Nigerian Journal of Technology (NIJOTECH)
Vol. 42, No. 3, September, 2023, pp.371 - 380
www.nijotech.com

Print ISSN: 0331-8443
Electronic ISSN: 2467-8821
https://doi.org/10.4314/njt.v42i3.10

A LINEAR MODEL-BASED SIMULATION TOOL FOR ESTIMATING NUMBER OF TRIALS NEEDED FOR UPPER LIMB STROKE RECOVERY IN A GIVEN REHABILITATION SESSION

AUTHORS:
B. E. Faremi[1,4,*], K. P. Ayodele[1], A. M. Jubril[1], A. A. Fakunle[1], M. O. B. Olaogun[2], M. B. Fawale[3], and M. A. Komolafe[3]

AFFILIATIONS:
[1]Department of Electronic and Electrical Engineering, Obafemi Awolowo University, Ile-Ife, Osun State, Nigeria.
[2]Faculty of Medical Rehabilitation, University of Medical Sciences, Ondo City, Nigeria.
[3]Department of Medicine, Obafemi Awolowo University, Ile-Ife, Osun State, Nigeria.
[4]School of Computing Sciences and Computer Engineering, The University of Southern Mississippi, USA.

***CORRESPONDING AUTHOR:**
Email: opefar@yahoo.com

ARTICLE HISTORY:
Received: 06 February, 2023.
Revised: 31 July, 2023.
Accepted: 05 August, 2023.
Published: 01 November, 2023.

KEYWORDS:
Performance stability, Linear models, Iterative learning algorithm, Trials, Estimation, Stroke, Kinematic accuracy.

ARTICLE INCLUDES:
Peer review

DATA AVAILABILITY:
On request from author(s)

EDITOR:
Ozoemena Anthony Ani

FUNDING:
TETFUND National Research Fund grant

HOW TO CITE:
Faremi, B. E., Ayodele, K. P., Jubril, A. M., Fakunle, A. A., Olaogun, M. O. B, Fawale, M. B., and Komolafe, M. A. "A Linear Model-Based Simulation Tool for Estimating Number of Trials needed for Upper Limb Stroke Recovery in a given Rehabilitation Session", *Nigerian Journal of Technology*, 2023; 42(3), pp. 371 – 380; https://doi.org/10.4314/njt.v42i3.10

Abstract
Traditional methods for assessing upper-limb functional outcomes in stroke patients often fail to estimate the number of trials required to achieve performance stability of a chosen kinematic metric. Limited non-model-based studies have attempted to tackle this issue. To bridge this gap, this study utilized an iterative learning algorithm (ILA) in MATLAB, employing linear models to represent the muscle dynamics and forearm extension of impaired patients. The reference task space trajectory was set as a straight-line point-point trajectory within a range of 0 - 0.2828m. By using the root mean square error (RMSE) as a metric for evaluating kinematic accuracy, a maximum kinematic deviation error of 0.01m was imposed with respect to the trajectory by the (ILA). Results indicate that over 16 trials, performance stability was obtained with improvement in deviation error from 0.0168m in the first trial to 0.0060 at sixteen trials. The result obtained is in line with similar non-model studies and our findings inform the potential of ILAs with linear models for estimation of trial numbers required to attain performance stability of a selected kinematic metric (i.e., kinematic accuracy).

1.0 INTRODUCTION
Stroke is a neurological condition that arises from death of brain cells due to obstruction of proper flow of blood or injuries leading to blood spillage within the cerebrum [1-2]. Globally, stroke accounts for 11.6% of total deaths and 5.7% of total disability adjusted life years, thereby making it the second leading cause of death and disability respectively [3]. Recovery from stroke is highly time-dependent and often categorized into phases. The most significant improvement is known to happen between the hyperacute (<24h), acute (first 7 days) and beyond the early sub-acute (3-months). Beyond the sub-acute phase, recovery is reported to be at its limit leading to chronic deficit [4]. In most situations, the functional deficits developed by impaired patients is due to the huge financial burden (cost) on the patient, family, and society [5]. To further this claim, burden arises from direct and indirect cost associated with expensive health care systems and loss of downtime (i.e., productive time) [6].

Despite the cost, rehabilitation from stroke is seen as a cornerstone to restoration of brain tissue and networks via relearning and compensating for lost functional abilities [7]. It involves plastic re-organization of entire regions and brain pathways for the generation of commands to the same muscles that produced unique motor actions and patterns before the occurrence of stroke [8]. Clinician's prognoses are said to be an important factor in determining how timely an impaired patient starts or access rehabilitation and how much is paid. Currently, the widely utilized traditional scales (such as the modified Rankin Scale (mRS)) only provide a binary good or bad general outcome prediction that's not sufficiently detailed, helpful for patients and families [9].

Consequently, a new yardstick for evaluating adequacies of prediction tools was declared [9]. First, these tools should be capable of predicting future function rather than correlating current function. Second, usage should be at the start of recovery and rehabilitation so that predictions can inform rehabilitation sessions and discharge planning. Third, the tools need to make a forecast for a specified time point rather than the expected outcome at discharge. Lastly, the tools provide context and meaning for the individual patients being rehabilitated. In upper limb impairment, several studies have considered classification and identification of upper limb recovery. Additionally, these studies have employed prediction models for estimating upper limb function post stroke, but few have been transferred successfully from research to clinical practice due to lack of time, need for specific equipment and lack of adoption by therapists over their experience [10].

