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Ensemble Voting Regressor for Enhanced Prediction in EMG-Based Prosthetic Wrist Control

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Abstract—**Accurately capturing user motion intention is crucial for effective wrist control in myelectronic prosthetic hands. While various regression models have been explored to improve prediction performance, each presents specific limitations when used independently. This study proposes a novel ensemble learning approach that utilizes a Voting Regressor to combine the strengths of several regression models ANN, ANFIS, fuzzy logic, and their combinations (ANN-ANFIS, ANN-Fuzzy, ANFIS-Fuzzy, and ANN-ANFIS-Fuzzy) to improve predictive performance. Surface EMG signals were collected from the FCR and ECRL muscles at five contraction levels: 20%, 40%, 60%, 80%, and 100% MVC. These signals were used to predict wrist velocity, which was then validated using a SimMechanics based prosthetic hand model in MATLAB 2017a. The ensemble model outperformed all individual and combination models at four MVC levels; 20%, 40%, 60%, and 100%. However, at 80% MVC, a single model achieved superior performance. Based on the average performance gain at the four winning MVC levels, the ensemble method achieved an overall improvement of 11.38%. When applied to the prosthetic hand simulation, the ensemble model showed slight additional improvements in RMSE at each MVC level, highlighting the practical applicability of the approach. To assign optimal and objective weights to the contributing models, MCDM-WSM approach was applied. This method combined multiple evaluation metrics (RMSE, %NRMSE, MAE, R^2, and p-value) into a single composite score, leading to the final weighted regression equation: YVR-HG-wrist = (0.5163)YANN + (0.2367)YANFIS + (0.2470)YFuzzy. Furthermore, the ensemble model reduced reliance on additional control strategies such as PID tuning, as its improvements in RMSE were comparable to those typically achieved through PID-based compensation. These findings highlight the potential of a performance-weighted ensemble approach to provide more accurate, robust, and practical EMG-based prosthetic wrist control especially in real-time applications.**

Keywords*—*Ensemble Learning; Voting Regressor; EMG Signal Processing; Wrist Velocity Prediction; ANN-ANFIS-Fuzzy Ensemble Model; Simmechanics Prosthetic Simulation; PID Controller Reduction.

I. INTRODUCTION

Losing a hand due to injury, illness, or congenital conditions can have a profound impact on a person's daily life and emotional well-being. To help restore lost functionality, prosthetic hands have been developed to mimic natural hand movements. Among these, myoelectronic prosthetic systems which controlled by surface electromyography (EMG) signals generated by muscle contractions represent a major advancement, enabling users to operate the prosthesis based on their motion intentions [1].

However, interpreting EMG signals accurately remains a major challenge. These signals are inherently nonlinear, variable, and often affected by noise. To model such complexity, researchers have applied various regression methods like artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), and fuzzy logic systems. Each of these models has its strengths as ANN is inspired by how the brain works using layers of connected "neurons" to learn patterns from data. The model adjusts the strength of these connections during training to improve its predictions while learning nonlinear patterns from data [2]. ANFIS combines the learning ability of neural networks with the Sugeno rule-based thinking of fuzzy logic. It uses a layered structure to adjust fuzzy rules and membership functions based on training data [3], [4]. Fuzzy Logic, on the other hand, works with Mamdani rules and human-like reasoning. Instead of learning from data, it uses predefined rules and membership functions to handle uncertainty and vague inputs, producing clear outputs [5]-[7].

Despite their benefits, these individual models also come with limitations. ANN models typically require large datasets and can perform poorly with noisy inputs [8], [9]. ANFIS may become inefficient as the number of input variables increases due to the complexity of tuning both neural and fuzzy parameters [10], [11]. Fuzzy Logic, while intuitive, can struggle with complex datasets because of the difficulty in defining accurate membership functions and rule sets [12], [13]. These challenges limit the overall reliability and responsiveness of prosthetic control systems.

While ensemble learning combining multiple models has proven effective in other fields, its potential remains underexplored in EMG-based prosthetic applications. This study addresses that gap by introducing a voting-based ensemble learning approach. The proposed method integrates multiple models, including ANN, ANFIS, Fuzzy Logic, and their combinations, to improve the prediction of wrist velocity from EMG signals. By aggregating model outputs through a voting regressor, the system can produce a more stable and accurate control signal, even across varying levels of muscle contraction [14]-[16]. This approach offers a well-rounded solution by improving user experience, enhancing functionality, and enabling more natural hand movements to better handle the complexity and variability of hand function.

The aim of this study is to evaluate the performance of this ensemble approach in the context of prosthetic wrist control. EMG data from key forearm muscles are used to predict wrist movement, and the system's performance is measured using metrics such as root mean square error (RMSE), percentage of normalized root mean square error %NRMSE, mean absolute error (MAE), coefficient of determination (R^2), and p-value. Additionally, a decision-making framework based on the multi-criteria decision making using weighted sum method (MCDM-WSM) is applied to fairly rank and weight the contributing models in the ensemble [17], [18].

By combining multiple regression techniques and optimizing their contributions, this research seeks to improve the prediction performance and reliability of myoelectric prosthetic wrist control thus ultimately making these devices more effective and intuitive for users [19].

The structure of this paper is as follows: Section II reviews recent developments in ensemble learning models. Section III outlines the methodology, including experimental setup and evaluation methods. Section IV presents the results and discussion, where all proposed methods are analyzed in detail. Finally, section V concludes the findings from section IV and highlights possible directions for future research.

II. Recent Development of Ensemble Laearning Model

Ensemble learning, specifically the voting regressor, has evolved as one of the most effective techniques in machine learning for improving prediction performance in various applications [20]-[23]. The concept of ensemble learning involve the need for combining multiple weak learners to form a stronger overall model [24]-[26]. In the voting regressor approach, multiple models such as linear regressors, decision trees, or more complex methods like neural networks, are trained independently [27]-[29]. The predictions from these models are then combined, either through averaging or selecting the majority output, which helps reduce the weaknesses of individual models by leveraging their collective strengths [30], [31]. This strategy enhances the robustness and stability of predictions, particularly in handling non-linear or noisy data [32]-[35].

Over time, voting regressors have found applications across diverse fields. In healthcare, for example, they are widely used for predictive analytics in disease diagnosis and treatment outcomes by integrating various models trained on patient data [24], [36]. In finance, voting regressors are employed to improve the predictive performance of stock market predictions by combining multiple forecasting models [37], [38]. Additionally, in energy and climate forecasting, ensemble models help predict demand patterns and environmental changes by combining insights from different meteorological and economic models [39]-[41]. Each of these areas benefit from the voting regressor's ability to reduce errors from different learning methods, and lead to more reliable output predictions [42]-[44].

