A Novel Robust and Intelligent Control Based Approach for Human Lower Limb Rehabilitation via Neuromuscular Electrical Stimulation

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August 19, 2019

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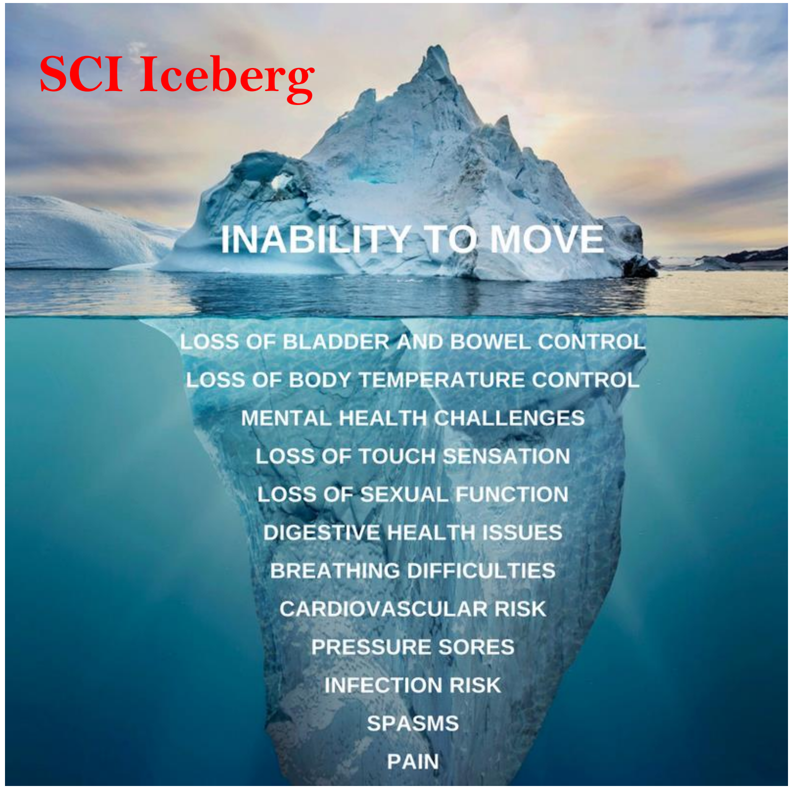
Introduction

- ## Context of the problem

Human lower limb rehabilitation for spinal cord injured patients:

- **Temporary or permanent changes in spinal cord function.**
- **Total or partial paralysis.**
- **Muscles atrophies and spasms.**
- **Often irreversible.**
- **Inability to complete daily and/or occupational activities.**

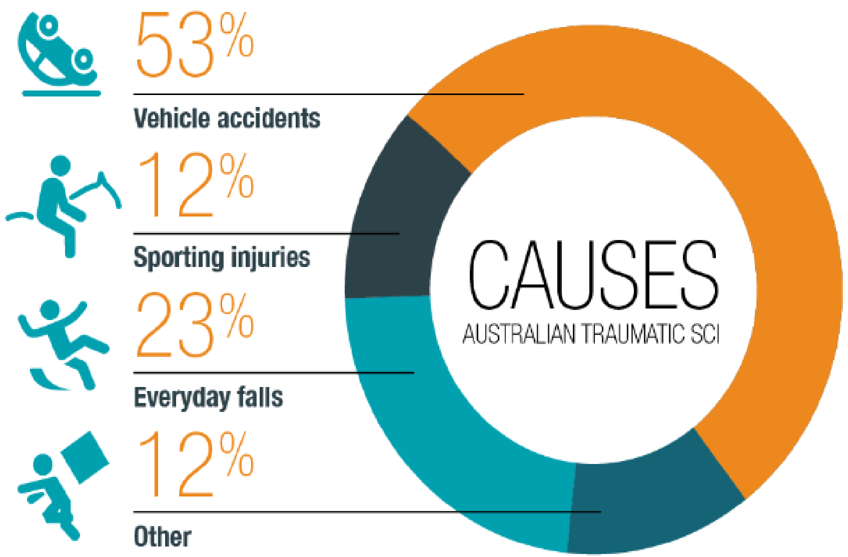


Introduction

- ## Context of the problem

Key facts provided by the World Health Organization (WHO):

- Every year, around the world, 250.000 to 500.000 people suffer SCI.
- The majority of SCIs are due to traumatic causes.
- People with a SCI are two to five times more likely to die prematurely.
  - Even worse survival rates in low- and middle-income countries.

