Bulletin of Electrical Engineering and Informatics
Vol. 14, No. 5, October 2025, pp. 3371∼3380
ISSN: 2302-9285, DOI: 10.11591/eei.v14i5.9395

Online PID-neural network for tracking lower limb rehabilitation exoskeleton angular position

Ummi Hanifah[1], Aura Adinda[1], Akif Rahmatillah[2,3], Imam Sapuan[2], Khusnul Ain[2,3], Harry Septanto[4], Rifai Chai[3,5]

[1]Master of Biomedical Engineering, Faculty of Science and Technology, Universitas Airlangga, Surabaya, Indonesia
[2]Biomedical Engineering, Faculty of Science and Technology, Universitas Airlangga, Surabaya, Indonesia
[3]Biomedical Signals and Systems Research Group, Faculty of Science and Technology, Universitas Airlangga, Surabaya, Indonesia
[4]Research Center for Smart Mechatronics, Research Organization for Electronics and Informatics, Badan Riset dan Inovasi Nasional, Bandung, Indonesia
[5]School of Science, Computing, and Engineering Technologies, Swinburne University of Technology, Melbourne, Australia

Article Info

Article history:

Received Oct 2, 2024
Revised Jul 7, 2025
Accepted Jul 20, 2025

Keywords:

Exoskeleton
External disturbance
Gait trajectory tracking
Lower limb rehabilitation
Neural network
Proportional-integral-derivative

ABSTRACT

Gait trajectory tracking control is an essential component of a lower limb rehabilitation exoskeleton (LLRE). Meanwhile, the proportional-integral-derivative (PID) controller remains popular for a variety of applications, including LLRE. Nonetheless, employing PID presents a significant issue, namely determining how to choose or tune the parameters. This paper addresses the LLRE's hip-knee angular position tracking system based on an online PID-NN controller, i.e., a PID controller, whose parameters are online modified by a trained neural network (NN). A proposed framework for designing the PID-NN controller is elaborated. Numerical verifications are carried out by comparing the performance of the PID-based control system, whose parameters have been tuned using Ziegler-Nichols (ZN), without and using NN. Performance comparisons involving the presence of external disturbance are also carried out. The simulation results show that the proposed PID-NN-based control system provides better performance with lower mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) values.

Corresponding Author:

Khusnul Ain
Biomedical Signals and Systems Research Group, Faculty of Science and Technology, Universitas Airlangga
Surabaya, Indonesia
Email: k_ain@fst.unair.ac.id

1. INTRODUCTION

The robotics exoskeleton for the lower limbs is a human-wearable mechatronics system that combines sensing, control, information, and other multidisciplinary domains to regulate joint movement [1], [2]. It may be classified into two sorts based on its function: *assistive* and *rehabilitative*.

The assistive one supports the body, boosts human strength, and alleviates the physical strain of manual labor at work. For example, Tu *et al.* [3] introduced E-Leg, an assistive robotic exoskeleton for the lower limb that may alleviate stress and tension on the musculoskeletal system during long-term squatting exercises by altering the needed squat height. Meanwhile, the rehabilitative one, also known as the lower limb rehabilitation exoskeleton (LLRE), is utilized to aid or constrain the user's movement to stimulate the muscle or nerve system exhibiting gait abnormalities. An LLRE can be used to treat persons with partial gait impairment, such as the elderly [2], stroke [4], spinal cord injury [5], spinocerebellar ataxia (SCA) [6], and other neuromuscular disorders. There are many subjects studied in this area, e.g., mechanism [7], virtual reality [8], and control [9], to name a few. This study focuses on an important part of LLRE: gait trajectory tracking.

Trajectory tracking control is a difficult challenge in robot control, particularly LLRE, because of the general nonlinear and complicated system and external disturbances [10]. A control algorithm or scheme is implemented in the LLRE to track the desired gait trajectory so that the limbs and exoskeleton can move together. The interface between the body and the exoskeleton necessitates a good controller for effective tracking performance. Besides, it improves the efficiency of rehabilitative therapy [11]. Parikesit and Maneetham in [12] improved the LLRE for the gait trainer using the computed torque controller (CTC) approach. Proportional-integral-derivative (PID)-based LLRE is used for comparison. Yu *et al.* [13], proposed a sliding mode controller optimized bu the grey wolf optimization algorithm for LLRE. In addition, a fractional proportional derivative with active disturbance rejection control(fractional PD-ADRC) to control knee exoskeleton for rehabilition is proposed by Alawad *et al.* [14].

PID is a controller that is still popular for many applications, e.g., process systems [15], [16] and power system [17], despite the existence of many other control techniques. These are due to the PID structure's simplicity, robustness, and ease of understanding [18]–[20]. In addition to [12], [14] we mentioned above, for the LLRE application, Zhu *et al.* [21] utilized biomechanical signals with PID control on LLRE that identify human gait characteristics and generate angular trajectory tracking close to the reference angle.

Selecting or tuning the PID parameters is a key stage in its use. Various optimization methods are widely applied in selecting PID parameters for LLRE. Amiri *et al.* [22] designed an LLRE control system using hybrid optimization based on a combination of genetic algorithm and particle swarm optimization. Another study by Al-Waeli *et al.* [23] utilized a trained neural network (NN) to optimize PID parameters offline on an LLRE for obtaining constant PID parameters to be used in the system operation.

