An In-depth Study of Ankle-Foot Orthosis Dynamics Modeling: Leveraging Non-Parametric Approach Via Artificial Neural Networks

Publisher: IEEE

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Abstract

Document Sections

I. Introduction

II. METHODS

III. Model estimation

IV. Results and discussion

V. CONCLUSIONS

Authors

Figures

References

Keywords

Abstract:

Walking is one of the most important daily activities for human beings. Patients that have abnormal walking gait are caused by foot drops, strokes, and other disabilities. Ankle-foot orthosis (AFO) are widely used to provide practical assistance for patients with injuries or defects in the lower limbs. There are many types of AFOs, including rigid, flexible rigid, and articulated AFOs, depending on the strength of the joint. Modelling ankle-foot orthosis is important because it has always been a challenging task to model ground reaction forces, particularly when the wearable rehabilitation robot is represented using high degrees of freedom and has multiple contact points with the ground. The research is aimed at modelling ankle-foot orthosis (AFO) using a multi-layer perceptron (MLP) neural network. Initially, data collection took place using an experimental rig. Subsequently, the model structure was chosen, followed by parameter estimation through the selected algorithm. Lastly, the models underwent a thorough validation process, which included evaluating their performance using mean-squared error (MSE) and correlation tests. The results showed that the MLP-NN outperformed the conventional method, LS in identifying the AFO system, with lower mean squared prediction error that is 0.000011034 and unbiased results across all models. In contrast to the conventional approach, the MLP-NN offers a good approximation of the AFO dynamic model. Although conventional methods like LS are valuable, the MLP approach exhibits superior performance. These findings provide valuable insights into AFO system modeling, implying that nonparametric methods like MLP neural networks hold significant potential for advancing AFO development and control.

Published in: 2023 IEEE 9th International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA)

Date of Conference: 17-18 October 2023

DOI: 10.1109/ICSIMA59853.2023.10373516

Date Added to IEEE Xplore: 03 January 2024

Publisher: IEEE

ISBN Information:

Conference Location: Kuala Lumpur, Malaysia

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2023 IEEE 9th International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA) | 979-8-3503-4338-0/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICSIMA59853.2023.10373516

***Abstract*—Walking is one of the most important daily activities for human beings. Patients that have abnormal walking gait are caused by foot drops, strokes, and other disabilities. Ankle-foot orthosis (AFO) are widely used to provide practical assistance for patients with injuries or defects in the lower limbs. There are many types of AFOs, including rigid, flexible rigid, and articulated AFOs, depending on the strength of the joint. Modelling ankle-foot orthosis is important because it has always been a challenging task to model ground reaction forces, particularly when the wearable rehabilitation robot is represented using high degrees of freedom and has multiple contact points with the ground. The research is aimed at modelling ankle-foot orthosis (AFO) using a multi-layer perceptron (MLP) neural network. Initially, data collection took place using an experimental rig. Subsequently, the model structure was chosen, followed by parameter estimation through the selected algorithm. Lastly, the models underwent a thorough validation process, which included evaluating their performance using mean-squared error (MSE) and correlation tests. The results showed that the MLP-NN outperformed the conventional method, LS in identifying the AFO system, with lower mean squared prediction error that is 0.000011034 and unbiased results across all models. In contrast to the conventional approach, the MLP-NN offers a good approximation of the AFO dynamic model. Although conventional methods like LS are valuable, the MLP approach exhibits superior performance. These findings provide valuable insights into AFO system modeling, implying that non-parametric methods like MLP neural networks hold significant potential for advancing AFO development and control.**

Keywords— Ankle-foot orthosis, modelling, multi-layer perceptron, Artificial Neural Network

I. INTRODUCTION

Individuals with walking disabilities, be it dorsiflexion, plantarflexion, or both, experience deviations from the normal walking pattern. Ankle-foot orthoses (AFOs) emerge as a valuable tool for aiding walking, offering stability and preserving the range of motion. Research consistently demonstrates that gait speed improves significantly when AFOs are used compared to situations without them [1]. For clinicians, a deep understanding of AFOs' mechanical properties and their impact on gait is essential to ensure patients derive the maximum benefit from these orthotic devices [2]. During clinical practice, adjusting the torque provided by ankle-foot orthoses to align with each patient's body function and gait abilities is a critical consideration [1].