The evolution of ensemble learning has also seen progress in the combination techniques used within voting regressors [45], [46]. Other than majority voting or averaging, more complex strategies like weighted voting have emerged, where odels contributing to the ensemble are assigned weights based on their performance [30], [31]. This ensures that more accurate models have a greater influence on the final prediction [47]-[49]. Today, with the integration of deep learning architectures and complex algorithms like ANNs and ANFIS, the voting regressor continues to evolve, making it a versatile and essential tool in industries ranging from autonomous driving systems to prosthetic hand control, where precision and adaptability are dominant [50]-[52].

III. Methodology

Fig. 1 shows a flowchart used for this experiment designed. First, EMG data were collected from the FCR and ECRL muscles at various levels from 20%, 40%, 60%, 80% and 100% of maximum voluntary contraction (MVC). The raw signals were then normalized and filtered to ensure clean input for the models. The based models network using ANN, ANFIS, fuzzy logic was trained and developed to predict wrist velocity from the processed EMG data. To enhance prediction performance, an ensemble method using an inverse RMSE-weighted average voting regressor was applied, combining outputs from all individual and combination models. The performance of these models was evaluated using performance metrics such as RMSE, %NRMSE, MAE, R^2, and p-values. The selected model which poses the lowest RMSE value of predicted wrist velocity was then tested on a SimMechanics based prosthetic hand model for validation. To further improve the system performance, PID-based tuning was used to assess how much the ensemble reduced reliance on traditional control methods. A slight improvement in RMSE during this simulation supported the practical relevance of the approach. Model weights were then optimized using MCDM-WSM based on metrics performance, and a final regression equation was constructed using these weighted outputs to represent the ensemble prediction model.

A. Participants and Setup

Ten healthy male volunteers aged 21–40 years participated in the study. All participants provided informed consent prior to data collection. Basic hand dimensions were recorded to assist in proper alignment with the prosthetic interface. The experiment focused on replicating a single degree of freedom wrist flexion and extension across three wrist target positions: neutral (0°), flexed (-45°), and extended (45°), as illustrated in Fig. 2.

B. Prosthetic Wrsit Design

A fully functional prosthetic wrist was designed using SolidWorks 2017 and simulated in a virtual environment using SimMechanics as shown in Fig. 3. The model was configured to perform natural wrist movements, with accurate control.

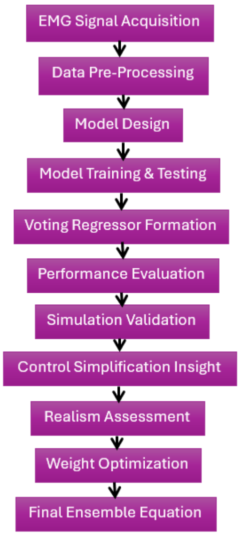
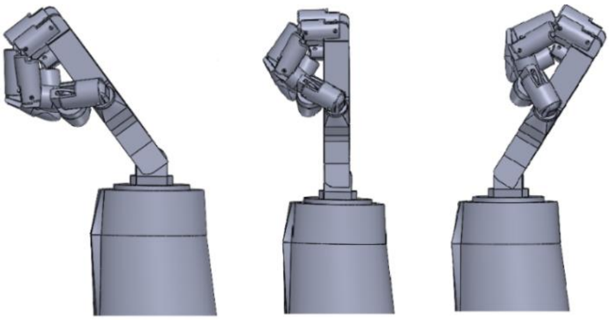


Fig. 1. Flowchart for the experiment designed

(a) (b) (c)

Fig. 2. Hand gripping positions for hand dynamometer at various wrist angle positions: (a) at -45°, (b) at 0°, and (c) at 45° [53]



(a) (b) (c)

Fig. 3. Solid work 3D hand designed (a) flexion wrist position, (b) neutral wrist position, and (c) extension wrist position [54]

C. EMG Signal Acquisition

Surface electromyography (EMG) signals were captured using the vernier system at a sampling frequency of 1,000 Hz. Electrodes were placed on the top of the muscle belly of two primary forearm muscles that response effectively towards wrist movement which are flexor carpi radialis (FCR) and extensor carpi radialis longus (ECRL) according to the book of anatomy [55]. Each electrode was spaced 2 cm apart, and skin preparation was performed to reduce impedance and electrical noise.

EMG recordings were taken during hand grip wrist movements performed at five effort levels: 20%, 40%, 60%, 80%, and 100% of each participant’s MVC. The concept of MVC has been applied due to the distribution of the data collection [56].

D. Signal Processing and Feature Extraction

Raw EMG signals were pre-processed through second order band pass filter (10–350 Hz) [57]. A sliding window segmentation technique with a 50% overlap was applied to preprocess the EMG signals before feature extraction process as this step effective in capturing relevant signal dynamics while balancing computational efficiency [58]. The process continued as the waveform length (WL) feature was extracted from the pre-processed EMG data [59]. This time-domain feature captures both amplitude and frequency characteristics of the EMG signal, illustrating lower standard deviation result preliminary tests compared to other features such as RMS, MAV, IEMG and ZC, hence offering higher prediction performance [60], [61]. At the end, MVC normalization has been selected as one of the commonly used forms of rectified EMG signals by dividing the instant amplitude obtained value when conducting the experiment [62].

E. Model Development

In ANN and ANFIS development system designed, three dataset for hand grip movement with three different wrist position (neutral, flexion and extension) and two of them will be taken to design a network for the system [63]. In the training dataset selected, 70% has been used as training, 15% has been used for testing and the other 15% has been used as validation. It left one dataset that will be used for cross-validation in testing environment. For fuzzy logic, the Mamdani rules were designed based on testing datasets.

1) ANN System Development

In this paper, the ANN architecture was developed using MATLAB coding. In this network designed process, the neuron must be chosen properly to minimize the number of errors produced. In this process, the optimum number of neurons was chosen based on training and validation dataset. The graph plotting was shown in Fig. 4. The red line graph came from the training dataset while the blue line graph came from validation dataset as the y axis represents the RMSE values and x axis are the number of neurons used to generate the RMSE error values. The number of neurons will be chosen based on the differences between these two lines RMSE error values. The lowest number of RMSE will reflect the number of neurons that the system will be chosen to design the system. The main objectives of plotting this graph were to determine the interaction between these two lines of graph plotting. The reason behind using only the training and validation datasets during selection of the optimum number of neurons is to avoid overfitting the test data by creating the best version of the model. The test data separation ensures that the performance metrics obtained reflected the model's true generalization ability, not just its ability to fit the data it has already been optimized against. This result is a significant improvement, which determined the optimal number of neurons to be 4 with an RMSE = 22.2106.

2) ANFIS System Development

For ANFIS, the network was designed using a single hidden layer. Each input was optional designed to have 2, 3 or 4 membership function (mf) with input and output was set using “gauss2mf” selected as constant at their mf type [63]. At the end, the combination of different mf for each dataset was combined which its performance was measured using the training dataset and validation dataset to design a particular network. The RMSE value was used as an indicator to select which combination gave the best result as lowest value of RMSE are preferable. Below shows the Fig. 5 as the value of mf is [2 2 2] with the value of RMSE = 19.7332 and Fig. 6 below shows the combination of mf of [4 4 4] with the value of RMSE = 18.9782.