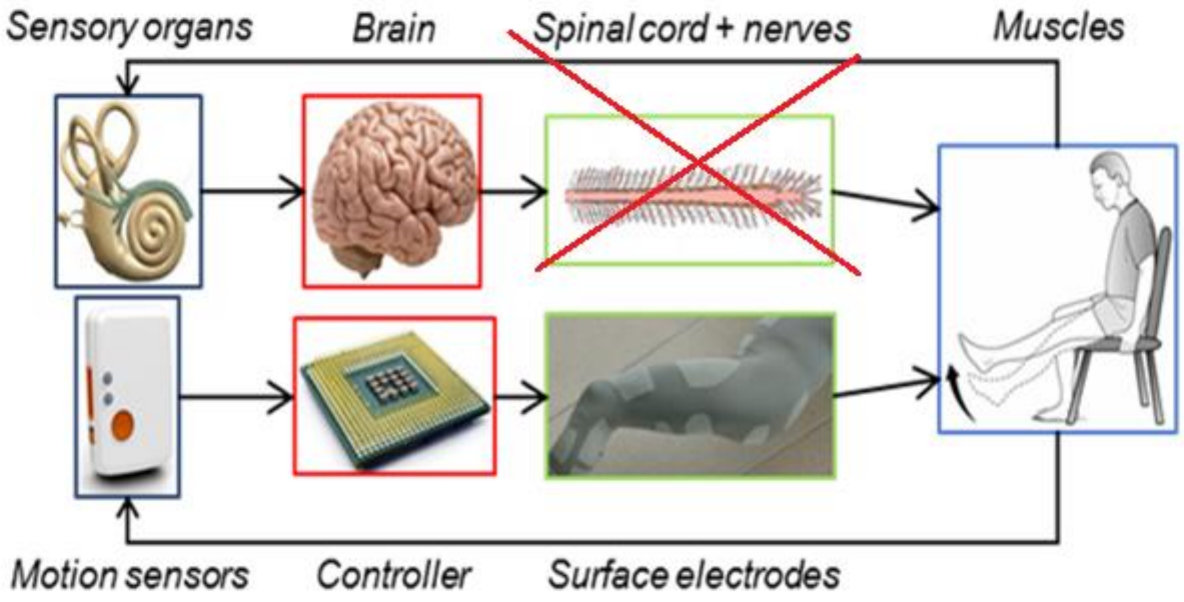


Introduction

- Context of the problem

Neuromuscular/Functional Electrical Stimulation (NMES/FES):

- Applies a potential field across the muscle to achieve the desired muscle contraction.
- Rehabilitation and strength training tool.
- Increases strength and range of motion.

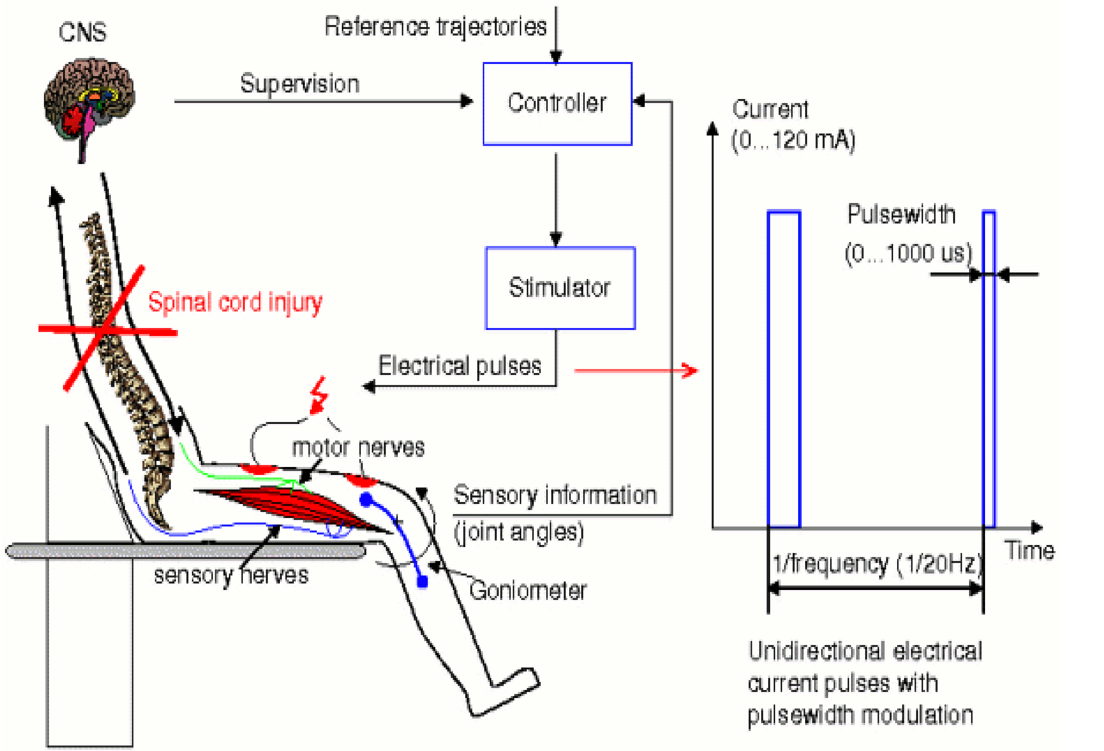


Introduction

- ## Main motivation

Commercial stimulators are available in open-loop, while real-world NMES/FES systems to rehabilitate SCI patients require control strategies that compensate for:

- **Modeling errors in the plant.**
- **System's fault.**
- **Individuals muscle's behavior.**
- **External disturbances.**
- **Nonideal muscles conditions.**



Introduction

- ## Specific motivations

Robust Integral of the Sign of the Error (RISE):

- **Continuous and robust technique for uncertain nonlinear systems.**
- **Asymptotic tracking even in spite of:**
  - **bounded smooth external disturbances;**
  - **bounded modeling uncertainties.**
- **Implicit learning characteristics.**
- **However, the controller parameters adjustment is the key factor.**

Question

As well as for many empirical controllers, how to select the gain parameters of the RISE controller?

