\omega_o)^3} u(s) \end{cases} \tag{16}$$

Substituting equation(15) into (14), we have:

$$u = \frac{1}{b_0} \frac{(s+\omega_o)^3}{(s+\omega_o)^3 + 2\omega_c s^2 + (\omega_c^2 + 6\omega_o\omega_c)s - \omega_o^3} [\omega_c^2 y_r - \frac{(3\omega_c^2\omega_o + 6\omega_c\omega_o^2 + \omega_o^3)s^2 + (3\omega_c^2\omega_o^2 + 2\omega_c\omega_o^3)s + \omega_c^2\omega_o^3}{(s+\omega_o)^3} y] \tag{17}$$

G(s); H(s) used in Fig 3. can be depicted as

$$G(s) = \frac{1}{b_0} \frac{(s+\omega_o)^3}{(s+\omega_o)^3 + 2\omega_c s^2 + (\omega_c^2 + 6\omega_o\omega_c)s - \omega_o^3}$$

$$H(s) = \frac{(3\omega_c^2\omega_o + 6\omega_c\omega_o^2 + \omega_o^3)s^2 + (3\omega_c^2\omega_o^2 + 2\omega_c\omega_o^3)s + \omega_c^2\omega_o^3}{(s+\omega_o)^3} \tag{18}$$

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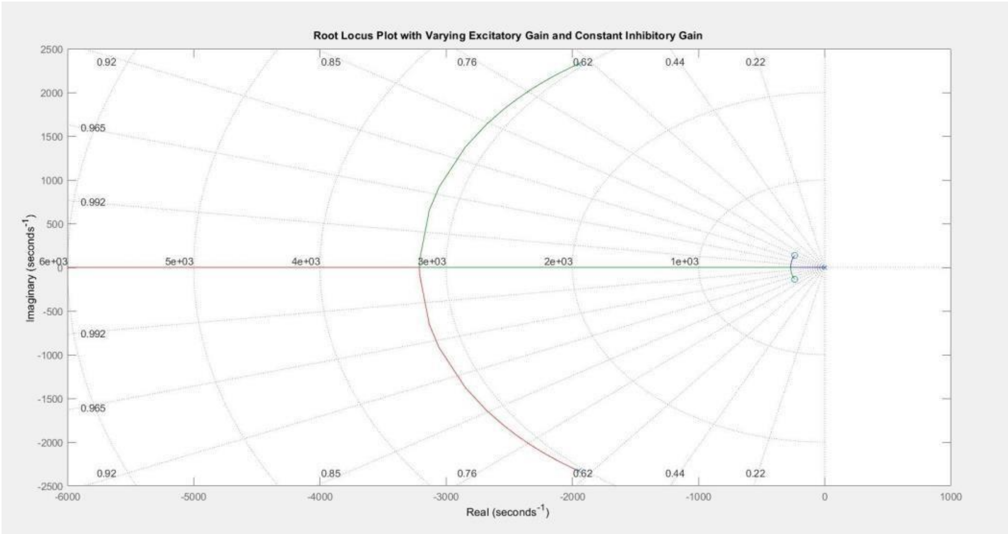