Traditional therapy methods rely on manual support from therapists, which can be physically demanding and taxing when carried out continuously for extended periods [3]. Although it is not yet clear whether robotic therapy outperforms traditional methods when achieved in equal amounts, it is apparent that intensive and extended therapy consistently leads to more favorable outcomes across a range of assessment criteria related to patient recovery. However, to implement an effective robotic therapy controller for automated ankle-foot orthosis (AFO) systems, a thorough modeling process is a prerequisite. Modeling AFO dynamics is of paramount importance due to the inherent complexities involved in capturing ground reaction forces, especially when representing the robot with a high degree of freedom and multiple points of contact with the ground [4].The walking gait phase is shown in Fig. 1 have to be considered.

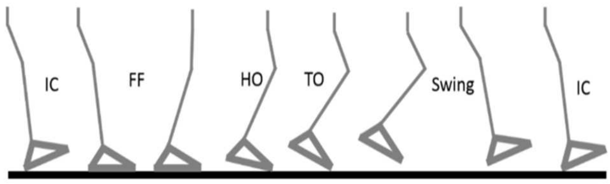

Fig. 1. Walking gait phase. Initial Contact (IC), Foot Flat (FF), Heel-Off (HO) and Toe-Off (TO) [10]

The prevalent method for developing such models includes 2D and 3D computational simulations, Monte Carlo simulations, direct multiple shooting methods, functional electrical stimulations, and musculoskeletal simulations via mathematical modeling [5]–[9].

Over the past two decades, the field has witnessed a surge in the application of system identification for modeling, gathering significant attention for its ability to accurately model dynamic systems. This process involves analyzing the input-output measurement system to derive the system's plant. The system identification of a system comprises two fundamental phases. The initial phase entails qualitative operations, establishing the system's structure that links the input and output. In essence, this phase revolves around characterizing and selecting an appropriate model structure. The subsequent phase, estimation, aims to minimize the disparity between the system being identified and its model. The estimation methods can incorporate soft computing techniques, including the application of metaheuristic algorithms for parametric models, while resorting to neural networks (NNs) and fuzzy logic for non-parametric models. In the context of a highly non-linear system, adopting non-parametric estimation method is the favorable approach.

Hence, this study aims to assess the effectiveness of a dynamic model for ankle-foot orthosis (AFO) using non-parametric modeling techniques, specifically employing multi-layer perceptron neural networks. These models are constructed through the system identification method, utilizing data collected from an experimental rig.

Subsequently, a comprehensive validation process is undertaken, meticulously comparing, and analyzing the obtained results. The implications of these findings are expected to contribute to the advancement and control of AFO systems.

II. METHODS

A. Experimental setup

Fig. 2(a) and 2(b) depict the experimental setup and schematic diagram, respectively, for this study. In this study, an ankle-foot orthosis (AFO) rig with one degree of freedom (DOF) movement is employed. Both plantarflexion and dorsiflexion will be supported by foot motion.