Introduction

- **Specific motivations**

RISE controller for lower limb tracking control.

Authors and years	Validation	Tuning
Stegath et al. (2007, 2008)	2 healthy subjects	Not informed
Sharma et al. (2009, 2012)	5 and 9 healthy subjects	Not informed
Kawai et al. (2014)	Simulation	Adjusted by simulation
Kushima et al. (2015)	7 healthy subjects	Not informed
Downey et al. (2015b)	4 healthy subjects	Pretrial tests

MOTIVATIONS:

1) **Lack of intelligent techniques (empiric tuning).**
2) **Experiments only (if done) with healthy subjects.**

Introduction

- **General and specific objectives**

To propose a novel robust and intelligent control-based methodology to human lower limb rehabilitation via NMES/FES.

Specific objectives:

- **Propose an improved genetic algorithm (IGA).**
- **Simulation and experimental results.**
- **Use of past rehabilitation data.**
- **Deep and dynamic neural networks for system identification.**

Introduction

- ## Hypotheses

Empirical tuning: a large number of poor performances
VS
Adequate tuning with a more representative identified model: better tracking control of the lower limb.

The use of past rehabilitation data for identifying a patient: the model will improve the description of the relationship between angular position and the delivered electrical stimulus.

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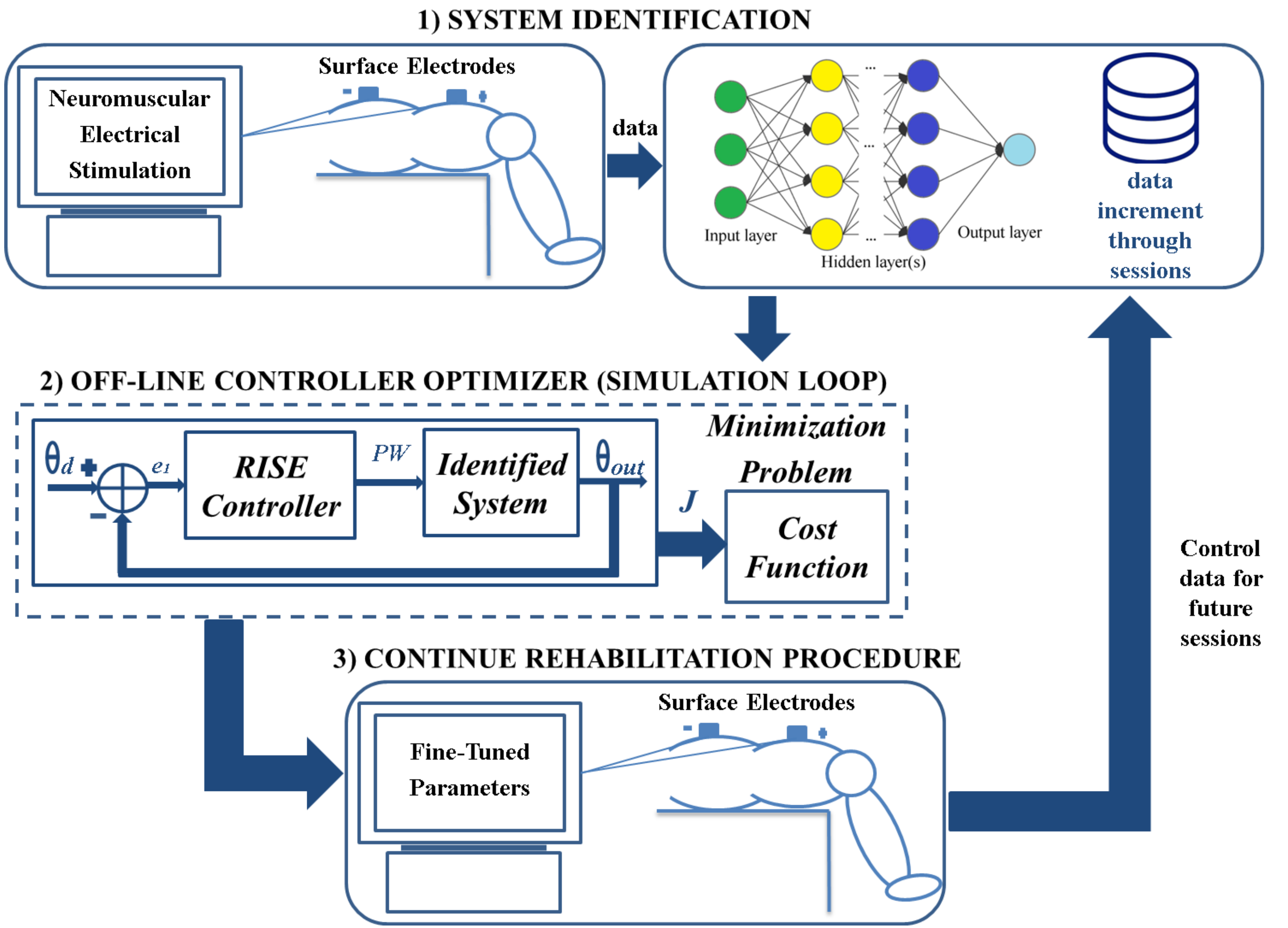
Proposed methodology