Fig 1. Root locus graph displaying variation in He and a constant Hi

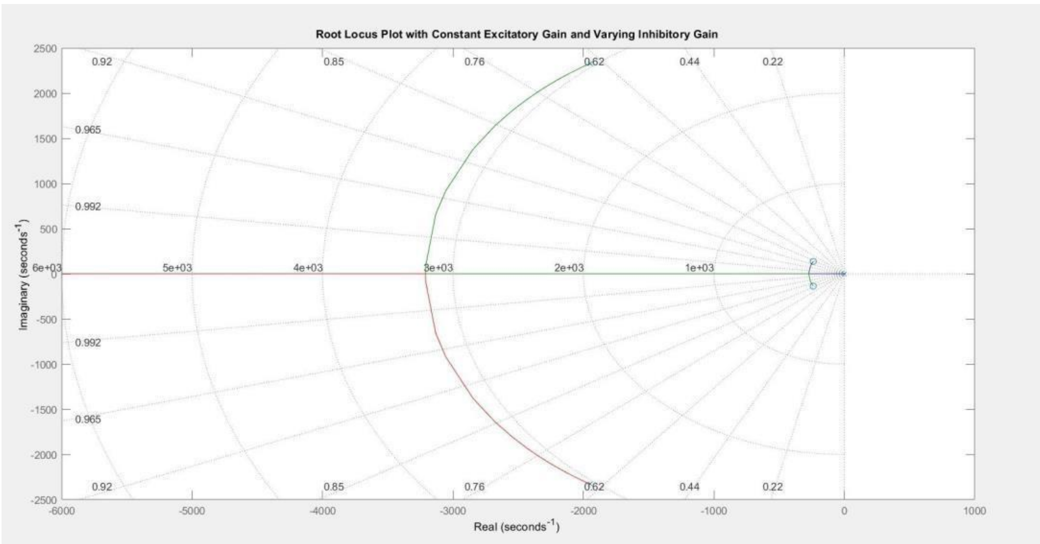

Fig 2. Root locus graph displaying variation in He and a constant Hi

ADRC block is an important part of the circuit and contains constants such as control gain (Kp and Kd) and yr, which interact with each other through the output bet of the collection point. This creates a powerful control loop in which ESO's state estimate is the main guide. The ADRC approach is unique in terms of response management, making it the first choice in situations where there is serious competition. To get the best results from ADRC-based management, electrical equipment should be located and installed according to the drawing. This involves teaching feedback and real-time results, such as EEG signals while maintaining precise time alignment.

Oscilloscopes at the factory-ESO junction monitor timing control. Adding a delay unit enhances model accuracy and ADRC's ability to handle disturbances.

This showcases ADRC's adaptability, making it ideal for critical interventions. The ADRC method is suitable for many applications that require precise control and interference.

Its ability to manage complex processes and disruptions with- out the need for multiple factory models makes it very popular. Thanks to careful design and efficient use, ADRC control systems can maintain stability and accuracy even with adverse effects.

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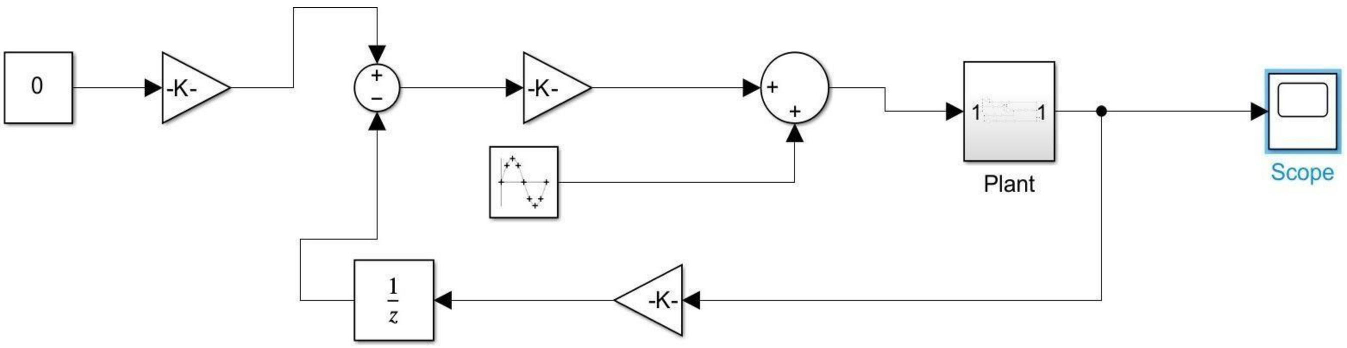

Fig 3. Equivalent structure of a closed-loop system by ADRC. ADRC: active disturbance rejection control.