In a previous study, an algorithm called PREP was developed to predict potential for upper limb function [11]. Biomarkers obtained from specialized equipment' were combined with clinical scores measured with the action research arm test (ARAT) as predictors for the algorithm. The outcome of the study indicated a high positive predictive power for estimation of functional recovery post stroke. A graph probability curve tool for prediction of upper limb and ambulatory function six months post-stroke was developed [12]. Predictors employed were the national institute of health stroke scale (NIHSS) and age for estimating recovery. The outcome of the study showed that models combining the age and severity of stroke obtained using NIHSS predicted the ambulation and ability to perform functional tasks. In another study, a decision tree based PREP2 algorithm for upper limb function after stroke was created [13]. The study improved on earlier studies by applying clinical, neurophysiological, neuroimaging biomarkers of corticospinal integrity for prediction of motor function 3 months post stroke. The outcome of the study proved to be more accurate, efficient, and accessible than the preceding algorithm.

Another previous research applied machine learning for prediction of individual upper limb motor impairment after therapy in chronic stroke subject [14]. Predictors required by the machine learning algorithms were obtained using the Fugl-Meyer Assessment (FMA). The study concluded that elastic-net algorithm outperformed other algorithms in predicting recovery. Similarly, a computerized mixed-effect model was developed for patient-specific prediction in the upper limb area 6 months post stroke [15]. The predictors for the model were clinical (i.e., finger extension, shoulder abduction) and obtained using the ARAT. The outcome of the study indicated that only ARAT time course model performed as good as models with covariates when predicting upper limb function. A predictive algorithm using traditional logistic regression and random forest for early prediction of upper-limb function after 3-months post stroke was developed [16]. Predictors for respective models were extracted using ARAT. The outcome produced high classification accuracy when used to predict probable class (i.e., poor, limited, and good) of the subject. Additionally, several studies have developed simulation frameworks that combine models describing the non-linear dynamics of stroke subjects with robotics to estimate the level of functional recovery of impaired patients [17, 18, 19]. Rehabilitation robots are known to offer repetitive, goal-oriented, and highly intense tasks that invoke plastic changes and reduce burdens on therapists [20, 21]. However, owing to the time taken in identifying the mechanistic non-linear models used by these simulation frameworks, these works have found little adoption amongst therapists in traditional rehabilitation settings [22, 23].

Indeed, it can be stated that scholars have invested considerable effort in estimating the eventual functional outcome for individuals who have suffered from a stroke. Nevertheless, only a few studies up to date have explored the possibility of determining the specific number of trials needed to achieve performance stability. In a recent study, a non-model approach was utilized in determining the smallest number of trials required to attain a good performance stability of desired kinematic variables in a reach-and-drink task amongst non-disabled and stroke population [24]. The outcome of the study declared little trials were sufficient for attaining most functional outcomes in both groups within a given session except for outcomes that required more trials like reaching task, returning task, time to peak velocity, joint coordination, and movement smoothness. In another study, virtual reality simulation environment was used to estimate the number trials necessary to obtain stable kinematic variables during reaching movements in non-stroke subjects [25]. The outcome of the study showed that after five and three trials reaching stabilized in kids and adults respectively. Unlike previous works that relied on physical iterative experiments, this study utilizes iterative learning algorithms with linear models to estimate the number of trials required for achieving performance stability of a desired kinematic outcome. Notably, the goal is to show visible improvements from trial to trial on a planar surface within a single rehabilitation session. The study's significance lies in its ability to easily assess patients' performance stability for a selected kinematic outcome without subjecting vulnerable stroke subjects to tasks that yield limited benefits. Specifically, we utilize a single kinematic metric for determining performance stability of linear models representing an impaired subject tracking a given trajectory. This metric is referred to as kinematic accuracy (trajectory error) as given in [26].

2.0 MATERIALS AND METHODS

2.1 Models Employed

The models employed in this study is described from a top-bottom approach. First, a linear model that couples a forearm and robotic effect that approximates the effect of a physical therapist opposing a movement is discussed. Second, a linear muscle component of an established muscle model is presented. Third, a controller that ensures the resulting muscle activation is stable is considered.

2.1.1 Linear forearm model

In the present section, a linear approximate model is adopted because it offers a means to rapidly model a patient's forearm and desired opposing effects to movements. In healthy subjects, coordination of the arm results from the brain recruiting some muscle fibers to produce contractions necessary for movement [27]. As a result, a single input and single output (SISO), linear, time-invariant transfer function that gives a relationship between output forearm elbow joint movement and linear activated muscular contraction at the input is chosen. Furthermore, Equation (1) embeds an effect of a stroke patient interacting with a 5-link manipulator robot for upper limb stroke rehabilitation. (PULSR) [28].

$$T_{ar}(s) = \frac{\vartheta_f}{T_\beta} = \frac{1}{s\left(\left(b_{a_3}+K_{M_2}\right)s+K_{B_2}\right)} \quad (1)$$

where parameter b_{a_3} represents the triceps-brachii region of the forearm desired for rehabilitation, K_{M_2} and K_{B_2} parameters incorporate the virtual load and viscous friction to movement that a traditional therapist will present to an impaired patient during a rehabilitation session, ϑ_f denotes the resulting forearm movement due to muscle contraction T_β.

Furthermore, to accommodate differences in forearm length, weight, and other physical attributes of impaired patients' parameter b_{a_3} can be computed using the equation below.

$$b_{a_3} = m_f l_{f1}^2 + I_f + I_e\left(\frac{s_\gamma}{1-c_f^2 c_\gamma^2}\right)^2 \quad (2)$$

where $c_{(.)}$, $s_{(.)}$ denotes cosine and sine of orientation of elbow angles, m_f represents mass of forearm, l_{f_1} is the length of forearm from the olecranon joint to the forearm center of gravity, I_e explains the moment of the forearm, γ gives static angle of elevation of the arm on a 2D task surface and $\frac{s_\gamma}{1-c_f^2 c_\gamma^2}$ defines the region in the elbow where muscle is stimulated applied. Next section describes how T_β is modelled to yield necessary contraction that drives Equation (i).