Theoretical background

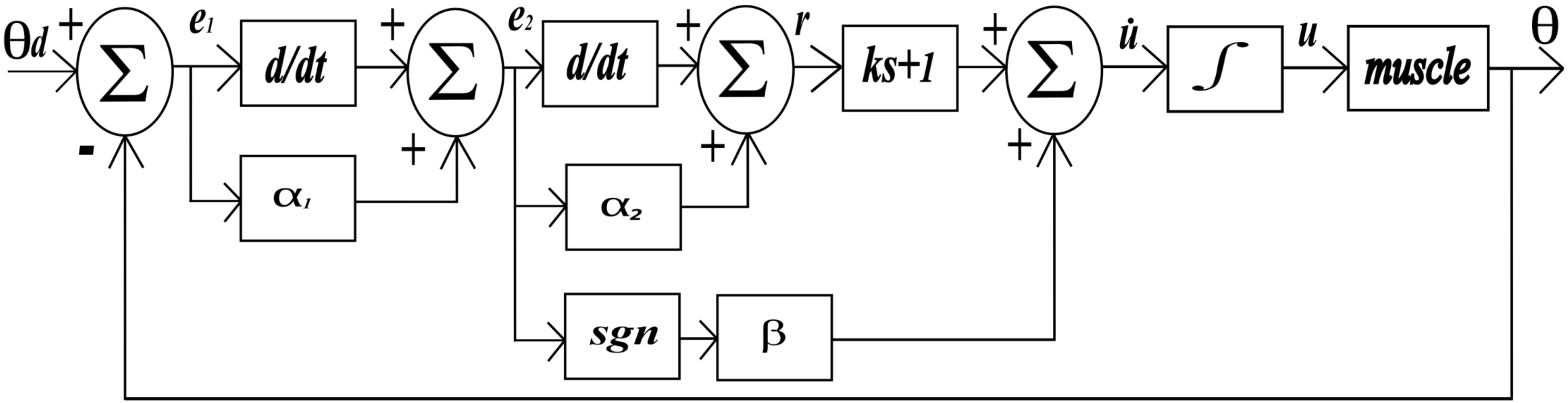
- **RISE control development**

The RISE controller yields an asymptotic stability result despite an uncertain nonlinear muscle model and in the presence of additive bounded disturbances.

Control law:

$$u = (k_s+1)e_2 - (k_s+1)e_2(0) + \int[(k_s+1)\alpha_2 e_2(\tau) + \beta sgn(e_2(\tau))d\tau]$$

$$\dot{u} = (k_s+1)r + \beta sgn(e_2)$$



Theoretical background

• Improved genetic algorithm

➢ **Preprocessing** step (**bound gain limits**).

➢ **Construction** phase (**fast genetic algorithm**).

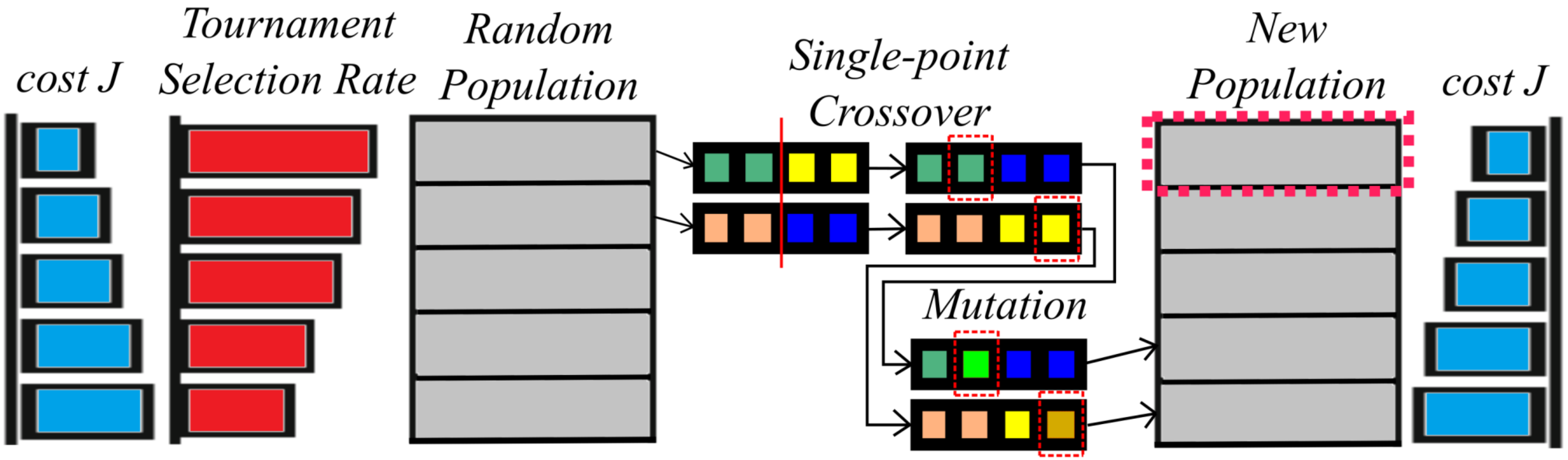
➢ **Local search** phase (**complete genetic algorithm**).