However, the approach in the above studies does not consider the system's adaptability. PID-based control system performance depends on the value of the PID parameters. If the system changes or there is a change in the environment that is regarded as an uncertainty, then the PID parameters might need to be changed dynamically so that the problem of the uncertainty can be resolved [24], [25]. Furthermore, uncertainties in LLRE systems could be divided into periodic uncertainties (due to interactions between users and LLRE) and non-periodic uncertainties (due to unmodeled LLRE dynamics and other additional disturbances) [11]. Therefore, a more adaptive and intelligent PID control scheme is essential in LLRE systems. One of the most widely used intelligent methods is NN because of its ability to handle periodic and non-periodic uncertainties simultaneously in control systems [11]. Principally, NN is a nonlinear mathematical structure consisting of a set of interconnected neurons, or nodes [26]. Aside from its features, the implementation for control system purposes is reasonably simple, with a variety of algorithms available both online and offline [25], [27].

In this work, we propose a framework that utilizes the NN algorithm for modifying the PID parameters online, which means that the PID parameters could be updated while the system is running. The main contributions of this paper are:

- This research provides a framework for designing an LLRE angular position tracking system that utilizes an NN to modify online PID parameters, including how to create the datasets and train the NN.
- This research compares the performance of properly tuned PID parameters by the Ziegler-Nichols (ZN) method with and without online changes by the trained NN.

This paper is organized as follows. In section 2, the LLRE mathematical model is presented. This subsection also elaborates our proposed framework for designing the online PID-NN-based angular position tracking control of the LLRE. In section 3, we present numerical examples to demonstrate the effectiveness of our proposed method and analysis. Conclusions are made in section 4.

2. METHOD

2.1. Modeling

The dynamics model of LLRE consists of external skeleton modeling and DC motor modeling as a joint driver in the patient's leg [28]. For representing basic movements such as walking, LLRE could be represented by a 2-degree of freedom (2-DoF) model that focuses on the dynamics of the hip and knee joints, which play an important part in these activities [29]. Linearized dynamics of the hip and knee joints in transfer function form, based on the LLRE dynamics modeling in [30], [31], is shown in (1), where θ_{sh_i} denotes the hip ($i = 1$) and knee ($i = 2$) link angles, U_i denotes input voltages of the hip and knee actuators, and the model parameters values are given in Table 1. Figure 1 illustrates the hip and knee link angle of the 2-DoF LLRE that focuses on the hip-knee dynamics.

$$G_i(s) = \frac{\theta_{sh\_i}(s)}{U_i(s)} = \frac{b}{a_{i1}s^3 + a_{i2}s^2 + a_{i3}s + a_{i4}} \tag{1}$$

Table 1. LLRE model parameters

Joint	i	b	a_{i1}	a_{i2}	a_{i3}	a_{i4}
Hip	1	26.4499	0.001	0.2362	1.6060	4.6603
Knee	2	25.9909	0.001	0.0641	0.5658	1.7326

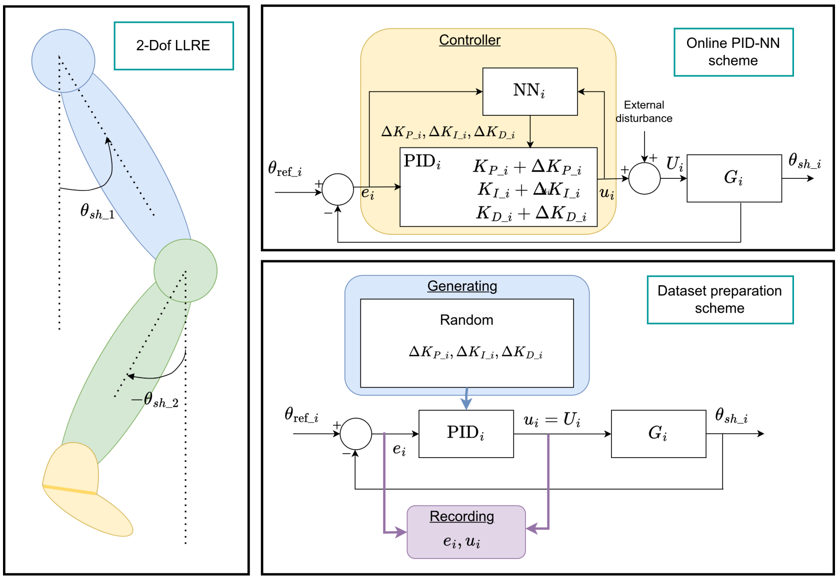

Figure 1. 2-DoF of LLRE model, online PID-NN control system, and dataset preparation scheme

2.2. Controller design framework

The scheme of the LLRE angular position tracking system is depicted in Figure 1. It describes that a trained NN would dynamically update the PID parameters by providing $(\Delta K_{P\_i}, \Delta K_{I\_i}, \Delta K_{D\_i})$ while the system runs. The proposed methodical design process for the LLRE angular position tracking system is described in detail below.

Step 1: Determining the nominal PID parameters.
Nominal PID parameters $(K_{P\_i}, K_{I\_i}, K_{D\_i})$ are the initial PID parameters before these are online updated by a trained NN, which is explained in steps 2–4. The nominal PID parameters must be selected properly. For example, it could be obtained by following the famous heuristic tuning method ZN [32].