2.1.2 Linear muscle model

There exist several methods such as the non-linear black box, light grey-box with physical insight approach and block-oriented approaches to capture dynamics of the muscle [29]. In the present work, a simplified block modelling approach given in Equation 3 is selected for its established dynamics in describing torque generated by the muscle as a function of stimulation delivered to the recruited muscle fibers, forearm movement dynamics and length. pulse-width, passive multiplicative effect of forearm length, active multiplicative effect of forearm displacement and velocity [30].

$$T_\beta = \left(H_{irc}(w_u) \times H_{lad}\right) \times F_{ma}(\dot{\vartheta}_f, \vartheta_f) + F_{mp}(l_f) \quad (3)$$

where $F_{ma}(\dot{\vartheta}_f)$ captures the active multiplicative effect of forearm displacement and its rate of change, $F_{mp}(l_f)$ denotes passive multiplicative effect of forearm length, H_{lad} represents linear activation dynamics and $H_{irc}(w_u)$ denotes the recruitment dynamics of the muscle based on applied stimuli w_u .

In accordance with [17, 31], the following equations approximated the inner blocks of Equation (3).

$$H_{irc} = f(u) = a_1 . \frac{e^{a_2 . w_u} - 1}{e^{a_2 . w_u} + a_3} \quad (4)$$

$$H_{lad} = \frac{{w_n}^2}{s^2 + 2s\zeta w_n + {w_n}^2} \quad (5)$$

$$F_{ma}(\dot{\vartheta}_f) = 0.54\tan^{-1}(5.69\dot{\vartheta}_f + 0.51) + 0.745 \quad (6)$$

$$F_{mp}(l_f) = e^{-\left(\frac{\bar{l}_f - 1}{\varepsilon}\right)^2} \quad (7)$$

where, a_1, a_2 and a_3 represents the static gain of the muscle contraction, $\dot{\vartheta}_f$ connotes the normalized rate of forearm displacement of the subject with respect to the maximum forearm displacement ability $(\frac{\vartheta_f}{\vartheta_{max}})$, $\bar{l}_f$ describes the normalized forearm length $(\frac{l_f}{l_{max}})$ and ε represents the shape-factor of force-length relationship. From [25], we approximate ζ to model damping factor and w_n oscillatory behavior of the muscle when excited.

With a focus on developing a linear simulation framework, the nonlinear torque elements contained in Equation (3) were linearized in the fashion below to leave the transfer function that describes only the activation or contraction dynamics of the muscle model in Equation (9) using Equation (8).

$$T_{\beta_{linearization}} = \left(\left(\left(\left(w_u + F_{mp}(l_f)\right)\left(H_{irc}{}^{-1}(H_{lad} \times H_{irc})\right)\right) \times F_{ma}{}^{-1}(\dot{\vartheta}_f, \vartheta_f)\right) \times F_{ma}(\dot{\vartheta}_f, \vartheta_f)\right) - F_{mp}(l_f) \quad (8)$$

$$T_\beta(s) = H_{lad} = \frac{T_\beta}{w_u} = \frac{w_n{}^2}{s^2 + 2s\zeta w_n + w_n{}^2} \quad (9)$$

2.1.3 Feedback controller

In an unimpaired patient with no stroke, joint coordination and movement requires relaying of fine-tuned, stable signals from the brain through the efferent pathways to the muscle [28]. Accordingly, it is deemed important to have a form of controller in the simulation framework that ensures transient response of the modelled unresponsive flaccid muscle of impaired subjects during a rehabilitative task to attain a steady state response rather than oscillatory response. Forthwith, an approximate form of a PD controller known as phase-lead compensator is selected to guarantee appropriate and stable physical characteristic during movement [32].

$$T_{pd}(s) = \frac{w_u}{e} = \frac{K_P}{1}\frac{\tau s + 1}{\varpi \tau s + 1} \quad (10)$$

where $\tau = \frac{K_D}{K_P}$, $0 < \varpi < 1$, and e is the feedback error between subject's movement error and the reference task given. The expression in (10) can be re-written as

$$T_{pd}(s) = \frac{w_u}{e} = \frac{(\frac{K_D}{K_P}s + 1)K_P}{\varpi\frac{K_D}{K_P}s + 1} \quad (11)$$

As $\varpi\frac{K_D}{K_P} \rightarrow 0$, the numerator approximates a typical PD controller. Next, an intelligent algorithm that estimates the number of trials that may be required by a subject to learn how to track a trajectory until a certain trajectory error is attained is discussed.

2.2 Feedforward Learning Algorithm

Iterative learning control (ILC) is a method that seeks to improve tracking accuracy of repetitive processes. The idea behind the technique is to use previous information from past operations to update the control input, in between iterations for better performance [33][34][35]. In the present study, ILC is formulated to estimate the number of trials required to attain certain level of tracking accuracy and to generate control efforts that causes the closed loop feedback system (i.e., the combination of the feedback controller, linear muscle model and subject's forearm) to have an improved performance at every trial within a given rehabilitation session.