Alfa1	Alfa2	Ks	Beta
α_1	α_2	K_s	β

$$min : J(\alpha_1, \alpha_2, k_s, \beta) = RMSE + penalty$$

$$RMSE = \int_0^T \sqrt{E((\theta_d - \theta)^2)}$$

$$penalty = \int_0^{TR} \sqrt{E((\theta_d - \theta)^2)}$$



Theoretical background

- System identification via NNs

The system identification problem is as follow: We have observed inputs, u(k), and observed outputs, y(k), from a discrete dynamical system.

$$u^k = [u(1), u(2), \ldots, u(k)]$$
$$y^k = [y(1), y(2), \ldots, y(k)]$$

where we are looking for a relationship between past observations $[\boldsymbol{u}^{k-1}, \boldsymbol{y}^{k-1}]$ and future output, y(k). Below, $\boldsymbol{f}(.)$ is an unknown nonlinear difference equation that represents the plant dynamics.

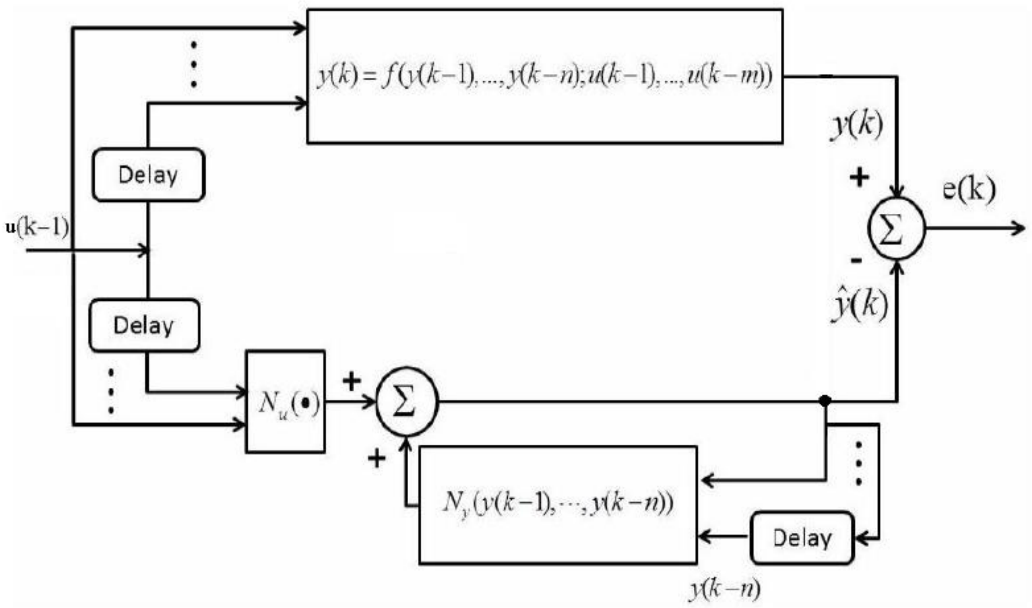
$$y(k) = f[y(k-1), \ldots, y(k-n); u(k-1), \ldots, y(k-n)]$$

Theoretical background

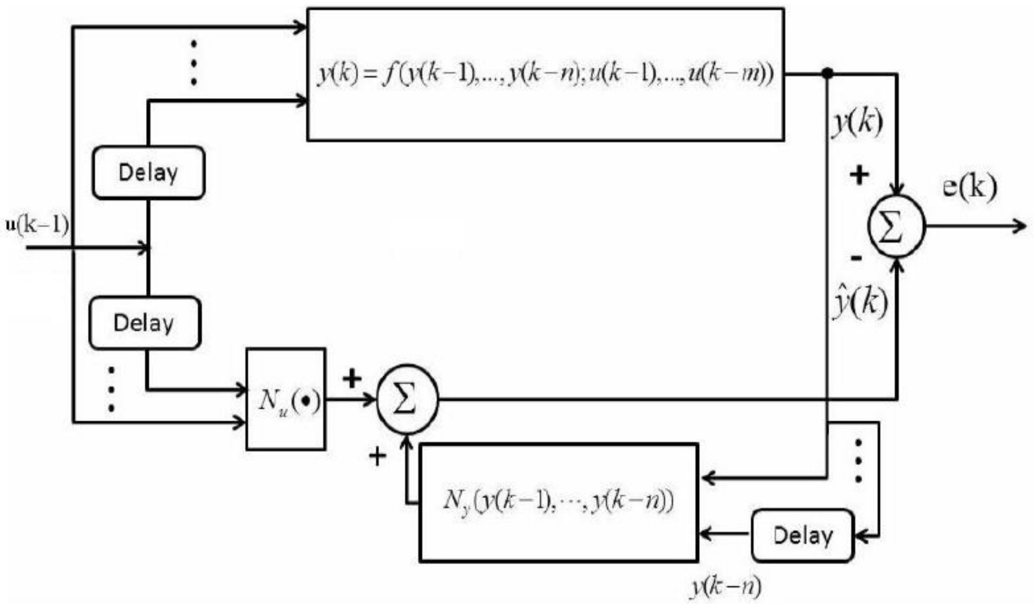
- **System identification via NNs**

Parallel and series-parallel identification models.