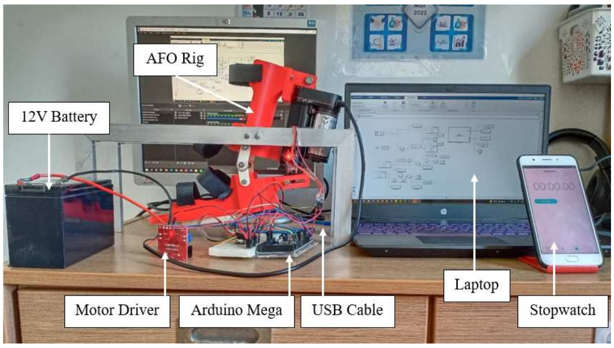

Fig. 2(a). The experimental setup of AFO

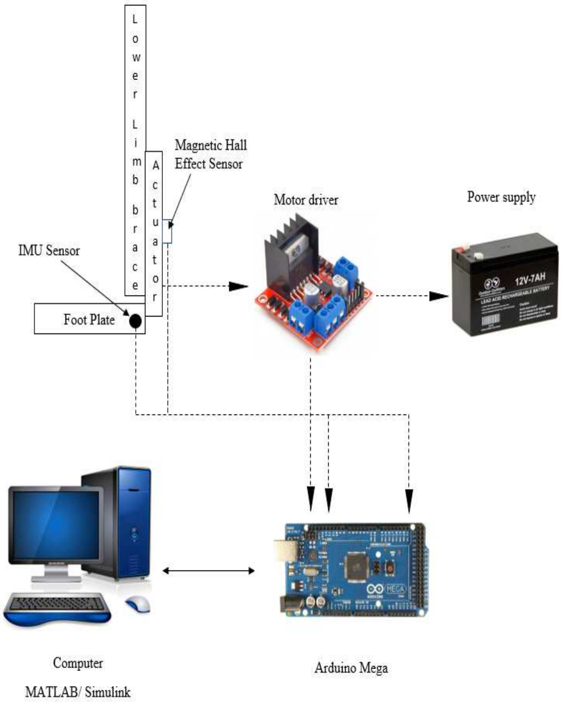

Fig. 2(b). The experimental setup of AFO

To provide mobility function, an actuator is attached to the backside of the foot brace, which transfers kinetic energy to the foot brace. The rig's configuration is adjusted to +20 degrees for dorsiflexion and -20 degrees for plantarflexion. For the intended driven ankle-foot orthosis (AFO), a linear actuator is utilized. A linear actuator is primarily used because it offers high torque, precise stroke duration, and long-term dependability. The chosen linear actuator has a 51 mm stroke length and a 900N load rating. The LIN-ACT1-02 Windynation linear actuator, 12 VDC, weighs 225 pounds. The L298N motor driver complements the linear actuator very well because it can handle 2A continuous current per channel and a supply range of 5V to 35V. A 12V power supply provides power to the motor driver. To measure the distance traveled when the actuator moves, a magnetic hall effect sensor is fastened to the side of the actuator. When the actuator moves, the IMU sensor (MPU 6050) placed underneath the footplate measures the positioning of the ankle. The Arduino Mega is connected to the motor driver and the sensors to capture input and output data. A USB cable is used to link the Arduino Mega to the computer. MATLAB / Simulink software is used as the modelling development environment.

B. System identification

System identification often involves several procedures. They are model estimation, model validation, model estimation, and model structure selection. Many different sets of data are acquired during data acquisition, which is a crucial step in modelling the dynamic system. The primary objective of identification is to estimate the model parameters after the model structure has been established. The estimated model must predict future output values and possess properties that are comparable to those of the genuine model. It is necessary to test the model once one has been created for the system. Model validity tests are processes to judge whether a fitted model is adequate. To make sure the model created adequately represents the system, this is crucial.

C. Experimentation set up and data acquisition

Before using the results for further system identification research, the experimental setup must be confirmed. To conduct an experimental test, data from an IMU angle and a bang-bang signal from the linear actuator were gathered. The tests' outcomes demonstrated that the data gathered from the experimental setup was appropriate for system identification. The input-output data needed for the modeling procedure were experimentally acquired during data collecting utilizing the AFO test rig. The data collection tool was created using the Simulink application. To provide the necessary torque to concurrently activate the actuator, a bang-bang signal with an amplitude of 1 V was used.

From the IMU angle, which stands for the system's longitudinal axis, one output was gathered. The longitudinal axis (roll axis), which is the IMU's X-axis, was used for modeling IMU sensor alignment axes. The roll angle is calculated by combining accelerometer and gyroscope data. The roll angle range is 90 degrees. The roll angle is positive when rotating counterclockwise with respect to the roll axis and negative when rotating clockwise. To filter out noise at the start of the program, the sensor is read multiple times while being held steady on the ground with the Z-axis perpendicular to the ground and offset values for pitch and roll angle are calculated. When pitch and roll angle is calculated at each step, these values are subtracted. This removes some of the steady noise from sensor readings. The experiment lasted 25 seconds with a sampling time of 0.03 seconds. A total of 6s of dorsiflexion and plantarflexion were collected in a 12s movement for each cycle. The experimental IMU angle (roll) and bang-bang signal responses were captured and recorded, as shown in Fig. 3(a) and Fig. 3(b).