2.2.1 Problem formulation

To begin with, a typical stroke rehabilitation is decomposed from an algorithmic perspective in this section. In rehabilitation scenarios, session starts with the clinicians assessing the physical impairment of the subject and using the relevant information obtained to define how long each session should be (i.e., number of repetitions per time unit/session) to avoid further injuries like ligament tears, capsule injuries and muscle fatigue [36, 37, 38, 39, 40]. For favorable outcomes, it is reported that a given session should last about 36 minutes to 1 hour per day [41]. In addition to this, recent consensus has established 15 trials as the least recommended number for functional task repetitions per session for both planar and 3D functional tasks [42]. Also, patient-specific tasks for each session must be developed to accommodate differences in physical attributes of patients and impairment stages [40]. Moreso, clinicians are occasionally tasked with setting the learning rate at which the subject should undertake the defined trajectory task [23, 39]. Accordingly, based on these real-life scenarios, these fundamental assumptions were established to formulate a proportional type of iterative learning algorithm for the linear simulation framework.

i. Definition of finite time interval for each trial for every given simulation/rehabilitation session.
ii. Availability or identification of system to be controlled. This refers to the closed loop feedback system. In this case is the linear models representing the stroke patients.
iii. Definition of the desired reference task plane trajectory to be tracked.
iv. Selection of a learning gain.

Likewise, fundamental ILC requirements that ensure the algorithm learns from repeating movement errors of an impaired subject were considered [43].

v. The bandwidth of the closed loop system must be known.
vi. Design of a Q-filter that removes ILC input signals that are above system's bandwidth at every iteration if noises exist in the feedforward input.
vii. The previous input signal applied by ILC must be stored in memory.
viii. The output displacement of the subject at every trial must be stored in memory.
ix. The error signal between the desired reference trajectory and the output displacement of the subject must be computed.

Consequently, a p-type linear-time invariant ILC structure is adopted in the present formulation [44]. It is indexed as a two-dimensional process over an iteration and fixed time domain [45].

$$U_{k+1}(t) = Q(U_k(t) + L_c e_k(t))$$
$$e_k(t) = Y_r(t) - Y_k(t) \quad (12)$$

where, t = trial period, k = iteration index, $U_k(t)$ is the ILC output over the present iteration index over t, $e_k(t)$ is the error at present iteration index over t, $Y_r(t)$ = reference trajectory over t , $Y_k(t)$ = subject forearm displacement over t, $U_{k+1}(t)$ = Next trial feedforward input over t, L_c = Proportional learning gain and Q = Filter.

2.2.2 Iterative learning algorithm (ILA) Development

The main objective or idea of the new algorithm is to estimate the number of trials k in the iteration domain that yields good forearm tracking performance under a given tracking error boundary $\bar{e}$ within a given rehabilitation period t. To start with,

i. Let $t_m = \frac{t}{t_s}$ be the length of vector space obtained from the ratio of trial time t and sample time t_s.
ii. Let the vector pair space of sample time and desired control variable be defined as
$$\mathbb{R}^{t_m \times 2} = \{(\chi, t_s)|\chi, t_s \in \mathbb{R}\} \quad (13)$$
where U_k, U_{k+1}, e_k, Y_r, $Y_k \in \chi$. Also let $Q, L_c \in \mathbb{R}$
iii. To obtain number of trials k which satisfies the objective, Equation (14) must be satisfied.
$$\text{Find } k: \|Y_r(t) - Y_k(t)\| \leq \bar{e} \quad (14)$$
$\bar{e}$ is the error threshold or boundary that must be met to predict k.
iv. With a defined desired reference trajectory $Y_r(t)$ and trial interval t, feedback controller parameters ϖ, K_D, K_p, muscle model parameters ζ, w_n, subject forearm parameter b_{a_3}, mechanical guide parameters K_{M_2}, K_{B_2}, given error threshold $\bar{e}$, sampling time t_s, learning gain L_c, and Q filter
Compute
i. Create storage variables $Y_h, e_h, \in \mathbb{R}^{t_m \times 2}$
ii. Initialize $Y_h \leftarrow (\chi, t_s)|\chi = 0 \,\forall\, t_s$ and $e_h \leftarrow (\chi, t_s)|\chi = 0 \,\forall\, t_s$
iii. Set $k \leftarrow 0$
iv. Compute $G(H) \leftarrow T_{ar}(s).\, T_\beta(s).\, T_{pd}(s)$
v. Develop the closed loop feedback transfer function $T_c \leftarrow \frac{\mathrm{G(H)}}{1+\mathrm{G(H)}}$
vi. while $(\mathrm{e} > \bar{\mathrm{e}})$ do
vii. while $(\mathrm{t_s} < \mathrm{t})$
viii. simulate $(\mathrm{T_c}, \mathrm{t_s}, \mathrm{U_k}, \mathrm{Y_r})$
ix. store $\mathrm{Y_k} \leftarrow [\mathrm{Y_h}, \mathrm{t_s}]$
x. store $\mathrm{e_k} \leftarrow [\mathrm{e_h}, \mathrm{t_s}]$
xi. $\mathrm{k} \leftarrow \mathrm{k} + 1$
xii. compute $\mathrm{U_{k+1}}$ in Equation (12)
xiii. $\mathrm{U_k} \leftarrow \mathrm{U_{k+1}}$
xiv. return k

2.3 Implementation

In the section, an end-to-end straight line task plane trajectory was developed in MATLAB/SIMULINK environment for a typical reach-extend task for the linear forearm model discussed in the earlier sections. Anthropometric variables and muscle parameters describing an impaired stroke patient with upper-limb extremity were adapted from [31, 46]. Desired end-effector gains that incorporates a challenging task were manually selected as $\mathrm{K_D} = 2$, $\mathrm{K_p} = 9.98$, $\varpi = 0.05$ over statistically observed value range. Via Equations 15 - 20 and Table 1, the forearm joint angle movement is converted into the task plane trajectory for determination of performance stability of the model's kinematic movement with respect to the reference trajectory of 0 – 0.2828m. Thereafter, the algorithm generate signals for improving performance stability of the modelled subject until the kinematic movement error $\mathrm{e} \leq \bar{\mathrm{e}} = 0.01$m is satisfied over a trial period of 10 s.