Step 2: Preparing dataset.
A training step must be conducted to completely design an NN using a predetermined structure for obtaining the weights. Dataset is needed to train the NN. The dataset is created by running the system employing the reference signals (the gait trajectories) θ_{ref_i} by substituting the NN with a random number generator to provide $(\Delta K_{P\_i}, \Delta K_{I\_i}, \Delta K_{D\_i})$ while recording the error value e_i and the control signals from the PID block u_i. Thus, the recorded (e_i, u_i) represents the feature and the generating random $(\Delta K_{P\_i}, \Delta K_{I\_i}, \Delta K_{D\_i})$ represents the target. Figure 1 depicts the scheme for preparing the dataset.
The complete dataset is a collection of several packages of data pairs. A package of data pairs consists of constant random values of $(\Delta K_{P\_i}, \Delta K_{I\_i}, \Delta K_{D\_i})$ and values of (e_i, u_i) obtained from a single

system run within the specified start and stop time ranges. It is important to note that, in addition to the start and ending time ranges, the dataset length is determined by time sampling. It is also worth noting that external disruption is not considered when compiling the dataset.

Step 3: Defining the NN structure.
This step consists of defining the hidden layer(s) and their nodes and selecting the activation function. Note that the input and output layers must be appropriately sized to match the features and targets of the prepared dataset.

Step 4: Training the NN.
In this step, the defined NN structure is trained using the prepared dataset once the training method has been specified.

Step 5: Verifying the designed online PID-NN controller.
In this step, we could have the controller structure as depicted in Figure 1. Thus, verification of the effectiveness of the designed control system for LLRE can be conducted.

These steps are detailed and illustrated in the next section, making it easier to follow the framework and replicate or even improve it. For comparison, a step-by-step explanation is not presented in [24], [25]. Meanwhile, Kumar *et al.* [19] provides a step-by-step explanation that focuses on the NN training procedure.

3. RESULT AND DISCUSSION

In this work, our proposed method is realized numerically using MATLAB/Simulink. Following the flow described in the previous section, we specify the setting below:

Step 1: The nominal PID parameters are determined by following the ZN rule [32]. The parameters values are given in Table 2.

Table 2. Nominal PID parameters

Joint	K_P	K_I	K_D
Hip	8.4990	4.4048	4.0997
Knee	0.7971	5.9842	0.0265

Step 2: Reference signals-the gait data from [33] are used as reference signals. Specifically, for the hip and knee link angles, respectively, we use the *right hip flexion/extension* and *right knee flexion/extension* data of $\{$*raw data participant00 - gait speed =* $0.5m/s$ *- corridor1 - straight*$\}$. It is worth noting that a package of data pairs is prepared by utilizing only $8s$ long reference signals, i.e., from $4s$ to $12s$ of *right hip flexion/extension* and from $5.8s$ to $13.8s$ of *right knee flexion/extension* data. Each signal is only about 18% of the total $44.333s$. These represent twice wavelengths. Figure 2 depicts the reference signals.
Generating $(\Delta K_{P\_i}, \Delta K_{I\_i}, \Delta K_{D\_i})$: in this numerical study, random signals between 0 and 1 are utilized.
Solver setting: simulations are run using *Variable-step* type and *Automatic solver selection*.
Dataset collection: the complete dataset is a collection of 100 packages of data pairs. In other words, the simulation is run 100 times using the same reference signals but random $(\Delta K_{P\_i}, \Delta K_{I\_i}, \Delta K_{D\_i})$. It yields dataset lengths of 151068 and 52229 for hip and knee joints, respectively. In addition, the dataset is normalized to be within a range between -1 and 1.

Step 3: NN structure: it has an input layer with 2 nodes, one hidden layer with 6 nodes, and an output layer with 3 nodes. Every node of hidden and output layers uses *hyperbolic tangent sigmoid* activation function. In addition, every node of hidden and output layers consists of weight and bias to be determined by training.

Step 4: Training setting and result: the NN training for each joint utilizes the *Gradient descent with momentum backpropagation*. Values of $(Epochs, Learning\ rate, Momentum\ constant)$ are $(1000, 0.5, 0.9)$ and $(1000, 0.25, 0.85)$ for hip and knee joints, respectively. The best mean square error (MSE) of the NN training for hip and knee joints are 0.0896 and 0.04365, respectively.

Step 5: Verification: the designed controllers for hip and knee joints are verified numerically by performing the designed control systems using the entire length of reference signals. It is important to note that the designed NN is represented within a MATLAB function block of Simulink in the verification step,

whereas using a MATLAB toolbox in the training step (see subsection 2.2.).
Two scenarios run are without and with the presence of external disturbances. Random numbers -30 to $30V$ and -1.5 to $1.5V$ are used to simulate external disturbances at U_1 (hip) and U_2 (knee), respectively.