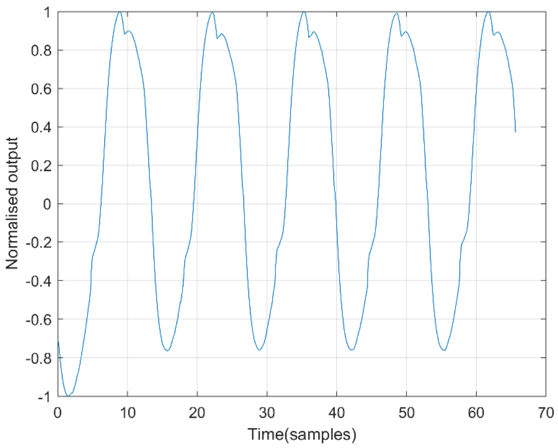

Fig. 3(a). The experimental IMU angle (roll)

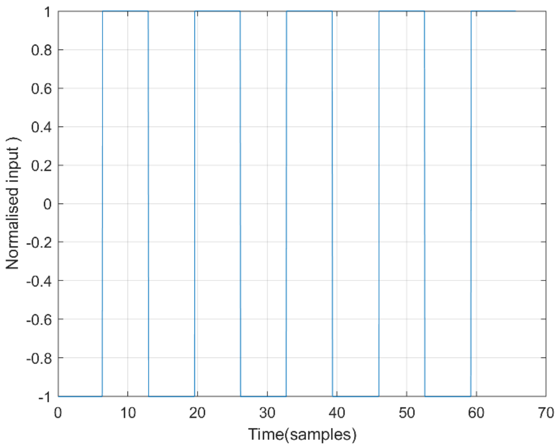

Fig. 3(b). Bang-bang signal responses

III. Model Estimation

The process of developing mathematical models of a dynamic system based on measured data is known as parametric system identification [11]. A good model is critical in most model-based control approaches. After determining model structure, the main task of identification is to estimate model parameters, which are typically determined using a global minimum criterion function. To identify nonlinear dynamical systems, neural networks can be used with a variety of modelling techniques. The state-output model, recurrent state model, and nonlinear autoregressive moving average process with exogenous (NARMAX) input model are examples of these. However, the literature shows that if the plant's input and output data are available, the NARMAX model is a good choice for modelling nonlinear systems using standard backpropagation learning algorithms.

Least square (LS) was used to predict the conventional model in this work, while neural networks were used to predict the non-parametric model (model estimation). The most practical way for identifying the best linear approximations is the least squares method, but there are also significant theoretical arguments in its favour [12]. The absolute deviation method does not provide adequate weight to a point that is much out of line with the approximation, whereas the minimax approach typically gives too much weight to a piece of data that is grossly in error. The least squares method significantly increases the weight of a point that deviates from the rest of the data, but it prevents that point from fully dominating the approximation.

The architectures of neural networks are modelled after biological neural networks [13]. The networks are made up of many identical or similar simple processing units that are highly interconnected. The adaptive nature of networks is an important feature. The networks can learn from the information they have gathered from their surroundings. For system modelling, neural networks typically employ two basic processing elements: the perceptron and the basis function neuron. The perceptron is a nonlinear neuron model. This basic neural model is made up of two parts: a linear combiner and a nonlinear activation function. A linear combiner computes the product of the neuron's input vector, x, and the parameter vector, w. A nonlinear activation function applied to the linear combiner output.

A. Multi-layer perceptron

Back propagation was used in research to model the ankle-foot orthosis (AFO) using a multi-layer perceptron (MLP) neural network. Because of its ability to provide a simple model and estimate a highly complicated formula association, the MLP is the most popular of the neural network family [13]. The MLP is made up of one layer of nodes that serves as the input layer and a second layer that serves as the output of the NN, with several intermediate or hidden layers in between. The network layer consists of an input layer, x_i, an output layer, y_j, and a hidden layer with varying strength weights, w_{ij}. The function f(.) can have the following properties: linear, threshold, sigmoid, hyperbolic tangent, and radial basis. The mapping enables the network to predict the output, $\hat{y}$ as accurately as possible. The MLP output is shown in (1):

$$\hat{y}(w,W) = F_i\left(\sum_{j=1}^{q} W_{ij}\cdot f_j\left(\sum_{i=1}^{m} w_{ij}X_i + w_{j0}\right) + W_{i0}\right). \qquad (1)$$

Although it requires more memory than other algorithms, Levenberg-Marquardt (LM) is chosen for network training due to its short convergence time. Based on the criterion in (2), the LM optimises the error by minimising the residual, $\varepsilon(t,\theta) = y(t) - \hat{y}(t,\theta)$:

$$L^i(\theta) = \left(\frac{1}{2N}\right)\sum_{t=1}^{N} \varepsilon^{-2}(t,\theta) \approx P_N(\theta, Z^N), \qquad (2)$$

where Z^N represents the training data set.