$$r = \sqrt{\mathrm{d_1}^2 + L^2} \quad (15)$$

where $\mathrm{d_1}$ and L are horizontal (x) axis and vertical (y) axis respectively.

$$\phi = tan^{-1}\frac{\mathrm{d_1}}{L} \quad (16)$$
$$Y_r(t) = [r, t_s] \quad (17)$$

With the output of $T_{ar}(s)$ been a joint variable ϑ_f and the designed trajectory paths mainly a resultant derived from cartesian plane components $\mathrm{d_1}$ and L.

https://doi.org/10.4314/njt.v42i3.10

Thus, the forward kinematic relationship employed for mapping the joint space ϑ_f into cartesian space is

$$(\vartheta_f) = \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} L_u \cos(k(\vartheta_f)) + L_f \cos(k(\vartheta_f) + \vartheta_f) \\ L_u \sin(k(\vartheta_f)) + L_f \sin(k(\vartheta_f) + \vartheta_f) \end{bmatrix} \quad (18)$$

$$r_h = \sqrt{x^2 + y^2} \quad (19)$$

$$Y_h(t) = [r_h, t_s] \quad (20)$$

Table 1: Trajectory Path Parameters

Trajectory Parameter Description	Notation	Data
Minimum length of reach from glenohumeral joint base on the table	r_1	0.1m
Maximum Length of reach (MALOR) from glenohumeral joint base	r_2	0.3m
Task space trajectory orientation angle	ϕ	0.6109 rad
Horizontal distance from Subject's body	d_1	0.2 m
Subject specific workspace (Difference between MALOR and MILOR)	L	0.2 m

3.0 RESULTS AND DISCUSSION

3.1 Results

In this section simulation results of ILA with linear models representing impaired patients' muscle dynamics and forearm extension kinematic movement on a planar surface is reported. The root means square error (RMSE) metric was used for assessing the performance stability of the model tracking accuracy. As seen from Figure 1, the desired threshold that satisfies kinematic stability error $e \leq \bar{e} = 0.01$m was met under 2, 8 and 16 trial length for learning gains 0.9, 0.8, 0.2 and 0.1 respectively.

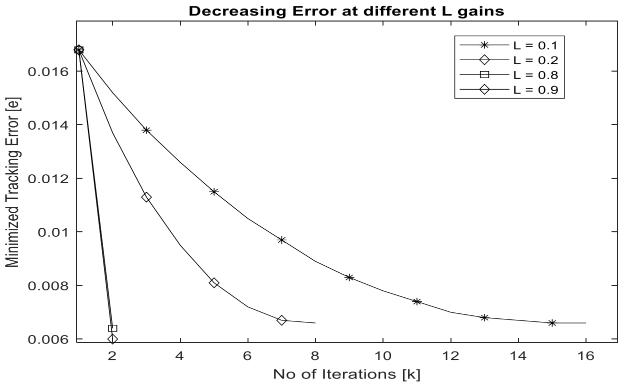

Figure 1: Plot of different kinematic stability error (e) at different learning gain (L) and trials (k)

Investigating further, Figure 2 shows the plot of kinematic movement of the subject's model around the given trajectory under an iterative learning gain of L = 0.1. Comparing the 1st and 16th trial of the simulation, the subject's model kinematic stability error e improved from a distance of 0.0168m to 0.0060m with respect to the trajectory. Furthermore, Figures 1 and 3 depict the impact of learning gain choice on kinematic stability performance. While it took the subject's computed model 16 trials to meet the desired error at L = 0.1, a step-by-step increase in learning gain depicts that a subject's computed model can be made to attain kinematic stability faster. Figure 3 confirms this claim by showing how the kinematic stability was attained under 2 iterations at L = 0.9.

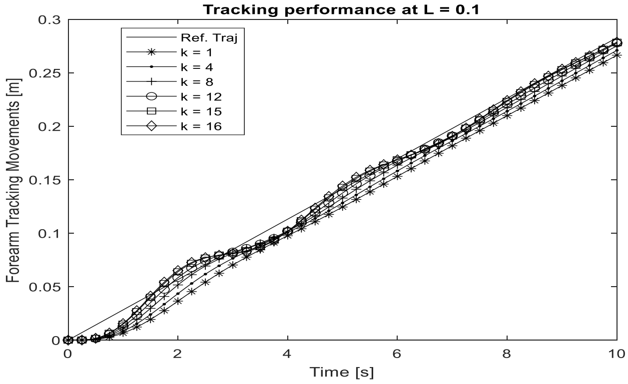

Figure 2: Plot of subject's model kinematic stability along reference trajectory at L = 0.1

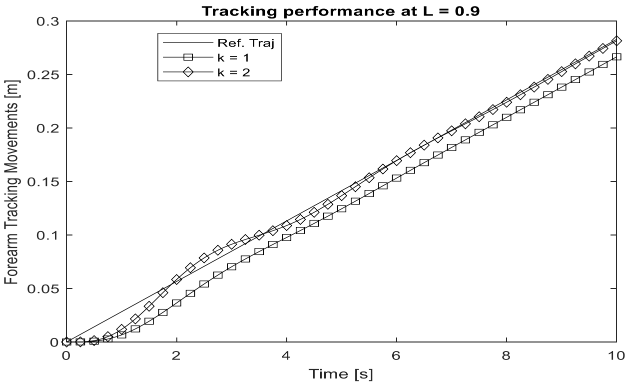

Figure 3: Plot of subject's model kinematic stability along reference trajectory at L = 0.9