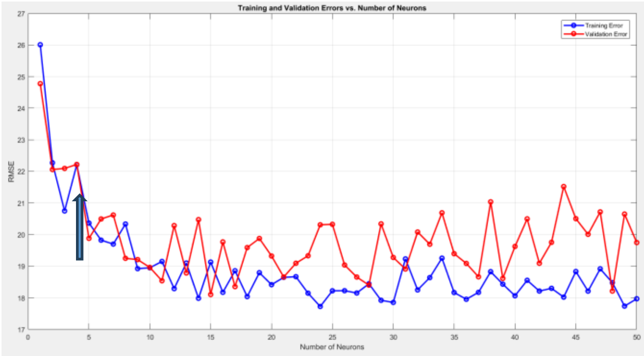


Fig. 4. Graph RMSE Vs number of Neuron for HG experiment

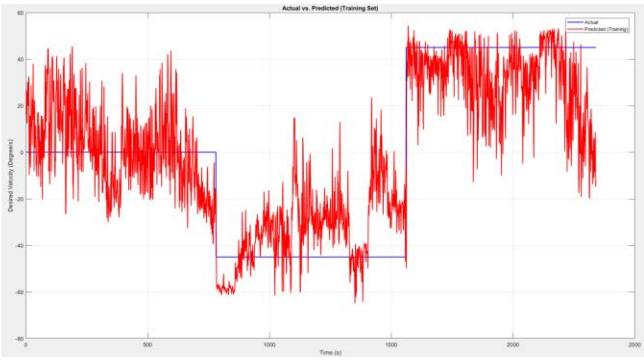


Fig. 5. ANFIS network training output: RMSE = 19.7332

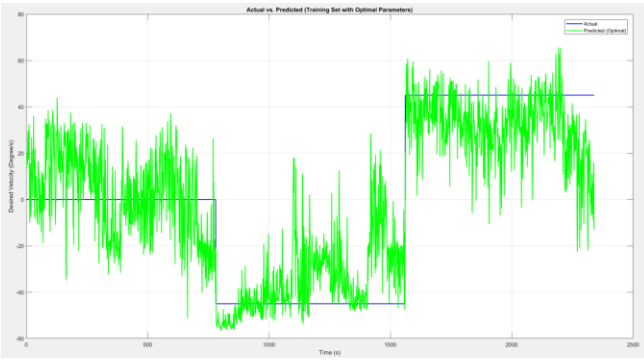


Fig. 6. ANFIS Optimal network training output: RMSE = 18.9782

3) Fuzzy Logic System Development

The structure of the FL comprises fuzzification, a rule table, a fuzzy inference system, and a defuzzification mechanism [64]. Fuzzy logic first fuzzifies the input variables before designing the rule table using membership functions. A fuzzy inference system of the Mamdani type is used to map inputs to outputs by merging all linguistic statements in the rule table. The concept of Mamdani is applied when fuzzy rules are designed based on the expert knowledge of a designer, and the fuzzy output is later converted into a crisp value using defuzzification. The defuzzification step is completed using a "centroid" technique that returns the area's center beneath the curve [65]. In this architecture, FCR and ECRL muscle values were simultaneously analyzed based on their performance at different MVC levels and wrist joint angle positions to estimate the wrist's velocity.

The 9 linguistic claims stated in rule Table I are synthesized into a Mamdani-style fuzzy inference system that maps inputs to outputs. In these phrases, the conjunction AND represents a minimum operator that selects only the lowest of the fuzzy inputs. For each IF-THEN rule statement, an implication operation is performed using the "minimum" method, which directly truncates the fuzzy output sets. Instead, a complex-shaped curve has been generated at the conclusion by aggregating all fuzzy output sets that have been trimmed using the "maximum" method.

TABLE I. 9 IF – THEN RULE STATEMENTS [53]

No		FCR Muscle		ECRL Muscle		WRIST VELOCITY
1	if	S	and	S	then	Z
2	if	M	and	M	then	Z
3	if	H	and	H	then	Z
4	if	M	and	S	then	FM
5	if	H	and	M	then	FM
6	if	H	and	S	then	FH
7	if	S	and	M	then	EM
8	if	M	and	H	then	EM
9	if	S	and	H	then	EH

F. *Ensemble Learning Approach*

Ensemble methods in machine learning are powerful techniques designed to improve the predictive performance and robustness of predictive models by combining the strengths of multiple individual models [66]. These methods work on the principle that combining the predictions of various models can lead to improve performance than relying on a single model [67]. The ensemble base learning algorithm are created from each combined method components [68]. The list of ensemble methods applicable to regression includes Bagging (Bootstrap Aggregating), where multiple models are trained on different subsets of the data, allowing each model to reduce variance through averaging; Boosting, which sequentially trains models to focus on correcting the errors of previous models, in that way reducing bias; Stacking (Stacked Generalization), a method that involves training a meta-model to learn how to best combine the predictions of base models coming from each model; and voting regressor, where multiple models vote on the final prediction by either averaging their outputs or using a weighted average [30], [31]. Below are the generalized methods of ensemble learning equations (1):

$$\hat{y} = \sum_{i=1}^{n=1} \hat{y}_i \tag{1}$$

$\hat{y}$ is the ensemble model, $\hat{y}_i$ represent a single model and n represent total number of models used shown in (1). An ensemble learning strategy was employed to combine the outputs of the ANN, ANFIS, and Fuzzy Logic models using a weighted voting regressor. The ensemble prediction was calculated as (2):

$$\hat{y} = \sum_{i=1}^{n} \omega_i \cdot \hat{y}_i \tag{2}$$

ω_i is the weight of the i-th model, $\hat{y}_i$ is the prediction from the i-th model and n is the total number of models in the ensemble shown in (2). However, in this paper the concept of RMSE of each model will be used to assign the weight for each model. Chen *et al*, used the concept of inverse RMSE as a weight for their use model in boosting ensemble learning methods [69]. Mingyuan *et al*, also use the same concept in improved stacking ensemble learning method [70]. In general, total weight to be used $\sum \omega_i$=1. Various combinations of models were evaluated, and the best performing ensemble was selected based on validation performance. This approach using ensemble learning bagging concept ensured that models with lower RMSE (i.e., higher prediction performance) contributed more significantly to the final output [71], [72].

$$\omega_i = \frac{\frac{1}{RMSE_i}}{\sum_{j=1}^{n} \frac{1}{RMSE_j}} \tag{3}$$

$RMSE_i$ is the RMSE of a model M_i and $RMSE_j$ is the total number of RMSE for each model. n is the total number of models in ensemble learning shown in (3). The implementation of this learning method shown at Fig. 7 flowchart below and were listed in the following steps: -

- The testing model input from each model ANN, ANFIS and Fuzzy Logic were generated.
- The possible combination models of ANN, ANFIS, Fuzzy, ANN-ANFIS, ANN-Fuzzy, ANFIS-Fuzzy, ANN-ANFIS-Fuzzy was applied to the proposed algorithm to obtain the lowest number of RMSE.
- The lowest RMSE from possible model combination was selected as the value of weight for this combination was calculated for each MVC's level.
- The Final selected model was tested to the prosthetic hand of the wrist to measure its predictive performance.