$$\hat{y}(k) = F[\hat{y}(k-1),\ldots,\hat{y}(k-n); u(k-1),\ldots,u(k-m)]$$



$$\hat{y}(k) = F[y(k-1),\ldots,y(k-n); u(k-1),\ldots,u(k-m)]$$



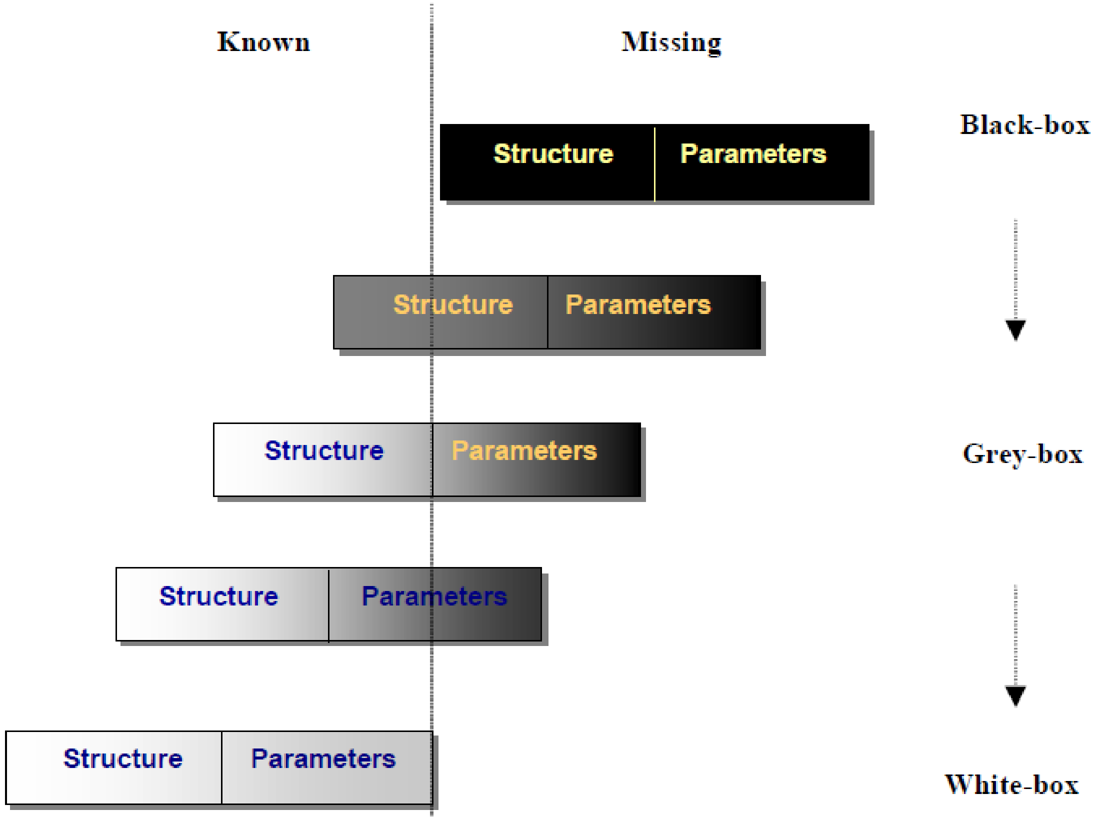
where *F* is the model structure (e.g., the NN or machine learning tools).

Theoretical background

- ## System identification via NNs

Why black-box models?

- ➢ Much simpler than physical modeling.
- ➢ Lack of knowledge of the underlying physiology.
- ➢ When physical knowledge is too complex.
- ➢ Big data (easy collection and storage).
- ➢ Powerful computation.



Theoretical background

- **System identification via NNs**

Why neural networks?

- For every patient, the number of data will increase during rehabilitation sessions.
  - As more data become available more accurate the model becomes.
  - Thus, muscular variability and nonlinear behavior over days will be detected (fatigue, tremors, spasms, etc).
- Are easier to train than: 1) mathematically modeling the knee joint dynamics; 2) executing tests for identifying parameters.

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Simulation results (mathematical model)

- Human lower limb

Lynch (2011) developed a model describing the relationship between electrical stimulus and joint torque with nonideal muscle conditions.