3.2 Discussion

This study employed an iterative learning algorithm (ILA) to determine the optimal number of trials needed for achieving performance stability. Linear models represented impaired subjects, facilitating the investigation of kinematic movement on a planar surface. To assess kinematic stability, a predefined maximum deviation threshold ($\bar{e}$ = 0.01m) was set, and simulation results showed that around 16 trials with a learning gain of L = 0.1 were required for attainment. Notably, the model's deviation error improves at every trial for instance, a noticeable improvement from 0.0168m to 0.0152m was observed between the 1st and 2nd trials, respectively. With $e > \bar{e}$, the simulation scheme continued until a good performance stability was attained at a constant error ($e < \bar{e}$) of 0.0066m at k = 16 trials. In comparison to other studies, ILA with linear model approach demonstrated progressive effectiveness in estimating the number of trials needed to achieve improved performance or meet the predefined maximum deviation threshold. According to [42], authors recommended at least a minimum of 15 trials per task for assessment of performance on a 2D planar surface. In [47], an approximate number of 15 – 25 trials were utilized for reaching tasks in chronic stroke patients. In [24], authors reported that it took 2 – 3 trials to reach good performance stability of simpler kinematic measures in healthy and stroke subjects but more trials were needed to attain complex kinematic movements like reaching and returning task. As such, different studies reported that varying numbers of trials are required for kinematic stability based on task complexity and subject health status [25].

Another noteworthy outcome that deserves discussion is the influence of the learning gain (L) and the predefined kinematic error threshold ($\bar{e}$) in estimating the number of trials required to achieve kinematic stability. In a study without a specific kinematic error threshold, it was reported that a total of 47 trials before terminating movement due to non-improving kinematic stability in healthy individuals [48]. However, in the present work, by defining $\bar{e}$ the iterative learning algorithm (ILA) successfully simulated scenarios representing slow, medium, and fast recovery based on the choice of learning gain (L). Notably, when L was set to 0.9, the simulated model achieved the desired performance stability in only 2 trials, while L values of 0.2 and 0.8 required 8 and 2 trials, respectively. The careful selection of the learning gain proves to be critical, especially for models representing impaired subjects. For impaired patients nearing full recovery, it is advisable to use learning gains close to L = 1, while for severely impaired patients, learning gains between L = 0.001 and L = 0.1 may be more appropriate. This finding highlights the importance of tailoring the learning gain parameter to suit the specific needs and progress of the individual's undergoing rehabilitation or intervention.

Performance stability of selected kinematic metrics has been declared important for identification of deviations from typical patterns and evaluation of effectiveness of possible intervention [25]. This model-based study validates the combination of the ILA algorithm with linear models for estimating the number of trials needed to achieve kinematic accuracy under a strict deviation setpoint. The trial estimation results align with prior research in this field. Furthermore, it highlights the adaptability of the ILA learning gain subspace for different impaired subjects. Nevertheless, several caveats need consideration. Firstly, the linear forearm model only assesses a single kinematic variable (i.e., accuracy of elbow extension on a planar surface). Secondly, parameter values were sourced from existing studies, and validation with actual stroke subjects is essential. Thirdly, the efficacy of the scheme depends on cautious selection of ILA gains and accurate parameters for modeling impaired subjects.

4.0 CONCLUSION

Modeling and simulation can be an important first step at the start of recovery and rehabilitation. This claim is because it offers multiple benefits such as forecasting the number of trials that may be needed to attain kinematic stability rather than a precise functional outcome. The future of this work would investigate and validate ILA + linear model results with impaired subjects during pilot studies. Additionally, future work will focus on estimating the number of sessions that may be required to attain more selected kinematic skills along with likelihood prediction of subject recovery.

5.0 ACKNOWLEDGEMENT

This research was sponsored by a TETFUND National Research Fund grant.

REFERENCES

[1] Markus, H. “Stroke: causes and clinical features”, *Medicine*, Vol. 36, Number 11, 2008, pp 586-91.

[2] Muir, K. W. “Stroke”, *Medicine*, Vol. 41, Number 3, 2013, pp 169–74.

[3] Jaberinezhad, M., Farhoudi, M., Nejadghaderi, S. A., Alizadeh, M., Sullman, M. J. M., Carson-Chahhoud, K., Collins, G. S., and Safiri, S. “The burden of stroke and its attributable risk factors in the Middle East and North Africa region, 1990-2019”. *Sci Rep*, Vol. 12, Number 1, 2022, pp 2700.

[4] Grefkes, C., and Fink, G. R. “Recovery from stroke: current concepts and future perspectives”, *Neurol Res Pract*, Vol 2, Number 17, 2020, doi: 10.1186/s42466-020-00060-6.

[5] Alawieh, A., Zhao, J., and Feng, W. “Factors affecting post-stroke motor recovery: Implications on neurotherapy after brain injury”, *Behav Brain Res*, Number 340, 2018, pp 94-101. doi: 10.1016/j.bbr.2016.08.029.

[6] Fadhilah, H., and Permanasari V. Y. “Economic Burden Bore by Patients and Families because of stroke: Policy Assessment”, *Journal of Indonesian Health Policy and Administration*, Vol. 5, Number 3, 2020, pp 91-95.

[7] Liu, Y., Hong, Y., and Ji, L. “Dynamic Analysis of the Abnormal Isometric Strength Movement

Pattern between Shoulder and Elbow Joint in Patients with Hemiplegia", *Journal of healthcare engineering*, Vol. 2018, Number 1817485, 2018, pp 7.

[8] Zavoreo, I., Bašić-Kes, V. A., and Demarin, V. "Stroke and neuroplasticity", *Periodicum Biologorum*. Vol. 114, Number 3, 2012, pp 393-6.