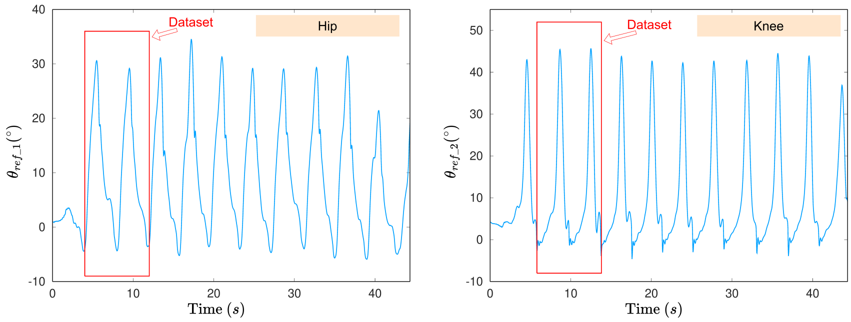

Figure 2. Reference signals

In this study, we evaluate the effectiveness of PID-based hip and knee joint control systems both with and without the intended NN to modify the PID parameters while the systems are in operation. When a control system employs PID without NN, it indicates that it solely uses the PID controller, whose nominal PID parameters are determined by applying the ZN rule. In the meantime, the PID with NN denotes the suggested control system, the detailed instructions for which are shown above.

The 2-DoF hip-knee LLRE time response comparisons are depicted in Figure 3. Meanwhile, control signal comparisons are shown in Figure 4. The performance of PID and PID-NN is identical in both scenarios, that is, without and with external disturbances. We can, however, verify that the 2-DoF LLRE with PID-NN is shown with lower mean squared error (MSE), root mean square error (RMSE), and mean absolute error (MAE) values. It demonstrates how effective the suggested 2-DoF LLRE-with PID-NN is. These values are shown in Tables 3 and 4 for without and with the presence of external disturbances, respectively. In addition, the changes in PID parameters of the PID-NN control systems are presented in Figure 5.