$$J\ddot{\theta} = \tau_{gravity} + \tau_{stiffness} + \tau_{damp} + \upsilon$$

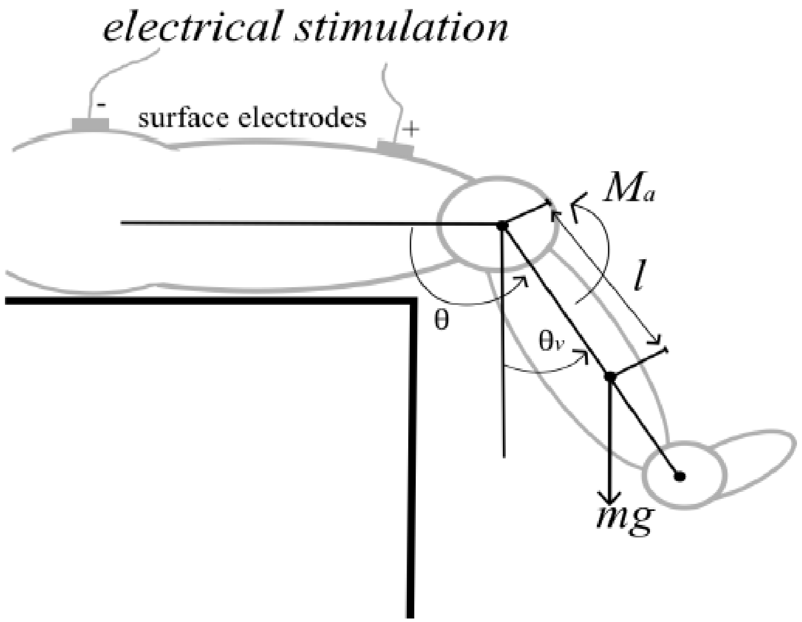
$$\tau_{gravity} = -mgl\sin\theta$$

$$\tau_{stiffness} = \lambda e^{-E(\theta+\frac{\pi}{2})}(\theta + \frac{\pi}{2} - \omega)$$

$$\tau_{damp} = -B\dot{\theta}$$

$$\upsilon = (1 + spm + tr)(M_a)fat$$

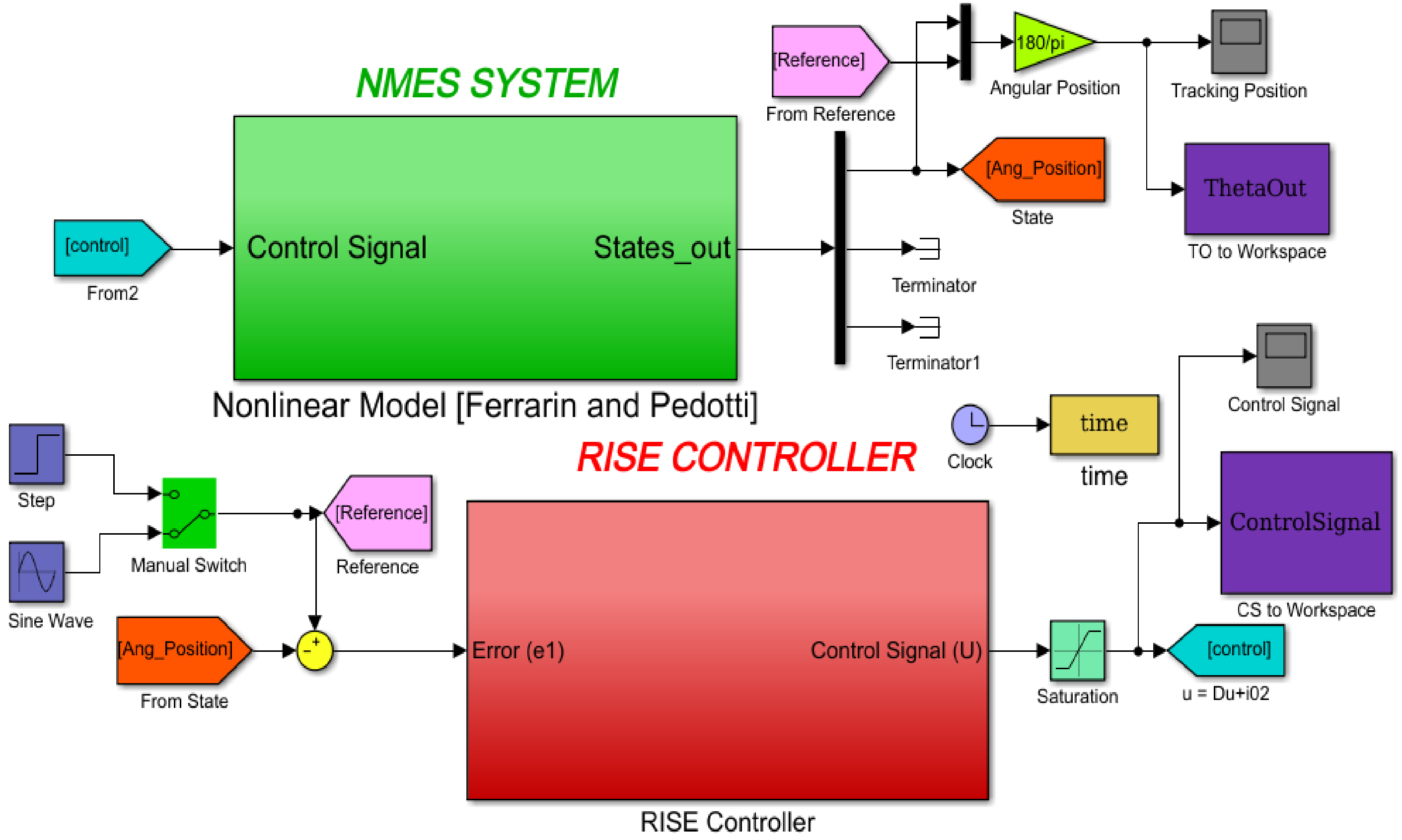
$$M_a = \frac{G}{1+\eta s}PW_{quad}(s)$$