[9] Stinear, C. M., Smith, M. C., and Byblow, W. D. "Prediction Tools for Stroke Rehabilitation", *Stroke*. Vol. 50, Number 11, 2019, pp 3314-3322. doi: 10.1161/STROKEAHA.119.025696

[10] Kiaer, C., Lundquist, C. B., and Brunner, I. "Knowledge and application of upper limb prediction models and attitude toward prognosis among physiotherapists and occupational therapists in the clinical stroke setting", *Top Stroke Rehabil*. Vol. 28,Number 2, 2021, pp 135-141. doi: 10.1080/1074935 7.2020.1783915

[11] Stinear, C. M., Barber, P. A., Petoe, M., Anwar, S., and Byblow, W. D. "The PREP algorithm predicts potential for upper limb recovery after stroke", *Brain*. Vol. 135, Number 8, 2012 pp 2527-35. doi: 10.1093/brain/aws146.

[12] Kwah, L. K., Harvey, L. A., Diong, J., and Herbert, R. D. "Models containing age and NIHSS predict recoveryof ambulation and upper limb function six months after stroke: anobservational study", *J Physiother*. Vol. 59, Number 3, 2013, pp 189-97. doi:10.1016/S1 8369553(13)70183-8.

[13] Stinear, C. M., Byblow, W. D., Ackerley, S. J., Smith, M. C., Borges, V. M., and Barber, P. A. "PREP2: A biomarker-based algorithm for predicting upper limb function after stroke", *Ann Clin Transl Neurol*. Vol. 4, Number 11, 2017, pp 811-820. doi: 10.1002/acn3.488.M klm

[14] Tozlu, C., Edwards, D., Boes, A., Labar, D., Tsagaris, K. Z., Silverstein, J., Pepper Lane, H., Sabuncu, M. R., Liu, C., and Kuceyeski, A. "Machine Learning Methods Predict Individual Upper-Limb Motor Impairment Following Therapy in Chronic Stroke", *Neurorehabil Neural Repair*. Vol. 34, Number 5, 2020, pp 428-439. doi: 10.1177/1545968320909796.

[15] Selles, R. W., Andrinopoulou, E. R., Nijland, R. H., Van der Vliet, R., Slaman, J., van Wegen, E. E., Rizopoulos, D., Ribbers, G. M., Meskers, C. G., and Kwakkel, G. "Computerised patient-specific prediction of the recovery profile of upper limb capacity within stroke services: the next step", *J Neurol Neurosurg Psychiatry*. Vol. 92, Number 6 , 2021, pp 574–81. doi: 10.1136/jnnp-2020-324637

[16] Alt Murphy, M., Al-Shallawi, A., Sunnerhagen, K. S., and Pandyan, A. "Early prediction of upper limb functioning after stroke using clinical bedside assessments: a prospective longitudinal study", *Sci Rep*. Vol. 12, Number 22053, 2022.

[17] Houda, B., Nahla, K., and Safya, B. "Musculoskeletal Modeling of Elbow Joint under Functional Electrical Stimulation", *International Conference on Advanced Systems and Emergent Technologies (IC_ASET)*, 2019, pp. 307-310.

[18] Freeman, C. T., Hughes, A. M., Burridge, J. H., Chappell, P. H., Lewin, P. L., and Rogers, E. "A robotic workstation for stroke rehabilitation of the upper extremity using FES", *Medical engineering and physics*. Vol. 31, Number 3, 2009, pp 364-73.

[19] Ayodele, K. P., Akinniyi, O. T., Oluwatope, A. O., Jubril, A. M., Ogundele, A. O., and Komolafe, M. A. "A Simulator for Testing Planar Upper Extremity Rehabilitation Robot Control Algorithms", *Nigerian Journal of Technology*. Vol. 40, Number 1, 2021, pp 115-128.

[20] Oña, E. D., Garcia-Haro, J. M., Jardón, A., and Balaguer, C. "Robotics in health care: Perspectives of robot-aided interventions in clinical practice for rehabilitation of upper limbs", *Applied sciences*. Vol. 9, Number 13, 2019, pp 2586.

[21] Li, S. "Spasticity, motor recovery, and neural plasticity after stroke", *Frontiers in neurology*. Vol. 8, Number 120, 2017.

[22] T. Herrgårdh et al., "Hybrid modelling for stroke care: Review and suggestions of new approaches for risk assessment and simulation of scenarios", *NeuroImage: Clinical*, vol. 31, p. 102694, Jan. 2021, doi: 10.1016/j.nicl.2021.10 2694.

[23] Hochstenbach-Waelen and Seelen, H. H. "Embracing change: practical and theoretical considerations for successful implementation of technology assisting upper limb training in stroke", *Journal of Neuroengineering and Rehabilitation*, vol. 9, no. 1, p. 52, Jan. 2012, doi: 10.1186/1743-0003-9-52.

[24] Frykberg, G. E., Grip, H., and Murphy, M. A. "How many trials are needed in kinematic analysis of reach-to-grasp?—A study of the drinking task in persons with stroke and non-disabled controls", *Journal of Neuroengineeri-*

ng and Rehabilitation, vol. 18, no. 1, Jun. 2021, doi: 10.1186/s12984-021-00895-3.

[25] Chen, Y. P., Garcia-Vergara, S., and Howard, A. M. "Number of trials necessary to achieve performance stability in a reaching kinematics movement analysis game", *Journal of Hand Therapy*, Jul. 2020, doi: 10.1016/j.jht.2019.04.001.

[26] Schwarz, A., Kanzler, C. M., Lambercy, O., Luft, A. R., and J. M. Veerbeek, "Systematic Review on Kinematic Assessments of Upper Limb Movements After Stroke," Stroke, vol. 50, no. 3, pp. 718–727, Mar. 2019, doi: 10.1161/strokeaha.118.023531.