B. Model validation

To ensure that the model being developed is adequate, the validation phase is required [13]. The model is validated using three methods: One Step Ahead (OSA) prediction, Mean Squared Error (MSE), and Correlation Test. The five correlation functions are as follows:

$$\varphi\_\varepsilon\varepsilon\,(\tau) = E[\varepsilon(t-\tau)\varepsilon(t)] = \delta(\tau), \qquad (3)$$

$$\varphi_{u\varepsilon}(\tau) = E[u(t-\tau)\varepsilon(t)] = 0, \forall\tau, \qquad (4)$$

$$\varphi_{\varepsilon^2\varepsilon}(\tau) = E[u^2(t-\tau) - \bar{u}^2(t)\varepsilon(t)] = 0, \forall\tau, \qquad (5)$$

$$\varphi_{\varepsilon^2\varepsilon^2}(\tau) = E[u^2(t-\tau) - \bar{u}^2(t)\varepsilon^2(t)] = 0, \forall\tau, \qquad (6)$$

$$\varphi_{\varepsilon(\varepsilon u)}(\tau) = E[\varepsilon(t)\varepsilon(t-1-\tau)u(t-1-\tau)] = 0, \tau \geq 0, \qquad (7)$$

$\varphi_{u\varepsilon}(\tau)$ represents the cross-correlation function between u(t) and ε(t), $\varepsilon u(t) = \varepsilon(t+1)u(t+1), \delta(\tau)$ is an impulse function. Because the MLP model is built with the NARX structure, which is a nonlinear system, all five conditions must be met. Another LS model that uses a linear system requires only three conditions to be met.

The study used 2188 data points for LS and MLP in the test. These data points were used as it complete 5 steps during children walking. The 95% confidence bands, which are approximately $\pm 1.96/\sqrt{N}$ (N data), are implied, and any significant correlation will be indicated by one or more points of the function lying outside the bands [14]. As a result, the model is considered adequate if the correlation functions are within the confidence intervals.

IV. Results and Discussion

This section presents the results of modelling the ankle foot orthosis using conventional and non-parametric techniques. One-step-ahead prediction, MSE of measured and predicted output, and correlation tests were used for validation.

A. Modelling using least square

Two sets of 1084 data points each were created from the 2188 data points in the parametric modelling using LS data set. While the second set (test set) was utilised for validation, the first set was used for modelling. The model's rank of two generated the best outcomes. The LS predictions for the roll axis angle are shown in Fig. 4. The graph shows that the LS could closely follow the real data. Actual and anticipated LS outputs diverge only a little.

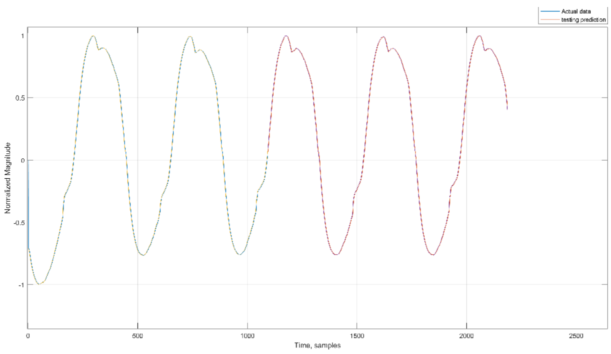

Fig. 4. The output and estimated output of roll axis angle (LS)

The correlation test for each roll axis angle is shown in Fig. 5. The model's accuracy is not supported by the LS findings, which are outside of the 95% confidence range.

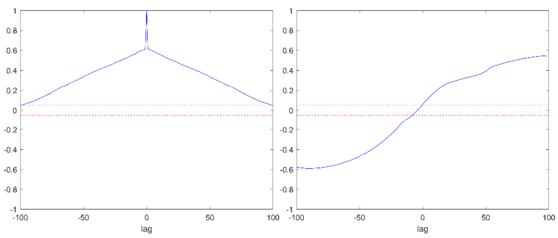

Fig. 5. The correlation test for roll axis angle (LS)

The roll axis angle stability test is shown in Fig. 6. The LS shows that the model can be controlled. The zeros are at the origin, and the poles may be seen inside the unity circle. The poles stand in for the word "X," while the zero stands for the letter "O." The system is stable since the poles are located inside the unit circle.