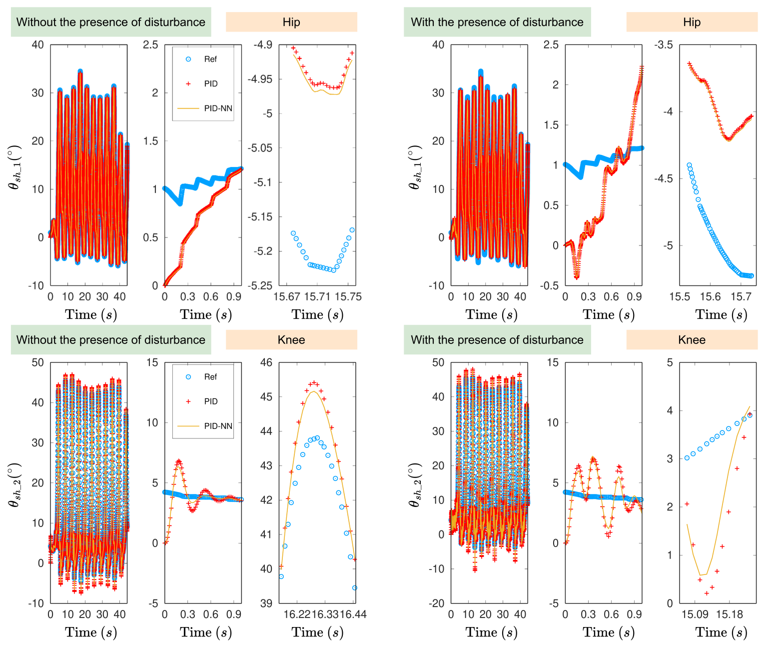

Figure 3. Time responses of the hip-knee dynamics

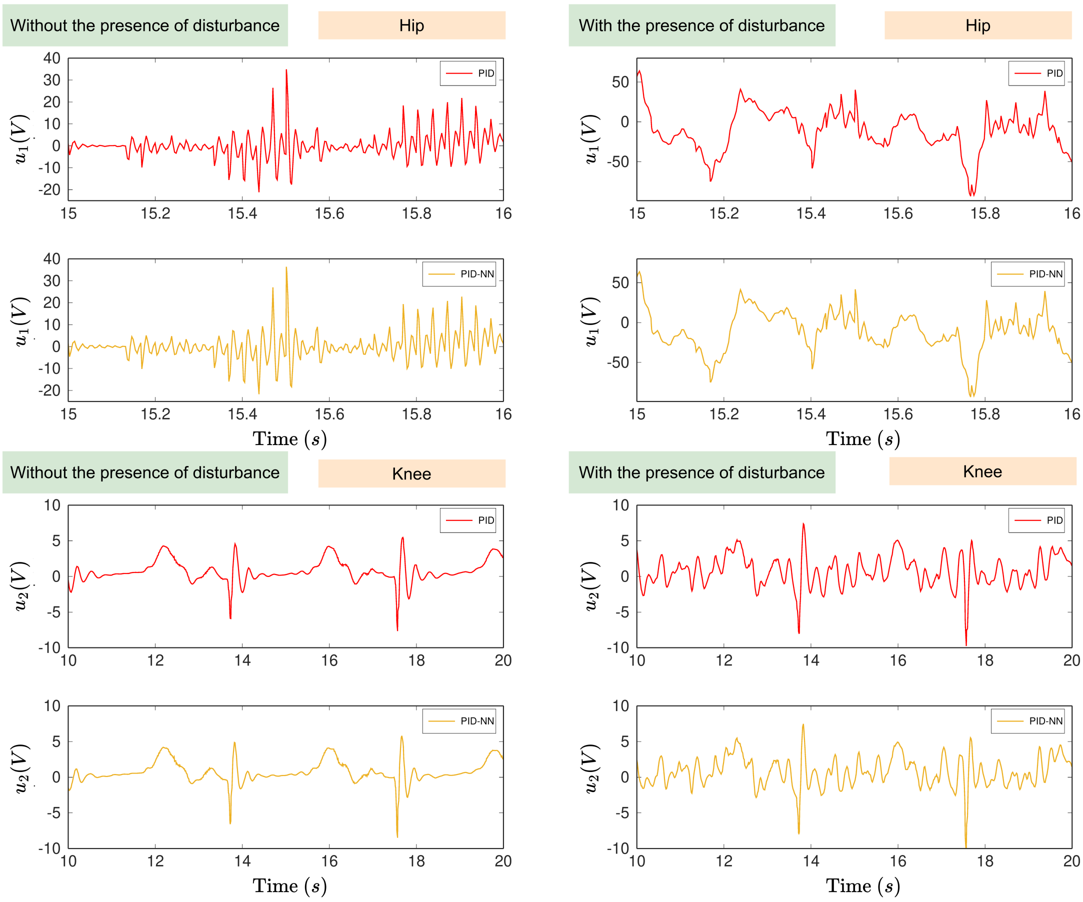

Figure 4. Control signals of the hip-knee PID-NN control system

Table 3. Performance comparisons without the presence of external disturbances

Index performance	Hip joint		Knee joint	
	PID	PID-NN	PID	PID-NN
MSE	0.0421	0.0399	1.8436	1.2780
RMSE	0.2051	0.1997	1.3578	1.1305
MAE	0.1684	0.1634	0.8837	0.7107

Table 4. Performance comparisons with the presence of external disturbances

Index performance	Hip joint		Knee joint	
	PID	PID-NN	PID	PID-NN
MSE	0.5245	0.5077	3.7315	2.3733
RMSE	0.7243	0.7125	1.9317	1.5405
MAE	0.5853	0.5770	1.4735	1.1710

Furthermore, one significant point should be highlighted in this work: in these numerical simulations, the NNs for hip and knee are trained with trivial datasets (see step 2 in this part). However, trained NNs may change the PID value, which improves performance for tracking LLRE systems that use PID-NN.

However, this designed control system is not without weakness. We might see that the control signal for the hip is relatively large; there are even value spikes up to the order of $+/-100$ (figure not shown). This may be difficult when applied in actual systems due to saturation of the DC motor, which is the joint actuator. This saturation will result in a mismatch between the calculated control signal from the controller and the actual control signal sent to the real system. To address this issue, an anti-windup compensator can be utilized [34], [35]. This will be fascinating for further research and development.

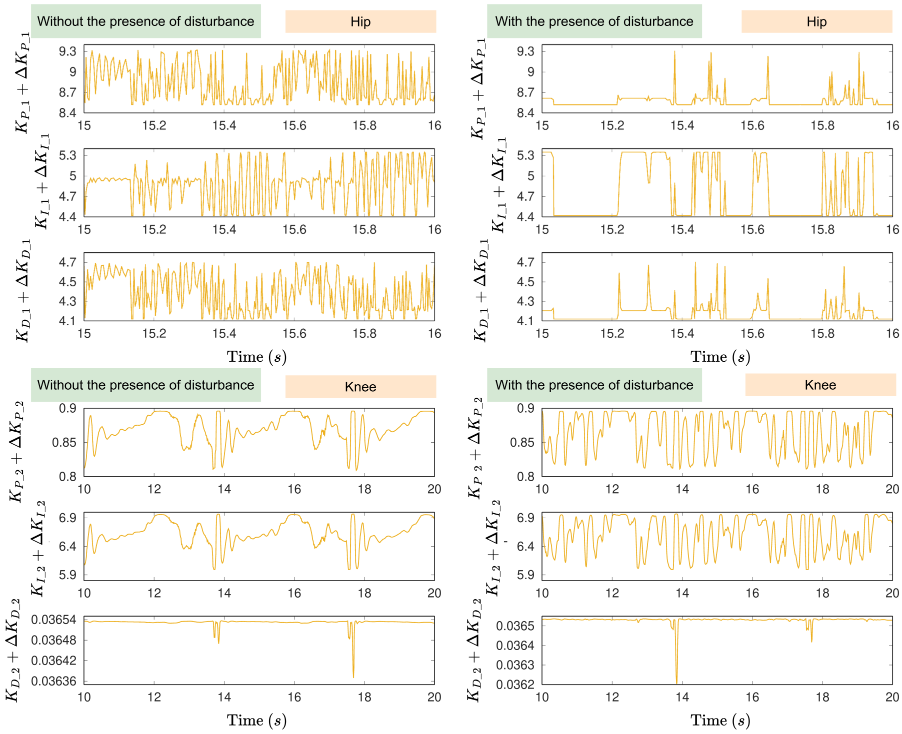

Figure 5. Parameters of PID changes for the hip-knee PID-NN control system

4. CONCLUSION

The proposed framework for designing Hip-Knee LLRE angular position control system based on PID that is online modified by a trained is presented. This framework consists of step-by-step design procedure, including how to create the datasets and train the NN. Numerical simulations confirm that the designed PID-NN-based LLRE control system demonstrates its superiority based on several performance index computations, i.e., MSE, RMSE, and MAE. According to the simulation findings, even if the dataset utilized by NN is very simple, performance improvements can be seen. This demonstrates that using better datasets has the potential to lead to greater speed improvements. In addition, the resulting control signal could be large. despite the fact that it only appears as spikes. This may degrade the performance due to the actuator's saturation, which results in a mismatch between the calculated control signal from the controller and the actual control signal sent to the real system. It would be fascinating to do further investigation into this topic, such as using an anti-windup compensator.