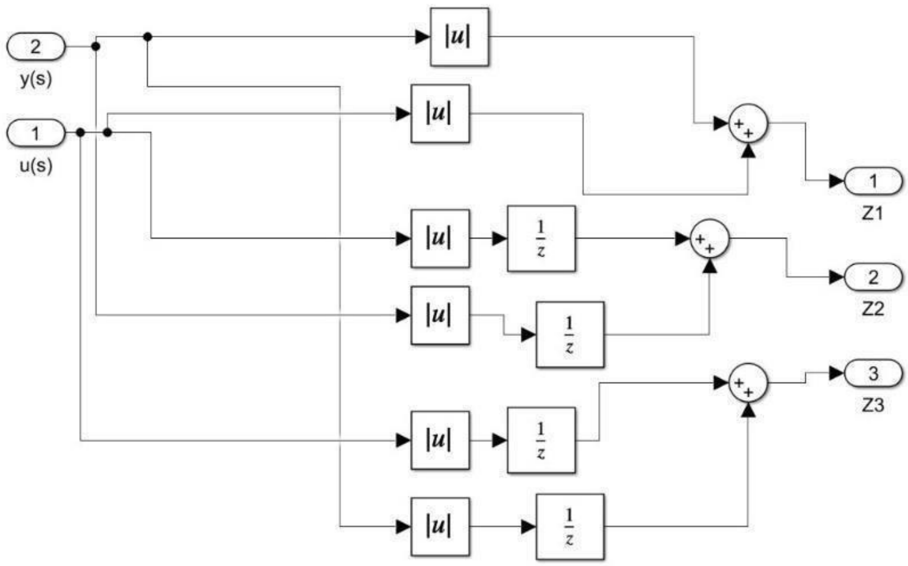

Fig 4. Variables for ADRC

In Fig 3. we observe the idealized equivalent structure of a closed loop system for ADRC wherein we have the plant, which is nothing but the scheme of the linearized neural mass model, on which the ADRC is being implied in order to obtain the equired graph. We observed the NMM model for discrete values and obtained a discrete sinusoidal graphical pattern.

Again in Fig 4. we observed the variables, z1, z2, and z3 which are outputs of the ESO, which estimate a system output, derivative of a system output, and the generalized disturbance, respectively have been obtained in discrete terms in order to get a precise value from the graph.

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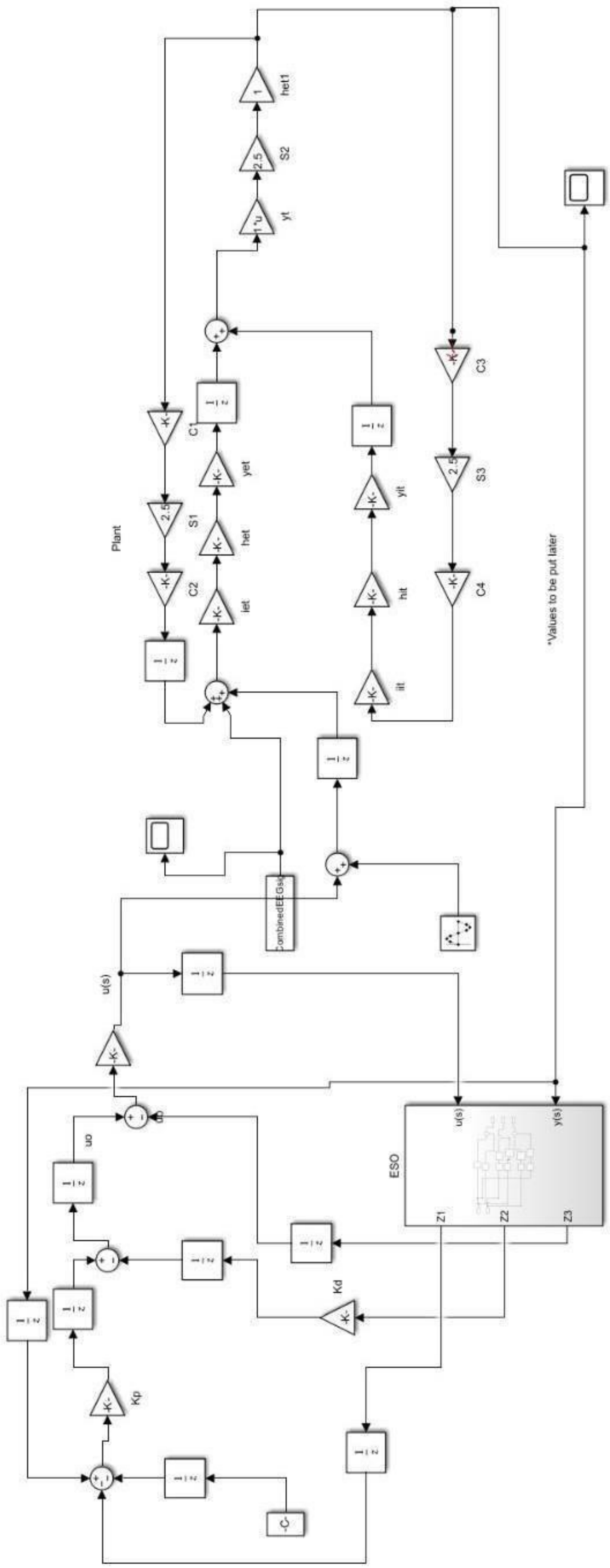

Fig 5. Structure of a closed-loop system by ADRC. ADRC: active disturbance rejection control.