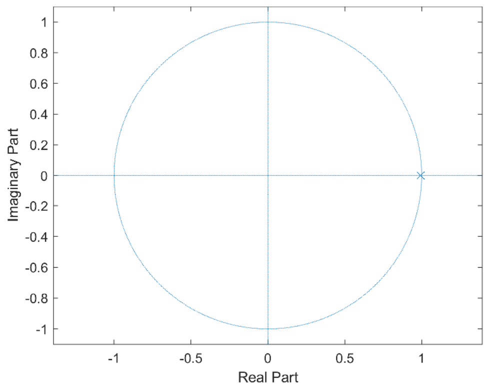

Fig. 6. The stability test for roll axis angle (LS)

The best model order's LS results are displayed in Table I. The lower mean squared error in testing data, a correlation test with a 95% confidence level, and strong stability should be taken into account when choosing the optimum model. With mean squared errors for the training and testing data sets of 8.6816 x10^{-4} and 4.1837 x10^{-4}, respectively, it was determined that model order 2 was the optimal model order.

TABLE I. Comparison of LS optimization performance in different numbers of model order

Model Order	MSE in training data	MSE in testing data	Stability	Correlation Test
2	8.6816 x10^{-4}	4.1837 x10^{-4}	Stable	Biased
4	9.7690 x10^{-4}	4.0323 x10^{-5}	Unstable	Biased
6	1.4 x10^{-3}	3.4918 x10^{-5}	Unstable	Biased
8	1.9 x10^{-3}	3.2613 x10^{-5}	Unstable	Biased
10	2.4 x10^{-3}	3.1245 x10^{-5}	Unstable	Biased

B. Modelling using multi-layer perceptron

The 2188-data-point data set for non-parametric modelling with NN MLP was divided into two sets of 1532 and 658 data points. The first set (estimation set) was used for modelling, while the second set (test set) was used for validation. For result validation, the NN MLP modelling was compared using MSE and 5 correlation tests. Given the lack of prior information about the appropriate delay numbers and the model structure for NN MLP, a heuristic method was used to realise the structure.

During the process, three major factors had to be considered: the number of delay signals, the size of the NN structure or the number of neurons, and the error. The final factor was evaluated as part of the process of determining the best number of delay signals and structure for each model. This was due to the stochastic nature of the procedure for obtaining the best model. The criterion was used to select the best model based on validation MSE, modelling MSE, and correlation tests. The number of neurons in this study begins with two neurons in the first hidden layer, two neurons in the second hidden layer, and one neuron in the output layer ([2 2 1] model structure). The input layer is represented by the delay number. The model's performance was improved by using eight delay signals, eight neurons in each of the first and second hidden layers, and one neuron in the output layer ([8 8 1] model structure).

The MLP predictions of the roll axis angle are shown in Fig. 7. The validated data are represented by a yellow vertical line at point 1532. The graph shows that the MLP could closely follow the actual data. The difference between actual and predicted MLP output is almost non-existent or close to zero.

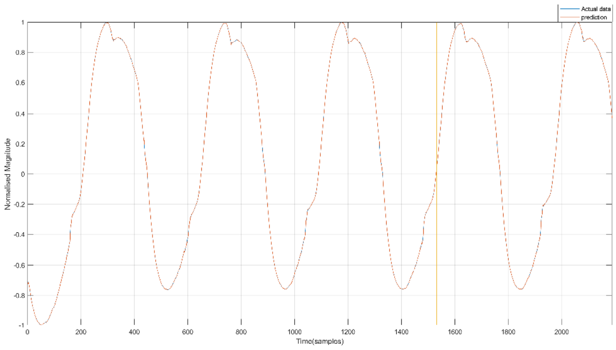

Fig. 7. The output and estimated output of roll axis angle (MLP)

Fig. 8 depicts the correlation test for each roll axis angle. The MLP results are within 95% confidence level, confirming the model's accuracy.