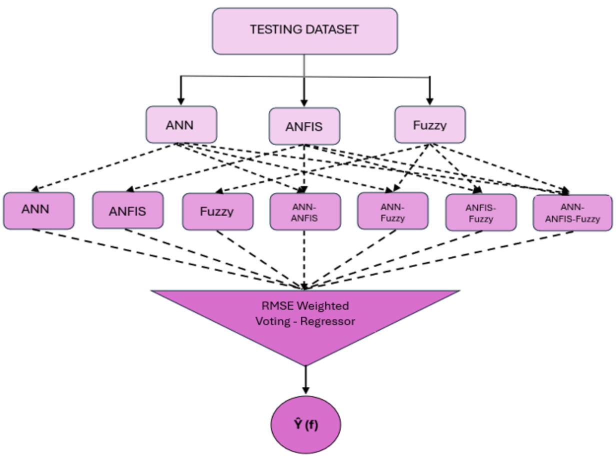


Fig. 7. Full system of proposed system for prosthetic hand for wrist movement using ensemble learning (Bagging) - inverse RMSE-weighted average voting regressor

Single-model approaches, such as linear discriminant analysis (LDA) and support vector machines (SVM), have been widely used in prosthetic hand control due to their simplicity and easier design. However, these models often struggle with adaptability, especially when faced with variations in EMG signals caused by factors like electrode displacement, muscle fatigue, or changes in limb position [73]. Such limitations can lead to decreased performance and reliability in real-world applications.

Peng *et al.* proposed an ensemble extreme learning machine (EELM) for EMG-based gesture recognition. By combining multiple ELM classifiers through majority voting, their method improved accuracy on the Ninapro DB5 dataset, achieving 77.9% and outperforming standard models like decision trees and random forests [74]. This highlights the value of ensemble techniques in handling EMG signal variability and boosting classification performance.

Proposing this approach for prosthetic hand for wrist movement using ensemble learning (Bagging) - inverse RMSE-weighted average voting regressor in which will combine multiple models to benefit from their individual strengths. This design aims to enhance the system's adaptability to dynamic conditions and improve the overall performance and user experience of myoelectric prosthetic control systems.

Fig. 8 shows the development of the prosthetic hand using SimMechanics using MATLAB 2017a version completed with proposed system (ensemble learning – inverse RMSE-weighted average voting regressor) physical modelled for output testing.

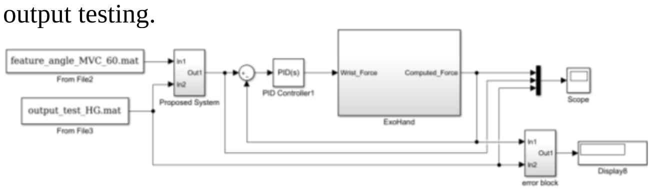


Fig. 8. Full proposed system of prosthetic hand for wrist movement

G. *Performance Evaluation*

Other than RMSE, %NRMSE, MAE, R^2, and p-value were obtained from the result calculation. %NRMSE scales the RMSE to the range of the actual output, expressed as a percentage. This enables fair comparison across different datasets or signal ranges. The function of MAE is to capture the average magnitude of errors without considering their direction, providing insight into the typical size of prediction errors. R^2 value indicates the proportion of variance in the observed data explained by the model. Values closer to 1 suggest a better model fit. T-test between each model design with actual values was recorded and presented as p-value to determine the significant relationship between these two groups.

For each experiment design, each stage requires a decision-making process that needs to be analyzed before the next step takes place. To guide the selection of the most suitable models, a decision-making Table II was used based on this five key performance metrics: RMSE, %NRMSE, MAE, R^2, and p-value. This table highlights different combinations of these metrics and provides clear suggested actions. For example, when a model shows low error values, a high R^2, and a p-value below 0.05, it is considered to have excellent performance and is selected as the optimal model.

On the other hand, models with high errors or low statistical significance are typically rejected. In some cases where only one or two metrics are slightly weaker, the model might still be accepted if further investigation justifies its performance, for example, by checking for outliers or signs of overfitting. This guidance helps ensure that the model selection process is consistent, transparent, and focused on both predictive performance and statistical reliability. "L" refers to Low, "M" refers to High and "H" refers to High.

TABLE II. DECISION-MAKING TABLE

Case	RMSE	NRMSE	MAE	R^2	P-value	Action/Decision
1	L	L	L	H	< 0.05	Select as optimal model.
2	L	L	M	H	< 0.05	Accept if RMSE is significantly lower than alternatives.
3	L	L	H	H	< 0.05	Investigate outliers; proceed if justified.
4	L	L	L	H	> 0.05	Accept if model outperforms others significantly.
5	L	L	L	M	< 0.05	Accept; consider for further refinement.
6	L	L	L	L	< 0.05	Investigate model structure; proceed with caution.
7	L	L	H	L	> 0.05	Reject unless no better alternatives exist.
8	M	M	L	M	< 0.05	Consider if better models are unsuitable.
9	M	M	M	M	> 0.05	Reject.
10	H	H	H	L	> 0.05	Definitely reject.
11	H	H	L	L	< 0.05	Reject; prioritize models with better overall metrics.

Realizing the outcome from each of the experiments might be a combination of various models, a statistical method called MCDM approach based on the WSM was employed. This method combines multiple performance indicators into a single composite score for each experiment, allowing consistent and explainable comparisons. However, this approach needs to be developed by considering and analyzing all the obtained performance metrics. RMSE was assigned the highest weight due to its sensitivity to large errors and its strong relationship with performance reduction in real-time systems. NRMSE followed as the second-most weighted metric, particularly important for comparing models trained on normalized EMG data, where scale independent performance is crucial. MAE, which is more robust to outliers than RMSE, was weighed moderately to complement RMSE without overshadowing it. R^2 and p-value were given lesser weights, showing their roles in explaining variance and assessing statistical significance, but not directly contributing to error reduction. This distribution is consistent with the decision-making shown in Table II, where models with strong error performance but moderate R^2 or marginal p-values were still considered acceptable. Based on this step of decision-making on selecting the best model representation, the weight was proposed. The total weight sums equal to 1.0. Table III displays the performance metrics, its objectives and proposed weights based on the importance of this value in final decision making.