ACKNOWLEDGMENTS

We acknowledge all anonymous reviewers and editors of an earlier manuscript for their insightful comments that helped improve it.

FUNDING INFORMATION

This work was supported by The Directorate General of Higher Education, Research, and Technology (DRTPM) 2023 under # 114/E5/PG.02.00.PL/2023 or contract derivative number 1299/UN3.LPPM/PT.01.03/2023.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ummi Hanifah			✓	✓	✓	✓				✓	✓			
Aura Adinda						✓				✓				
Akif Rahmatillah	✓									✓				
Imam Sapuan					✓					✓				
Khusnul Ain		✓								✓		✓		✓
Harry Septanto	✓	✓		✓					✓	✓		✓		
Rifai Chai					✓					✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal Analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject Administration
Fu : **Fu**nding Acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

Human gait data were obtained from the open-source [33], and therefore, consent for publication was not required.

ETHICAL APPROVAL

According to the ethical guidelines, it was determined that formal ethical approval was not required.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] T. Wang *et al.*, “A review on the rehabilitation exoskeletons for the lower limbs of the elderly and the disabled,” *Electronics*, vol. 11, no. 3, pp. 1-16, 2022, doi: 10.3390/electronics11030388.
[2] D. Shi, W. Zhang, W. Zhang, and X. Ding, “A review on lower limb rehabilitation exoskeleton robots,” *Chinese Journal of Mechanical Engineering*, vol. 32, no. 1, pp. 1-11, Aug. 2019, doi: 10.1186/s10033-019-0389-8.
[3] Y. Tu, A. Zhu, J. Song, X. Zhang, and G. Cao, “Design and experimental evaluation of a lower-limb exoskeleton for assisting workers with motorized tuning of squat heights,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 184-193, 2022, doi: 10.1109/TNSRE.2022.3143361.
[4] S. V. Kotov *et al.*, “Efficiency of leg exoskeleton use in rehabilitation of cerebral stroke patients,” *Experimental and Applied Biomedical Research (EABR)*, vol. 22, no. 3, pp. 257–264, 2021, doi: 10.2478/sjecr-2021-0045.
[5] X. Xue *et al.*, “The improvement of the lower limb exoskeletons on the gait of patients with spinal cord injury: A protocol for systematic review and meta-analysis,” *Medicine*, vol. 101, no. 4, pp. 1-6, Jan. 2022, doi: 10.1097/MD.0000000000028709.
[6] S.-H. Kim, J.-Y. Han, M.-K. Song, I.-S. Choi, and H.-K. Park, “Effectiveness of robotic exoskeleton- assisted gait training in spinocerebellar ataxia: A case report,” *Sensors*, vol. 21, no. 14, pp. 1-8, 2021, doi: 10.3390/s21144874.
[7] R. S. Gonçalves and L. A. O. Rodrigues, ”Development of nonmotorized mechanisms for lower limb rehabilitation,” *Robotica*, vol. 40, no. 1, pp. 102–119, Jan. 2022, doi: 10.1017/S0263574721000412.
[8] Y. Liu, Q. Zhang, and W. Li, ”Enhancing lower-limb rehabilitation: a scoping review of augmented reality environment,” *Journal of NeuroEngineering and Rehabilitation*, vol. 22, no. 1, p. 114, May 2025, doi: 10.1186/s12984-025-01643-7.
[9] S. Mefoued and D. E. C. Belkhiat, “A Robust Control Scheme Based on Sliding Mode Observer to Drive a Knee-Exoskeleton,” *Asian Journal of Control*, vol. 21, no. 1, pp. 439–455, Jan. 2019, doi: 10.1002/asjc.1950.
[10] X. Jin and J. Guo, ”Disturbance rejection model predictive control of lower limb rehabilitation exoskeleton,” *Scientific Reports*, vol. 13, no. 1, p. 19463, Nov. 2023, doi: 10.1038/s41598-023-46885-4.
[11] Y. Yang, D. Huang, and X. Dong, “Enhanced neural network control of lower limb rehabilitation exoskeleton by add-on repetitive learning,” *Neurocomputing*, vol. 323, pp. 256–264, Jan. 2019, doi: 10.1016/j.neucom.2018.09.085.
[12] E. Parikesit and D. Maneetham, “Two-link lower limb exoskeleton model control enhancement using computed torque,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 6, pp. 6204–6215, Dec. 2023, doi: 10.11591/ijece.v13i6.pp6204-6215.

[13] J. Yu, S. Zhang, A. Wang, W. Li, Z. Ma, and X. Yue, ”Humanoid control of lower limb exoskeleton robot based on human gait data with sliding mode neural network,” *CAAI Transactions on Intelligence Technology*, vol. 7, no. 4, pp. 606–616, Dec. 2022, doi: 10.1049/cit2.12127.