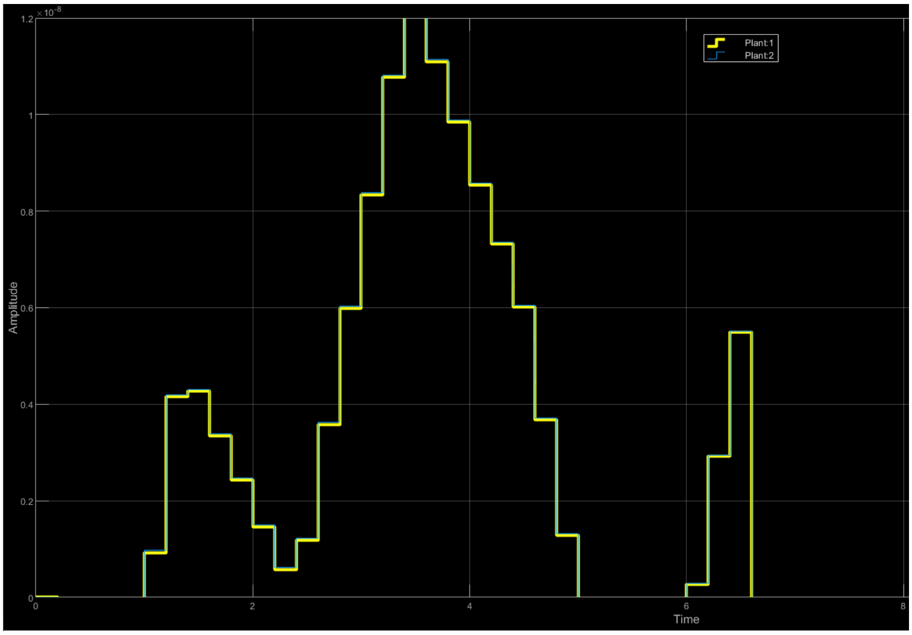

Fig 6. Equivalent structure of a closed-loop system by ADRC. ADRC: active disturbance rejection control.

The ADRC approach promotes effective response management through the use of general guidelines and ESO and ensures that the management process is aligned with specific guidelines. Our simulation results show that our ADRC controller can maintain good conditions even when the average excitatory synaptic gain (It) changes from 3.25 to 10 and the average inhibitory synaptic gain (Hi), remains at 22 mV. The margin of stability indicates the body's ability to maintain an increased or slower speed without becoming unstable. The root locus diagram shows that the system is stable without branches to the right of the plane.

In Fig 7(b) and (d) we check the data whose value is fixed at 3.25mV, while Hi is set in the range of 0.5 to 21. Again, by analyzing the source, we can see the performance of the ADRC controller. The branches of the path remain on one side of the s-plane, indicating the stability of our control. This result clearly shows that our controller can adapt well to changes in the system without affecting stability, which is a necessary tool in many control applications.

The graphs obtained for the NMM model have a time period of signal on the X-axis and the amplitude is present along the Y-axis. Similarly, the same parameters have been enabled for each of the scope-generated graphs. Therefore, the ADRC approach combined with baseline assessmentprovides a comprehensive view of behavioral control. While the central location chart indicates ownership balance, the ADRC method ensures stability even in the event of change. This performance is important in practical applications where accurate control and adverse effects are important. The combination of these techniques allows management professionals to design and deliver management systems that can adapt to changing workloads while delivering high performance and sustainability.

IV. Results and Observations

Throughout this comprehensive study, we have made significant observations at the crossroads of control system analysis and the Active Disturbance Rejection Control (ADRC) approach. Our journey began with the integration of ADRC into a specific circuit, and what unfolded was truly remarkable. ADRC, comprising the 'Plant,' 'ESO' (Extended State Observer), and 'Controller,' proved its mettle by skillfully repelling disturbances without the need for an overly complex model of the system. This finding holds great promise for practical applications, especially in fields like EEG signal processing, robotics, and chemical engineering, where disturbances are the norm rather than the exception.