[27] Geng, Y., Chen, Z., Zhao, Y., Cheung, V. C., Li, G. "Applying muscle synergy analysis to forearm high-density electromyography of healthy people", *Frontiers in Neuroscience*. Vol. 16, 2022. https://doi.org/10.3389/fnins.2022.1067925

[28] Freeman, C., Hughes, A. M., Burridge, J., Chappell, P. H., Lewin, P. L., and Rogers, E. "Iterative learning control of FES applied to the upper extremity for rehabilitation", *Control Engineering Practice*, vol. 17, no. 3, pp. 368–381, Mar. 2009, doi: 10.1016/j.conengprac.2008.08.003.

[29] Le, F., Markovsky, I., Freeman, C. T., and Rogers, E. "Identification of the Dynamics of Human Arms After Stroke", *Proceedings of the 23rd IAR Workshop on Advanced Control and Diagnosis*, 2008.

[30] Durfee, W. K., and Palmer, K. I. "Estimation of force-activation, force-length, and force velocity properties in isolated, electrically stimulated muscle", *IEEE Transactions on Biomedical Engineering*. Vol. 41, Number 3, 1994, pp 205-16.

[31] Le, F., Markovsky, I., Freeman, C. T., and Rogers, E. "Identification of electrically stimulated muscle models of stroke patients", *Control Engineering Practice*. Vol 18, Number 4, 2010, pp 396–407.

[32] Fadali, M. S., and Visioli, A. "Digital control engineering", *Analysis and design*. Elsevier, Waltham, 2013, pp. 157-165.

[33] Delchev, K. "Iterative learning control for nonlinear systems: A bounded-error algorithm", *Asian Journal of Control*, Vol. 15, Number 2, 2013, pp 453–460.

[34] Bristow, D., Tharayil, M., and Alleyne, A. "A Learning-Based Method for High-Performance Tracking Control", *Ieee Control Systems Magazine*, Vol. 1066, Number 033X, 2006, pp 96–114.

[35] Ahn, H., Chen, Y., and Moore, K. L. "Iterative learning control: brief survey an categorization", *IEEE Control Systems*, Vol. 37, Number 435, 2004, pp 1–54.

[36] Ramli, N. N. N., Asokan, A., Mayakrishnan, D., and Annamalai, H. "Exploring Stroke Rehabilitation in Malaysia: Are Robots Better than Humans for Stroke Recuperation?", *Malays J Med Sci*, vol. 28, no. 4, pp. 14–23, Aug. 2021, doi: 10.21315/mjms2021.28.4.3.

[37] Keeling, B., Piitz, M. A., Semrau, J. A., Hill, M. D., Scott, S., and Dukelow, S. P. "Robot enhanced stroke therapy optimizes rehabilitation (RESTORE): a pilot study", *Journal of Neuroengineering and Rehabilitation*, vol. 18, no. 1, Jan. 2021, doi: 10.1186/s12984-021-00804-8.

[38] Xu, W., Chu, B., and Rogers, E. "Iterative learning control for robotic-assisted upper limb stroke rehabilitation in the presence of muscle fatigue", *Control Engineering Practice*, vol. 31, pp. 63–72, Oct. 2014, doi: 10.1016/j.conengprac.2014.05.009

[39] Bessler, J., et al., "Safety Assessment of Rehabilitation Robots: A Review Identifying Safety Skills and Current Knowledge Gaps", *Frontiers in Robotics and AI*, vol. 8, Mar. 2021, doi: 10.3389/frobt.2021.602878.

[40] Desplenter, T., and Trejos, A. L. "A Control Software Framework for Wearable Mechatronic Devices", *Journal of Intelligent & Robotic Systems*, vol. 99, no. 3–4, pp. 757–771, Jan. 2020, doi: 10.1007/s10846-019-01144-5.

[41] Clark, B., Whitall, J., Kwakkel, G., Mehrholz, J., Ewings, S., and Burridge, J. "Time spent in rehabilitation and effect on measures of activity after stroke", *The Cochrane Library*, Mar. 2017, doi: 10.1002/14651858.cd012612.

[42] Kwakkel, G., et al., "Standardized measurement of quality of upper limb movement after stroke: Consensus-based core recommendations from the Second Stroke Recovery and Rehabilitation Roundtable", *International Journal of Stroke*, vol. 14, no. 8, pp. 783–791, Sep. 2019, doi: 10.1177/1747493019873519.

[43] Taragna, M., Cannizzaro, D., and Votano, S. "Vibration compensation for robotic manipulators by iterative learning control", *POLITECNICO DI TORINO*. 2018.

[44] Moore, K. L., Chen, Y., and Ahn, H. S. "Iterative learning control: A tutorial and big picture view", *In Proceedings of the IEEE Conference on Decision and Control*. Vol. 45, 2006, pp 2352-2357.

[45] Ardakani, M. G., Khong, S. Z., and Bernhardsson, B. "On the convergence of iterative learning control", *Automatica*. Vol. 78, 2017, pp 266 – 273.

[46] Freeman, C., Hughes, A. M., Burridge, J., Chappell, P. H., Lewin, P., and Rogers, E. "A model of the upper extremity using FES for stroke rehabilitation", *Journal of Biomechanical Engineering*, vol. 131, no. 3, Jan. 2009, doi: 10.1115/1.3005332.

[47] Subramanian, S., Baniña, M. C., Turolla, A., and Levin, M. F. "Reaching performance scale for stroke – Test retest reliability, measurement error, concurrent and discriminant validity", *Pm and R*, vol. 14, no. 3, pp. 337–347, Apr. 2021, doi: 10.1002/pmrj.12584

[48] Blinch, J., Kim, Y., and Chua, R. "Trajectory analysis of discrete goal-directed pointing movements: How many trials are needed for reliable data?", *Behavior Research Methods*, vol. 50, no. 5, pp. 2162–2172, Dec. 2017, doi: 10.3758/s13428-017-0983-6.