[14] N. A. Alawad, A. J. Humaidi, and A. S. Alaraji, “Fractional proportional derivative-based active disturbance rejection control of knee exoskeleton device for rehabilitation care,” *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 28, no. 3, pp. 1405–1413, Dec. 2022, doi: 10.11591/ijeecs.v28.i3.pp1405-1413.

[15] S. W. Harcum, K. S. Elliott, B. A. Skelton, S. R. Klaubert, H. Dahodwala, and K. H. Lee, ”PID controls: the forgotten bioprocess parameters,” *Discover Chemical Engineering*, vol. 2, no. 1, p. 1, Dec. 2022, doi: 10.1007/s43938-022-00008-z.

[16] J. Bhookya, M. V. Kumar, J. R. Kumar, and A. S. Rao, ”Implementation of PID controller for liquid level system using mGWO and integration of IoT application,” *Journal of Industrial Information Integration*, vol. 28, p. 100368, Jul. 2022, doi: 10.1016/j.jii.2022.100368.

[17] G. Çetin, O. Özkaraca, and A. Keçebaş, ”Development of PID based control strategy in maximum exergy efficiency of a geothermal power plant,” *Renewable and Sustainable Energy Reviews*, vol. 137, p. 110623, Mar. 2021, doi: 10.1016/j.rser.2020.110623.

[18] J. Chen and T.-C. Huang, “Applying neural networks to on-line updated PID controllers for nonlinear process control,” *Journal of Process Control*, vol. 14, no. 2, pp. 211–230, Mar. 2004, doi: 10.1016/S0959-1524(03)00039-8.

[19] R. Kumar, S. Srivastava, and J. Gupta, “Artificial neural network based pid controller for online control of dynamical systems,” in *2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES)*, Delhi, India, 2016, pp. 1-6, doi: 10.1109/ICPEICES.2016.7853092.

[20] R. Sharma, P. Gaur, S. Bhatt, and D. Joshi, “Optimal fuzzy logic-based control strategy for lower limb rehabilitation exoskeleton,” *Applied Soft Computing*, vol. 105, pp. 1-12, 2021, doi: 10.1016/j.asoc.2021.107226.

[21] S. Zhu, S. Zhou, Z. Chen, W. Song, and L. Jin, “Gait-stride-and-frequency-based human intention recognition approach and experimental verification on lower limb exoskeleton,” *Transactions of the Institute of Measurement and Control*, vol. 44, no. 5, pp. 1149–1160, 2022, doi: 10.1177/01423312211044031.

[22] M. S. Amiri, R. Ramli, and M. F. Ibrahim, ”Hybrid design of pid controller for four dof lower limb exoskeleton,” *Applied Mathematical Modelling*, vol. 72, pp. 17–27, 2019, doi: 10.1016/j.apm.2019.03.002.

[23] K. H. Al-Waeli, R. Ramli, S. M. Haris, Z. B. Zulkoffli, and M. S. Amiri, “Offline ANN-PID controller tuning on a multi-joints lower limb exoskeleton for gait rehabilitation,” *IEEE Access*, vol. 9, pp. 107360-107374, 2021, doi: 10.1109/ACCESS.2021.3101576.

[24] Y.-S. Lee and D.-W. Jang, “Optimization of neural network-based self-tuning pid controllers for second order mechanical systems,” *Applied Sciences*, vol. 11, no. 17, pp. 1-12, 2021, doi: 10.3390/app11178002.

[25] Q. Yang, F. Zhang, and C. Wang, “Deterministic learning-based neural pid control for nonlinear robotic systems,” *IEEE/CAA Journal of Automatica Sinic*, vol. 11, no. 5, pp. 1227-1238, May. 2024, doi: 10.1109/JAS.2024.124224.

[26] A. Marino and F. Neri, ”PID tuning with neural networks,” *Intelligent Information and Database Systems*, vol. 11431, pp. 476–487, 2019, doi: 10.1007/978-3-030-14799-0_41.

[27] R. Jacob and S. Murugan, ”Implementation of neural network based pid controller,” in *2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT)*, Chennai, India, 2016, pp. 2769-2771, doi: 10.1109/ICEEOT.2016.7755199.

[28] N. Aliman, R. Ramli, S. M. Haris, M. S. Amiri, and M. Van, “A robust adaptive- fuzzy-proportional-derivative controller for a rehabilitation lower limb exoskeleton,” *Engineering Science and Technology, an International Journal*, vol. 35, pp. 1-14, Nov. 2022, doi: 10.1016/j.jestch.2022.101097.

[29] Z. Chen, Q. Guo, H. Xiong, D. Jiang, and Y. Yan, “Control and implementation of 2-dof lower limb exoskeleton experiment platform,” *Chinese Journal of Mechanical Engineering*, vol. 34, no. 1, pp. 1-17, Feb. 2021, doi: 10.1186/s10033-021-00537-8.

[30] M. S. Amiri, R. Ramli, M. F. Ibrahim, D. A. Wahab, and N. Aliman, “Adaptive particle swarm optimization of pid gain tuning for lower-limb human exoskeleton in virtual environment,” *Mathematics*, vol. 8, no. 11, pp. 1-16, 2020, doi: 10.3390/math8112040.