TABLE III. WEIGHT ASSESSMENT TABLE

Performance Metric	Symbol	Objective	Weight
Root Mean Square Error	RMSE	Minimize	0.35
Normalized RMSE (%)	NRMSE	Minimize	0.25
Mean Absolute Error	MAE	Minimize	0.15
Coefficient of Determination	R^2	Maximize	0.15
p-value	p	Neutral	0.1

Since these metrics were measured on different scales, each value was normalized using Min-Max normalization method. Throughout this process, all the listed metrics use can be analyzed using the same scale. The normalized metrics were then multiplied by their respective weights, and a composite score for each experiment was calculated using (4):

$$Composite\ Score_i = \sum_{j=1}^{n} w_j \cdot x'_{ij} \tag{4}$$

Where w_j is weight for performance metric, x'_{ij} is the normalized value of performance metric j for experiment i and n is the total number of performance metric. This composite score ranges from 0 to 1 as this value get higher, the better the overall performance across the define performance metric. As this composite score were obtained, the experiment will be ranked in descending order. This ranking will be used to compare the effectiveness of the selected model for each experiment.

IV. RESULT AND DISCUSSION

The experiment of hand grip was done with a different variation of wrist position (neutral, flexion and extension) at 20%,40%, 60%, 80% and 100% MVC level. Recent study Salatiello *et. al* shown that incorporating dynamic movement data using LSTM networks during activities of daily living significantly improves the generalization and performance of myoelectric control systems [75].

The RMSE of output from ANN, ANFIS, fuzzy logic, ANN-ANFIS, ANN-fuzzy logic, ANFIS-fuzzy logic and ANN-ANFIS-fuzzy logic combination have been used to analyze the performance of each combination offering a new level of adaptability in EMG-based wrist velocity prediction. Unlike traditional single model approaches, this proposed approach captures nonlinearities and uncertainty in EMG signals more effectively. Recent works such as Li *et al.* have employed SVM classifiers experience a decline in accuracy over repeated sessions due to factors like electrode displacement and muscle fatigue [76]. Similarly, Diu *et al.* used deep learning architectures but required large datasets and lacked interpretability [77]. The selection of the chosen model was done after considering all the performance metric as shown in Table II.

In addition to model performance, a PID controller was employed to smooth out signal fluctuations from the output mapping process, providing a more stable and continuous control signal to become an input for prosthetic hand. Recent advancements, stated by Won *et al.*, have demonstrated that incorporating a ZPETC+PID controller into myoelectric prosthesis systems can significantly enhance real-time responsiveness, reducing actuation delay by approximately 0.240 seconds [78]. This PID-based approach improves system accuracy while minimizing the calibration burden typically associated with user specific EMG variability, thereby enhancing practical usability for end users in dynamic environments. In this paper, metaheuristic algorithm has been applied to obtain the value for Kp, Ki and Kd and were fixed for all experiments with parameters: $Kp = 3.97 \times 10^{-9}$, $Ki = 0.47$, $Kd = 1.44 \times 10^{-6}$ [79]. An improvement in RMSE value is getting slightly better as PID has been applied before the signal supplied to the prosthetic hand.

All figures and tables present a detailed comparison of each method based on RMSE, %NRMSE, MAE, R^2, and p-value. Additionally, the figures illustrate the effect of model weighting on prediction performance for wrist movement estimation. From all output figures below the red line graph represents the estimated chosen combination method. The blue line graph shows the prosthetic hand output wrist velocity tuned by PID, and the black line graph showed the actual wrist velocity output recorded during the experimental procedure.

A. *Hand Grip Wrist at 20% of MVC Level*

Fig. 9 shows an output from selected model voting regressor complemented with an output from PID tuning prosthetic hand wrist movement at 20% MVC level. Table IV shows a prediction input form by combination of ANN-Fuzzy model was selected as it gave the lowest RMSE value equal to 20.82 and %NRMSE value achieves 23.13%. Moreover, the MAE gave the lowest value of 18.0044 among all its MAE members. This model again manages to give the highest R^2; 0.6782 as possible as compared to all other models. The p-value from all the models illustrates a value <0.05 (highly significant) which concludes that the bias may be negligible and the decision making still acceptable to follow decision on lowest RMSE value obtained. By having said that, the ANN-Fuzzy model has been selected as a model to represent the input for prosthetic wrist velocity for 20%MVC level. The regression model analysis reveals the following weights: ANN = 0.4734, ANFIS = 0, and Fuzzy = 0.5256, as detailed in Table V to fulfil this condition. Moreover, by choosing ANN-Fuzzy as a selected model, it shows the highest percentage of predictive performance of 6.72%. The RMSE value was slightly reduced to 19.3 on the prosthetic hand movement while PID was used.

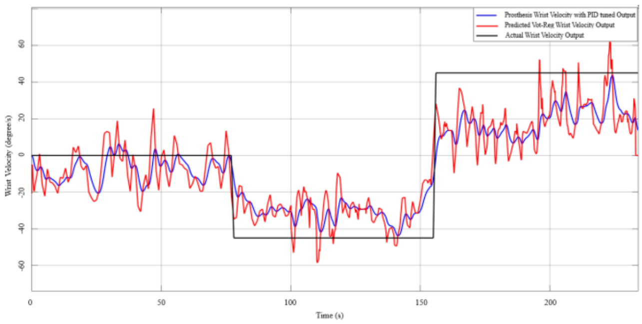


Fig. 9. Voting regressor output for 20% MVC state

In this experiment, classified as low intensity level, the ANN-Fuzzy model outperformed others due to its ability to manage the noisy, low amplitude EMG signals common at minimal muscle activation. Its highest predictive performance, even without contribution from ANFIS, suggests that rule-based inference (Fuzzy) combined with data-driven learning (ANN) provided a better balance of generalization and specificity. The Inverse RMSE-weighted average voting regressor required minimal PID correction, highlighting its stability under these conditions.