Moving forward, our exploration took us into the realm of control system analysis via the root locus method. This intricate dance between ADRC and root locus analysis unveiled invaluable insights. Notably, we witnessed that the ADRC controller maintained its composure even as critical parameters, such as the average synaptic gains (He and Hi), underwent variations. The stability of the control system remained unwavering, as illustrated bythe absence of branches on the right-hand side of the complex plane. These findings have profoundimplications for the world of control system design. They signify a path forward where engineers and researchers can harness the fusionof ADRC and root locus analysis to craft control systems capable of gracefully adapting to ever-changing operating conditions while ensuring consistent and reliable performance. This research marks a significant stride in the quest for control strategies that thrive inthe presence of disturbances—a critical requirement in the advancement of modern technologies.

From Fig 5. we obtain the final structure of a closed loop ADRC, wherein we have now installed and used z1, z2 and z3, which we can now analyze using all the available variables to obtain the seizure control graph, and do further research on it. In Fig 6. We obtain the graph from the Fig 5. scope analysis and its very evident thatits clearly predictive of the seizures.

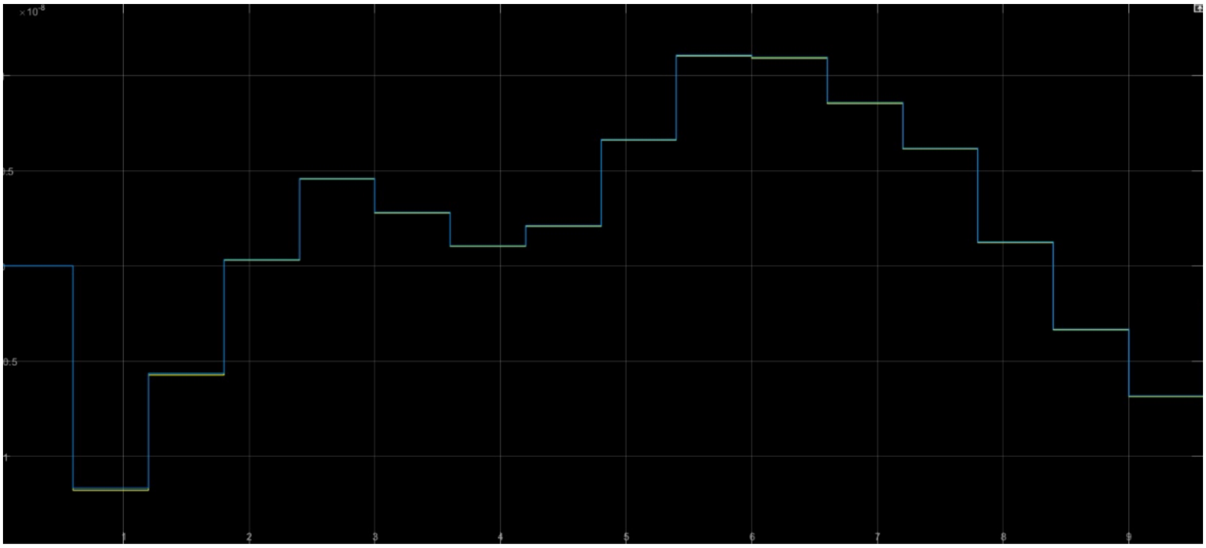

Fig 7. Discrete step analysis for 0.6 sec sample time

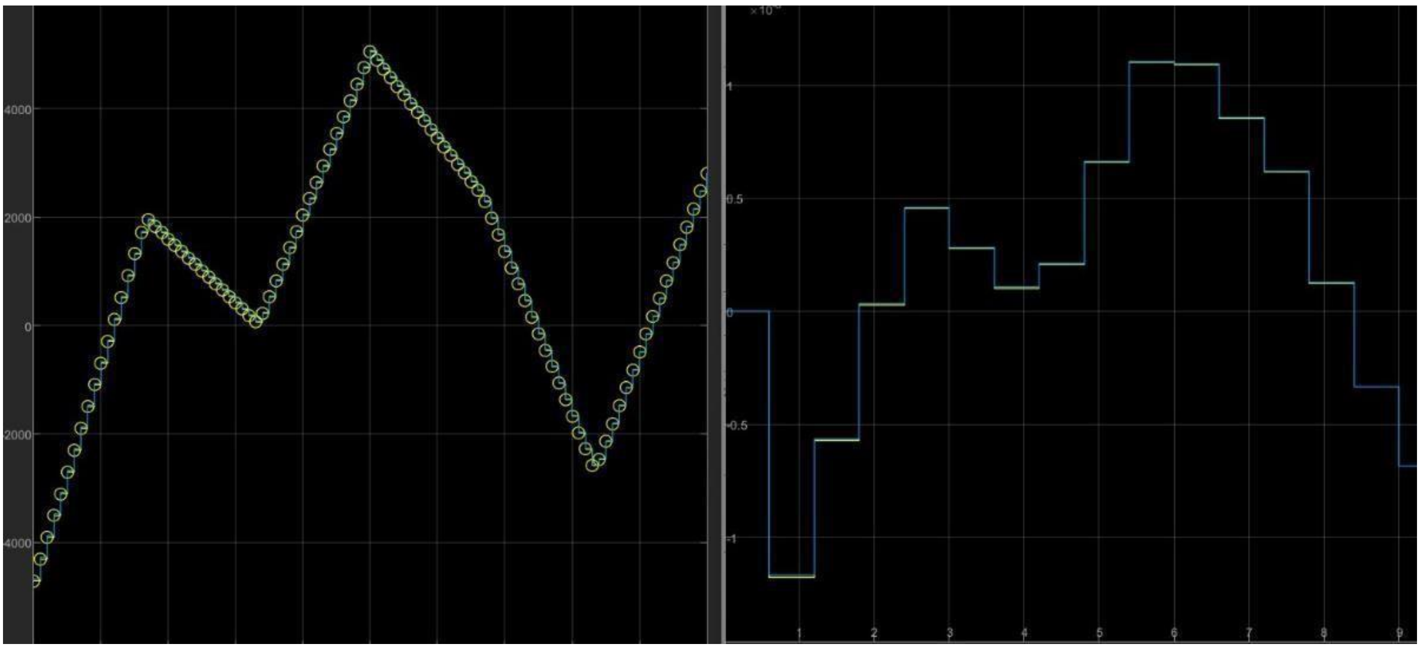

Fig 8. Final scope analysis with ADRC application

V. CONCLUSION

In conclusion, this research emphasizes the potential of Active Disturbance Rejection Control (ADRC) in revolutionizing seizure prevention. ADRC's real-time adaptability and predictive accuracy offer a novel approach to epilepsy management. It excels in distinguishing preictal states, enabling proactive interventions that can significantly enhance the lives of those living with epilepsy. The incorporation of ADRC into closed-loop systems promises a