[31] M. S. Amiri, R. Ramli, and M. F. Ibrahim, “Genetically optimized parameter estimation of mathematical model for multi-joints hip–knee exoskeleton,” *Robotics and Autonomous Systems*, vol. 125, pp. 1-10, 2020, doi: 10.1016/j.robot.2020.103425.

[32] J. Wilkie, M. Johnson, and R. Katebi, *Control Engineering*, Macmillan Education UK, 2001.

[33] M. Palermo, J. M. Lopes, J. Andre, A. C. Matias, J. Cerqueira, and C. P. Santos, “A multi-camera and multimodal dataset for posture and gait analysis,” *Scientific Data*, vol. 9, no. 1, pp. 1-11, Oct. 2022, doi: 10.1038/s41597-022-01722-7.

[34] H. Septanto, E. Yulihastin, E. Kurniawan, and D. Suprijanto, “Simulation study of attitude control using a reaction wheel on an air bearing platform with anti-windup compensator,” *AIP Conference Proceedings*, vol. 2663, no. 1, 2022, doi: 10.1063/5.0108502.

[35] H. Septanto, A. Syaichu-Rohman, and D. Mahayana, “Static anti-windup compensator design of linear sliding mode control for input saturated systems,” in *Proceedings of the 2011 International Conference on Electrical Engineering and Informatics*, Bandung, Indonesia, 2011, pp. 1-4, doi: 10.1109/ICEEI.2011.6021650.

BIOGRAPHIES OF AUTHORS

Ummi Hanifah received the Bachelor of Engineering in Biomedical Engineering from Airlangga University, Indonesia, in 2023 and currently became a master student in biomedical engineering from Universitas Airlangga. Her research interests include biomedical instrumentation and artificial intelligence. She can be contacted at email: ummi.hanifah-2023@fst.unair.ac.id.

Aura Adinda received the Bachelor degree in Biomedical Engineering from Airlangga University, Indonesia, in 2023, a Master degree in Biomedical Engineering from Airlangga University, Indonesia, in 2024. Her research focus on instrumentation and the application of artificial intelligence in healthcare technologies. She can be contacted at email: aura.adinda-2023@fst.unair.ac.id.

Akif Rahmatillah is a lecturer at the Biomedical Engineering study program, Faculty of Science and Technology, Universitas Airlangga Indonesia. He received his B.Eng. degree in Engineering Physics (minor in Instrumentation and Control) from Universitas Gadjah Mada and M.Eng. in Control and Intelligent Systems from Institut Teknologi Bandung. He is now pursuing his doctoral studies in Instrumentation and Control at the Department of Engineering Physics. Insitut Teknologi Sepuluh Nopember. His research interests include biomedical control systems and biomechatronics. He can be contacted at email: akif-r@fst.unair.ac.id.

Imam Sapuan received B.Sc. degree in Physics Science from Airlangga University, Indonesia, in 1998, M.Sc. degree in Physical Science from Gadjah Mada University, Indonesia, in 2005, and a Doctoral degree in Mathematics and Natural Sciences from Faculty of Science and Technology, Airlangga University, Indonesia, in 2021. Currently, he is Assistant Professor at the Physics science Study Program, Department of Physics, Faculty of Science and Technology, Universitas Airlangga, Indonesia. His research interests include biomedical, industries instrument, and electrical impedance. He can be contacted at email: i_sapuan@fst.unair.ac.id.

Khusnul Ain received B.Eng. degree in nuclear engineering from Gadjah Mada University, Indonesia, in 1995, M.Sc. degree in Physical Sciences from Gadjah Mada University, Indonesia, in 2002, and Ph.D. degree in Engineering Physics from Bandung Institute of Technology, Indonesia, in 2014. Currently, he is a Professor at the Biomedical Engineering Study Program, Faculty of Science of Technology, Universitas Airlangga, Indonesia. His research interests include biomeasurement, electrical impedance spectroscopy, electrical impedance tomography, computational modeling, and bioinstrumentation. He can be contacted at email: k_ain@fst.unair.ac.id.

Harry Septanto is a Research Professor at the National Research and Innovation Agency (BRIN), Indonesia. He received his B.Eng., M.Eng., and Ph.D. degrees from Institut Teknologi Bandung in Engineering Physics, Electrical Engineering, and Electrical Engineering & Informatics, in 2002, 2010, and 2015, respectively. He is currently a Section Editor of the Jurnal Elektronika dan Telekomunikasi (JET). His research interests include nonlinear control theory, multi-agent system, and signals & systems. He can be contacted at email: harry.septanto@brin.go.id.

Rifai Chai received the B.Eng. degree from Krida Wacana Christian University (UKRIDA) Jakarta, Indonesia in 2000 and the Ph.D. degree in Biomedical Engineering from the University of Technology Sydney (UTS), Sydney, Australia in 2014. From 2000 to 2011 he has worked as electronic-product development engineer with companies in Indonesia and Australia. Currently, he is working as Senior Lecturer with Faculty of Science, Engineering and Technology, Swinburne University of Technology, Melbourne, Australia. His research interests are brain-computer interfaces, rehabilitation, medical technologies, and artificial intelligence. Currently, he is a senior member of IEEE and serves as Associate Editor for Electronics Letters. He can be contacted at email: rchai@swin.edu.au.