TABLE IV. WRIST MOVEMENT FOR HG AT 20% MVC LEVEL

Hand Part	Wrist				
Analysis / Model	***RMSE*** (°/s)	***% NRMSE***	***MAE (°/s)***	***(R^2)***	***P-value***
ANN	23.16	25.73	19.1101	0.6018	0
ANFIS	22.97	25.52	20.0001	0.6084	0
Fuzzy	20.83	23.14	18.1084	0.6781	6.47E-241
ANN-ANFIS	22.09	25.45	19.1066	0.6379	0
ANN-Fuzzy	**20.82**	**23.13**	**18.0044**	**0.6782**	**0**
ANFIS-Fuzzy	21.31	23.68	18.6291	0.6630	0
ANN-ANFIS-Fuzzy	21.15	23.50	18.3939	0.6680	0

TABLE V. WEIGHT DISTRIBUTION FOR HG AT 20% MVC LEVEL

Chosen Method	Model	Weight Value
ANN-Fuzzy	ANN	0.4734
	ANFIS	0
	Fuzzy	0.5266

B. *Hand Grip Wrist at 40% of MVC Level*

Fig. 10 shows an output from selected model voting regressor complemented with an output from PID tuning prosthetic hand wrist movement at 40% MVC level. Table VI shows a prediction input form by combination of ANN-ANFIS model was selected as it gave the lowest RMSE value equal to 23.64 and %NRMSE value achieves 26.27%. Moreover, the MAE gave the lowest value of 20.0854 among all its MAE members. This model manages to give the highest R^2; 0.5848 as possible as compared to all other models. The p-value from all the models illustrates a value <0.05 (highly significant) which concludes that the bias may be negligible and the decision making still acceptable to follow decision on lowest RMSE value obtained. By having said that, ANN-ANFIS model has been selected as a model to represent the input for prosthetic wrist velocity for 40% MVC level. The regression model analysis reveals the following weights: ANN = 0.4986, ANFIS = 0.5014, and Fuzzy = 0, as detailed in Table VII to fulfil this condition. Moreover, by choosing ANN-ANFIS as a selected model, it shows the highest percentage of predictive performance of 8.84%. The RMSE value was slightly reduced to 21.94 on the prosthetic hand movement while PID was used.

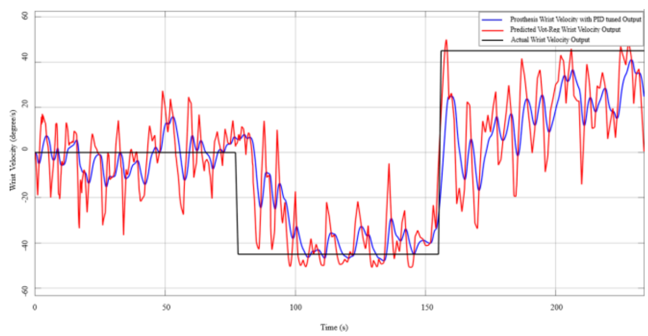


Fig. 10. Voting regressor output for 40% MVC state

In this second experiment, the EMG signals became clearer and slightly more complex, the ANN-fuzzy model continued to lead, confirming its robustness. The inverse RMSE-weighted average voting regressor remained reliable, suggesting the ensemble had not yet fully distributed among all models. Physiologically, this level reflects increased motor unit recruitment, and the combination model appeared better adaptation to capture the associated signal dynamics.

TABLE VI. WRIST MOVEMENT FOR HG AT 40% MVC LEVEL

Hand Part	**Wrist**				
Analysis / Model	***RMSE*** (°/s)	***% NRMSE***	***MAE (°/s)***	***(R^2)***	***P-value***
ANN	24.07	26.74	20.5273	0.5697	0
ANFIS	23.93	26.59	20.2311	0.5746	1.46E-43
Fuzzy	29.80	33.11	24.1278	0.3405	0
ANN-ANFIS	**23.64**	**26.27**	**20.0854**	**0.5848**	**1.32E-225**
ANN-Fuzzy	25.87	28.74	21.6508	0.5030	0
ANFIS-Fuzzy	25.97	28.86	21.5487	0.4990	2.24E-229
ANN-ANFIS-Fuzzy	24.89	27.65	20.9298	0.5400	0

TABLE VII. WEIGHT DISTRIBUTION FOR HG AT 40% MVC LEVEL

Chosen Method	**Model**	**Weight Value**
ANN-ANFIS	ANN	0.4986
	ANFIS	0.5014
	Fuzzy	0

C. Hand Grip Wrist at 60% of MVC Level

Fig. 11 shows an output from selected model voting regressor complemented with an output from PID tuning prosthetic hand wrist movement at 60% MVC level. Table VIII shows a prediction input form by combination of ANN-ANFIS-Fuzzy model, which was selected as given the lowest RMSE value equal to 13.32 and %NRMSE value achieves 14.80%. However, the MAE gave the value of 11.5898 which still belongs to the lowest group among all its MAE members. This model again manages to give the highest R^2; 0.8681 as possible as compared to all other models. The p-value from all the models illustrates a value <0.05 (highly significant) including ANN-ANFIS-fuzzy which concludes that the bias may be negligible and the decision making still acceptable to follow decision on lowest RMSE. The ANFIS-Fuzzy gave a p-value value of 0.2357 thus explaining this result there is a 23.57% chance that this result is due to random variation or not a meaningful pattern (not reliable). By having said that, ANN-ANFIS-fuzzy model has been selected as a model to represent the input for prosthetic wrist velocity for 60% MVC level. The regression model analysis reveals the following weights: ANN = 0.3706, ANFIS = 0.4060, and Fuzzy = 0.2232, as detailed in Table IX to fulfil this condition. Moreover, by choosing ANN-ANFIS-Fuzzy as a selected model, it shows the highest percentage of predictive performance of 23.76%. The RMSE value slightly reduced to 12.79 on the prosthetic hand movement while PID was used.

At 60%MVC experiment, the ANN-ANFIS-Fuzzy combination was selected, indicating that mid-range combining benefited the most from all usable based models. The ensemble showed stronger performance than at lower MVCs, especially when guided by inverse RMSE-weighted average voting regressor, suggesting its suitability for tasks involving moderate complexity.

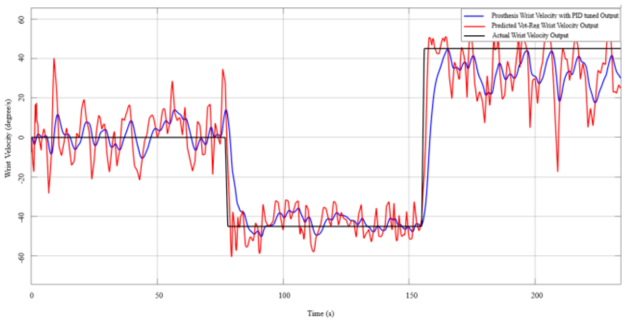


Fig. 11. Voting regressor output for 60% MVC state

TABLE VIII. WRIST MOVEMENT FOR HG AT 60% MVC LEVEL

Hand Part	**Wrist**				
Analysis / Model	***RMSE*** (°/s)	***% NRMSE***	***MAE (°/s)***	***(R^2)***	***P-value***
ANN	14.66	16.29	11.5840	0.8402	1.97E-18
ANFIS	13.39	14.88	11.2864	0.8667	3.39E-104
Fuzzy	24.36	27.07	20.3262	0.5593	3.62E-215
ANN-ANFIS	13.65	15.17	11.0901	0.8616	1.25E-56
ANN-Fuzzy	14.94	16.60	13.3699	0.8343	2.53E-25
ANFIS-Fuzzy	13.42	14.91	11.9240	0.8663	0.2357
ANN-ANFIS-Fuzzy	**13.32**	**14.80**	**11.5898**	**0.8681**	**0.0058**