future where patients can enjoy increased autonomy and reduced seizure-related disruptions. To summarize, this study underscores the transformative nature of ADRC in epilepsy care. Its adaptability and personalized forecasting capabilities represent a shift towards precision medicine in epilepsy management. Collaborative efforts between ADRC and existing treatments hold the potential for a more holistic approach to care. This research illuminates a pathway to proactive and patient- centered seizure prevention, providing optimism for an improved quality of life for individuals affected by epilepsy.

AUTHOR'S CONTRIBUTION

Authors Abhinav Kar, Rishab Das, A Sharmila, and Aayush Gupta contributed to conducting research and development of the subject.

Author Abhinav Kar and Rishab Das- Simulation and modeling analysis of the various attributes of the subject

Author Abhinav Kar, A. Sharmila, and Aayush Gupta-Documentation and citations.

All authors have approved the final version.

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DATA AVAILABILITY

EEG (Electroencephalogram) signals display both positive and negative values, stemming from the bipolar electrode setup. These variations reflect the dynamic neural activity within the brain. Positive values often represent heightened neural synchronization or cognitive engagement, while negative values indicate desynchronization or inhibitory processes. EEG captures diverse waveform patterns like alpha, beta, delta, and theta waves, each with unique frequencies. Electrode placement impacts signal polarity by recording activity from specific brain regions. In essence, EEG offers insights into cognitive function, revealing the brain's temporal dynamics and neurophysiological processes.
The time durations referred to by the model as time vectors, for the generation of each signal had to be processed along with each signal input, hence, the signal data values as well as the time vectors had to be integrated to give the signal input as a unit.

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