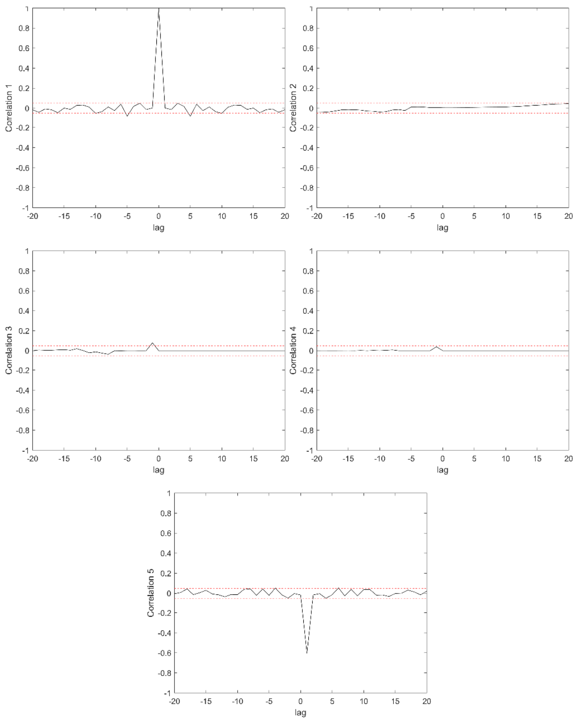

Fig. 8. The correlation test for roll axis angle (MLP)

Table II contains a list of the numerical outcomes of the best model structure and delay of NN MLP. With the lowest mean squared error of 1.1034x10-5, model structure [8 8 1] with 8 delay was found to be the best model structure.

TABLE II. COMPARISON OF NN MLP PERFORMANCE

Model Structure	Delay	MSE	Correlation Test
[2 2 1]	2	2.3829×10^{-4}	Unbiased
[4 4 1]	2	3.5671×10^{-4}	Unbiased
[6 6 1]	6	2.7149×10^{-4}	Unbiased
[8 8 1]	7	1.8625×10^{-4}	Unbiased
[8 8 1]	8	1.1034×10^{-5}	Unbiased

C. *Comparative assessment and discussion*

The LS and NN MLP-based models have been validated using training and testing procedures. Every set of correlation tests has also been run. The results of all such tests show that the various modelling techniques considered in this study performed adequately well. All these tests show that the various modelling techniques considered in this study performed satisfactorily. Table 3 summarizes the comparative performance of conventional and non-parametric modelling approaches in terms of mean-squared error and correlation test of the system.

The comparison of the performance of NN MLP and LS modelling in Table 3 shows that the NN MLP based non-parametric modelling technique provides a better approximation to the system response than the LS technique. This agrees well with other findings in [15]. The correlation test results also revealed that the NN MLP outperformed the LS. NN MLP has a lower mean-squared error than LS.

The least squares approach is useful for tackling linear fitting and quadratic optimisation issues [16]. However, outliers and noisy data are problematic for the least squares technique. Outliers can sway the fitting process and alter model parameters, resulting in erroneous findings. When the model is too sophisticated for the available data or there aren't enough data points, the LS method may overfit the model to the training data. Overfitting can produce a model that performs well on training data but badly on unobserved data. LS presupposes that the variables being modelled have a linear connection. If the underlying connection is nonlinear, LS may provide biassed estimates and an erroneous model.

This result shows that it is possible to use the NN MLP to resolve challenging nonlinear issues. It effectively manages large amounts of input data. After training, it produces prompt predictions, making it a valuable tool for researchers and practitioners in a variety of fields. Even with smaller samples, the same accuracy ratio is still possible.

TABLE III. PERFORMANCE OF CONVENTIONAL AND NON-PARAMETRIC MODELLING APPROACHES.

Algorithm	MSE	Correlation test
NN MLP	0.000011034	Unbiased
LS	0.000868160	Biased

V. CONCLUSIONS

The modelling of an ankle-foot orthosis using LS and NN MLP, both conventional and non-parametric modelling techniques, has been presented. The ankle foot orthosis is moved along the x-axis by applying bang-bang torque to the system. Simulink is used to collect the movement of the motors. The IMU sensor was used to measure the angle of the ankle foot orthosis. The whole signal was sent to an Arduino Mega. The modelling is created through simulation in the MATLAB/Simulink environment. Various modelling techniques' results have been validated using a variety of tests, including training and test validation, mean-squared error, and correlation tests. The least squares approach is useful for tackling linear fitting and quadratic optimisation issues. However, it can be inferred from the investigations that non-parametric modelling, such as NN MLP, performs better in the identification and modelling of ankle foot orthoses than conventional modelling, such as LS technique. In order to develop control strategies for the ankle angle of the AFO, the best model of the ankle foot orthosis that could be obtained from NN MLP will be applied. Prior to the experimental study, the developed models will be used as a preliminary test to investigate and comprehend the control schemes responding to the variation of control constraints or disturbances.

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