TABLE IX. WEIGHT DISTRIBUTION FOR HG AT 60% MVC LEVEL

Chosen Method	**Model**	**Weight Value**
ANN-ANFIS-Fuzzy	ANN	0.3706
	ANFIS	0.4060
	Fuzzy	0.2232

D. Hand Grip Wrist at 80% of MVC Level

Fig. 12 shows an output from selected model voting regressor complemented with an output from PID tuning prosthetic hand wrist movement at 80% MVC level. Table X shows a prediction input form by single combination of ANN model was selected as it gave the lowest RMSE value equal to 21.02 and % NRMSE value achieves 23.35%. Moreover, the MAE gave the value of 19.6474 was the lowest value group among all its MAE members. This model manages to give the highest R^2; 0.6719 as possible as compared to all other models. The p-value from all the models illustrates a value <0.05 (highly significant) including ANN which concludes that the bias may be negligible and the decision making still acceptable to follow decision on lowest RMSE obtained. By having said that, the ANN model has been selected as a model to represent the input for prosthetic wrist velocity for 80% MVC level. The regression model analysis reveals the following weights: ANN = 1.0, ANFIS = 0, and Fuzzy = 0, as detailed in Table XI to fulfil this condition. Moreover, by choosing ANN as a selected model, it shows the improvement on predictive performance of 8.45%. The RMSE value was slightly reduced to 20.51 on the prosthetic hand movement while PID was used.

For this experiment, the overall performance of all models began to decrease, as seen through higher RMSE values. This reduction in predictive performance caused by the increasing complexity of the EMG signals at higher contraction levels, possibly due to muscle fatigue and overlapping motor unit activity. This suggests that fixed weight ensemble approaches may have difficulty adapting to rapidly changing muscle conditions.

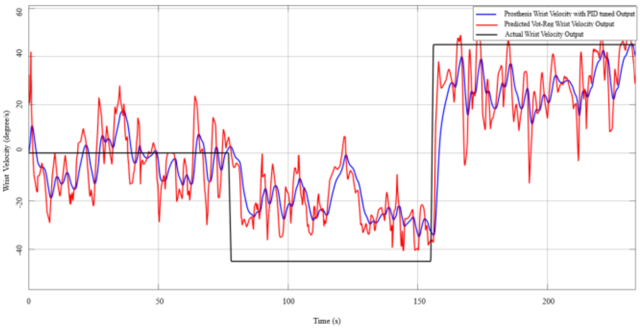


Fig. 12. Voting regressor output for 80% MVC state

TABLE X. WRIST MOVEMENT FOR HG AT 80% MVC LEVEL

Hand Part	Wrist				
Analysis / Model	*RMSE* (°/s)	*% NRMSE*	*MAE (°/s)*	*(R^2)*	*P-value*
ANN	**21.02**	**23.35**	**19.6474**	**0.6719**	**1.06E-109**
ANFIS	22.43	24.92	20.1984	0.6266	2.79E-60
Fuzzy	25.43	28.25	21.4856	0.5200	0
ANN-ANFIS	21.53	23.92	19.8803	0.6560	6.14E-83
ANN-Fuzzy	21.76	24.17	19.3574	0.6484	1.55E-69
ANFIS-Fuzzy	22.79	25.32	19.8892	0.6143	1.82E-78
ANN-ANFIS-Fuzzy	21.65	24.05	19.4145	0.6519	2.21E-12

TABLE XI. WEIGHT DISTRIBUTION FOR HG AT 80% MVC LEVEL

Chosen Method	Model	Weight Value
ANN-ANFIS-Fuzzy	ANN	1.0000
	ANFIS	0
	Fuzzy	0

E. *Hand Grip Wrist at 100% of MVC Level*

Fig. 13 shows an output from selected model voting regressor complemented with an output from PID tuning prosthetic hand wrist movement at 20% MVC level. Table XII shows a prediction input form by combination of ANFIS-Fuzzy model was selected as it gave the lowest RMSE value equal to 33.69 and %NRMSE value achieves 37.43%. However, the MAE gave the value of 29.8800 was the second lowest value among all its MAE members. This model again manages to give the highest R^2; 0.1574 as possible as compared to all other models. The p-value from all the models illustrates a value <0.05 (highly significant) including ANFIS-Fuzzy which concludes that the bias may be negligible and the decision making still acceptable to follow decision on lowest RMSE obtained. By having said that, ANFIS-Fuzzy model has been selected as a model to represent the input for prosthetic wrist velocity. The regression model analysis reveals the following weights: ANN = 0, ANFIS = 0.5177, and Fuzzy = 0.4823, as detailed in Table XIII to fulfil this condition. Moreover, by choosing ANFIS-Fuzzy as a selected model, it shows the highest percentage of predictive performance of 6.19%. The RMSE value was slightly reduced to 33.15 on the prosthetic hand movement while PID was used.

At full muscle contraction (100% MVC), prediction errors increased further, reflecting the increment of the complexity of EMG signals under maximal effort. The ANN-Fuzzy model continued to deliver the most accurate results, while the Inverse RMSE-Weighted Average Voting Regressor model remained reliable but showed signs of reduced adaptability. The relatively poor performance of the standalone Fuzzy Logic model suggests it lacks the flexibility required to respond to the rapidly changing dynamics of high-intensity muscle signals. These findings highlight the need for more adaptive or context-sensitive ensemble strategies to maintain its prediction performance under extreme conditions.

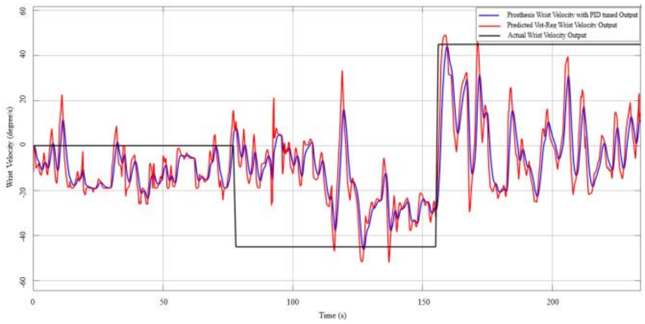


Fig. 13. Voting regressor output for 100% MVC state

TABLE XII. WRIST MOVEMENT FOR HG AT 100% MVC LEVEL

Hand Part	Wrist				
Analysis / Model	*RMSE* (°/s)	*% NRMSE*	*MAE (°/s)*	*(R^2)*	*P-value*
ANN	36.56	40.62	31.2604	0.0075	0
ANFIS	34.33	38.14	29.2178	0.1252	0
Fuzzy	36.85	40.94	32.6359	0.0082	6.36E-29
ANN-ANFIS	35.22	39.13	30.1718	0.0790	0
ANN-Fuzzy	34.87	38.74	30.8971	0.0974	3.67E-104
ANFIS-Fuzzy	**33.69**	**37.43**	**29.8800**	**0.1574**	**1.97E-122**
ANN-ANFIS-Fuzzy	34.06	37.84	29.9516	0.1386	1.16E-278

TABLE XIII. WEIGHT DISTRIBUTION FOR HG AT 100% MVC LEVEL

Chosen Method	Model	Weight Value
ANFIS-Fuzzy	ANN	0
	ANFIS	0.5177
	Fuzzy	0.4823

Through observation from all the experiments conducted, the ensemble learning approach using voting regressor demonstrated an average improvement of 11.38% in predictive performance across all cases. Huo *et al.* utilized wavelet packet transform (WPT) for decomposing sEMG signals and applied principal component analysis (PCA) for feature dimensionality reduction and manage to obtain 96.03% for hand movement recognition, however they focused on a classification task [80].

As this method was implemented in a system, it not only improves in terms of predictive performance, moreover it helps to improve prosthetic hand user experience, enhancing prosthetic hand functionality and enabling more natural hand movements.

F. Overall Weightage Score and Ensemble Configuration

To further evaluate the overall performance of these experiments a composite score was calculated for each trial using the MCDM-WSM as described in the methodology section. Most recent ensemble strategies shown by Nidal *et al.* assign equal weights or optimize based on a single error metric [81]. This approach combined five best experiment performance characteristics (RMSE, %NRMSE, MAE, R^2, and p-value) into a single weighted score after normalization and applying importance weights. This structured and objective weighting mechanism enhances model fairness and reliability, addressing known limitations in performance metric interpretation and benchmarking [81], [82].

Table XIV shows the ranking of all experiments based on their composite score along with their selected models. The experiment with the highest composite score was ranked first, indicating the best overall performance across all selected characteristics. In this analysis, experiment 60% MVC achieved the top rank, reflecting strong performance in their RMSE, %NRMSE, MAE, R^2 and p-value. This experiment selected ANN-ANFIS-fuzzy as their model representation. On the other hand, experiment 100%MVC which selected ANFIS-Fuzzy model received the lowest composite score representing a weaker performance compared to others.

This ranking structure allows a clear and measurable comparison of model effectiveness, helping identify which modeling approaches yield the most reliable outcomes in terms of predictive performance and statistical fit.

TABLE XIV. RANK AND COMPOSITE SCORE TABLE

Rank	Experiment	Composite Score	Selected Models
1	60% MVC	1	ANN-ANFIS-Fuzzy
2	20% MVC	0.6864	ANN-Fuzzy
3	80% MVC	0.6657	ANN
4	40% MVC	0.5665	ANN-ANFIS
5	100% MVC	0.1	ANFIS-Fuzzy

In the final MCDM evaluation illustrated in Fig. 14 the individual models (ANN, ANFIS, and fuzzy logic) were assessed using five performance metrics: RMSE, NRMSE, MAE, R^2, and p-value. Among them, ANN achieved the highest normalized composite score (0.5163), followed by Fuzzy Logic (0.2470) and ANFIS (0.2367). These scores were derived using WSM, which aggregates multi-criteria performance into a single understandable value.

Rather than selecting a single best model, these results were used to formulate a proposed new weightage scheme for the ensemble model. The ensemble was first constructed using inverse RMSE-weighted average voting regressor method, in which the aggregation is biased toward the model with the lowest RMSE, thus prioritizing predictive performance in the final output. However, through the MCDM-WSM approach, derived weights indicate the relative strengths of each base model, assigning more influence on ANN, followed by fuzzy and then ANFIS.

This structure allows the ensemble model to benefit from ANN's strong predictive capability while also utilizing the explainability and domain adaptability offered by Fuzzy and ANFIS models. As a result, the proposed ensemble configuration is expected to offer improved generalization and robustness, outperforming any individual model when evaluated from a whole system performance.

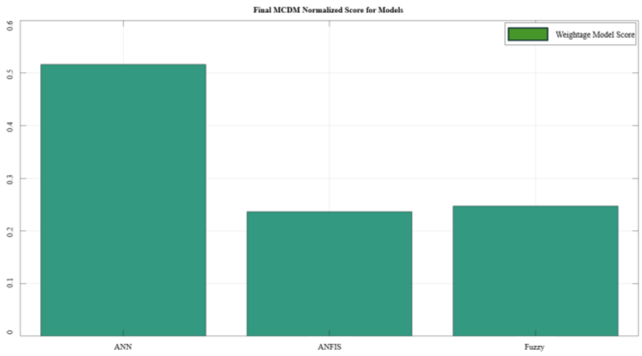


Fig. 14. Weightage tabulation for HG based models used

The final proposed ensemble model for wrist prediction is expressed as voting regressor equation where each base model contributes to the final prediction according to its performance derived weight. The equation is given by: -

$$Y_{VR-HG-wrist} = (0.5163)Y_{ANN} + (0.2367)Y_{ANFIS} + (0.2470)Y_{Fuzzy}$$

Where $Y_{VR-HG-wrist}$ is the predicted output from voting regressor for wrist estimation, Y_{ANN} is the prediction from ANN model, Y_{ANFIS} is the prediction from ANFIS model and Y_{Fuzzy} is the prediction from fuzzy logic model.

V. CONCLUSION

This study investigated EMG-based prosthetic wrist control using an ensemble learning approach that combines ANN, ANFIS, and Fuzzy Logic models. A voting regressor was employed to integrate predictions, with weightings guided by model prediction performance which favors the base model with the lowest RMSE to enhance its reliability. Model performance was assessed using multiple metrics, including RMSE, %NRMSE, MAE, R^2, and p-values, providing a comprehensive evaluation across five contraction levels (20%, 40%, 60%, 80%, and 100% MVC).

The ensemble method outperformed individual models at most MVC levels particularly 20%, 40%, 60%, and 100% offering improved predictive performance and more stable outputs. Only 80% of the MVC level favored a single model (ANN) over the ensemble, likely due to signal fluctuations. To ensure fair model comparison and derive the final weight configuration, the WSM from the MCDM framework was applied, enabling balanced evaluation across all performance criteria.

Despite these strengths, the limitations are also being considered. Prediction performance decreased at higher contraction levels (80% and 100% MVC), due to muscle fatigue, increased signal noise, and overlapping motor unit activations. These factors pose a significant challenge for EMG-based control systems in high MVC cases. Additionally, while the ensemble model reduced the need for

PID tuning by achieving slight improvements in their RMSE value, the system's robustness under dynamic real-world conditions remains to be validated.

Practically, this study highlights the potential of weighted ensemble learning to improve EMG driven prosthetic control by adapting predictions to the physiological variability of users. However, future work should explore adaptive or context aware ensemble strategies capable of responding to changes in signal quality, particularly at higher MVC levels. Further investigations using real-time datasets, more diverse user groups, and comparisons with commercial prosthetic systems are recommended to strengthen the clinical relevance and applicability of the proposed approach.

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