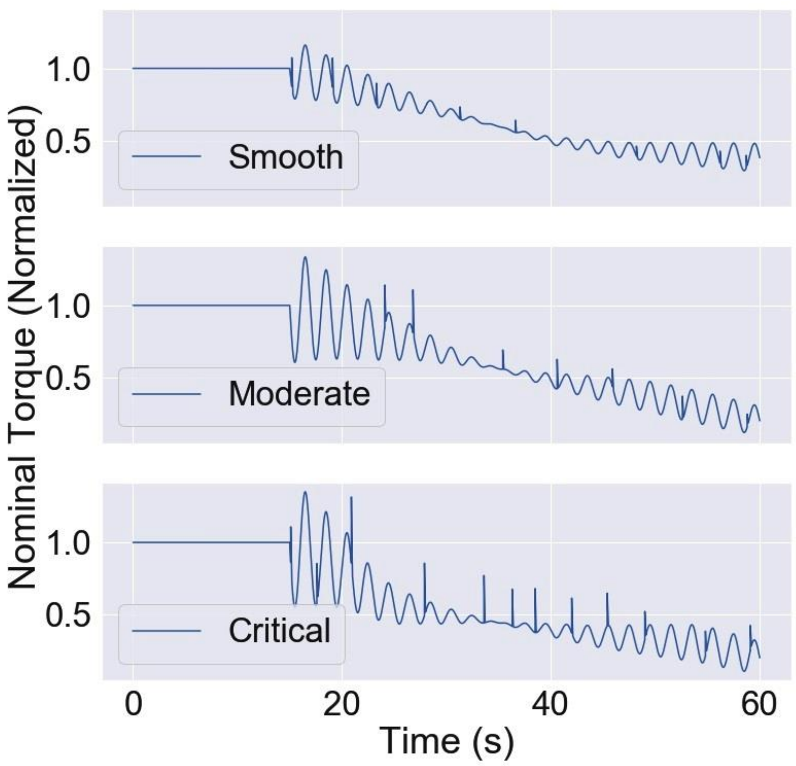
Source: Adapted from Ferrarin and Pedotti (2000)

Simulation results (mathematical model)

- ## Materials and methods



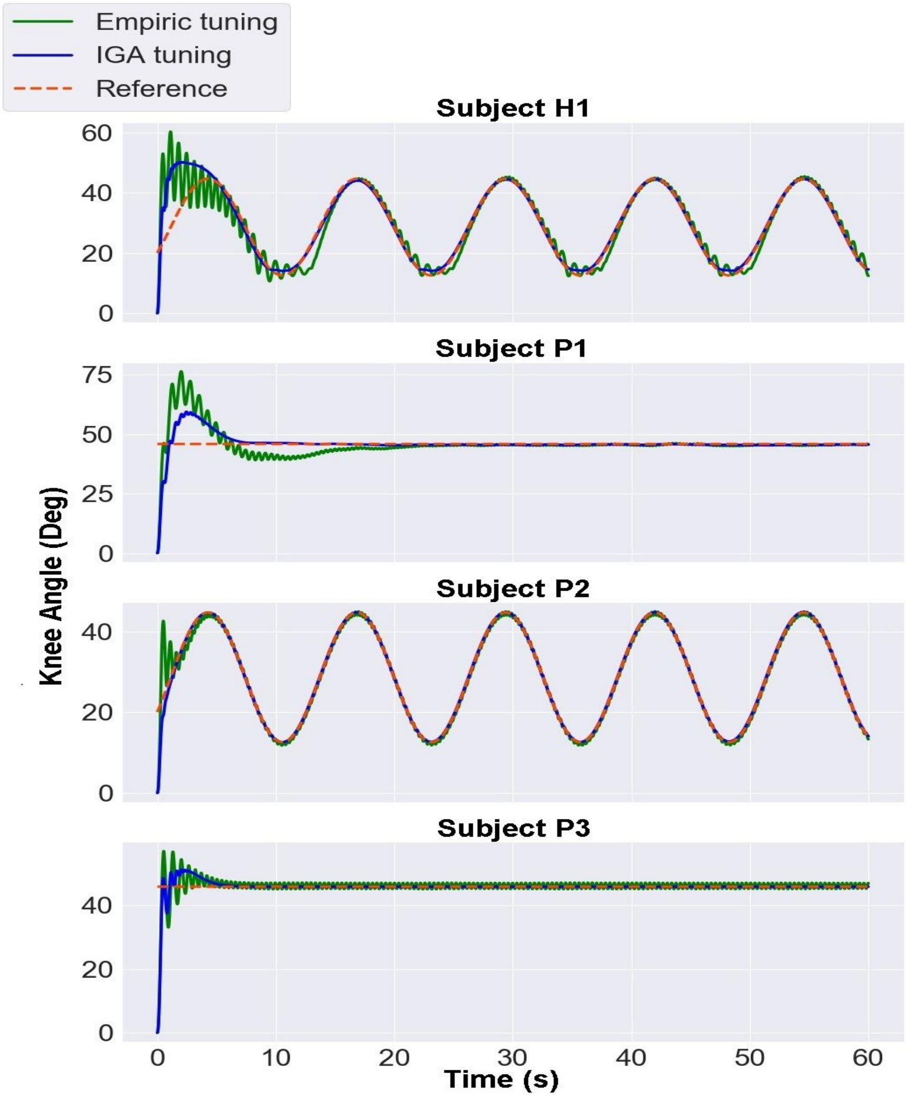
simulink model



non-idealities

Simulation results (mathematical model)

- ## Results and discussion



Empiric VS IGA tuning (ideal conditions):

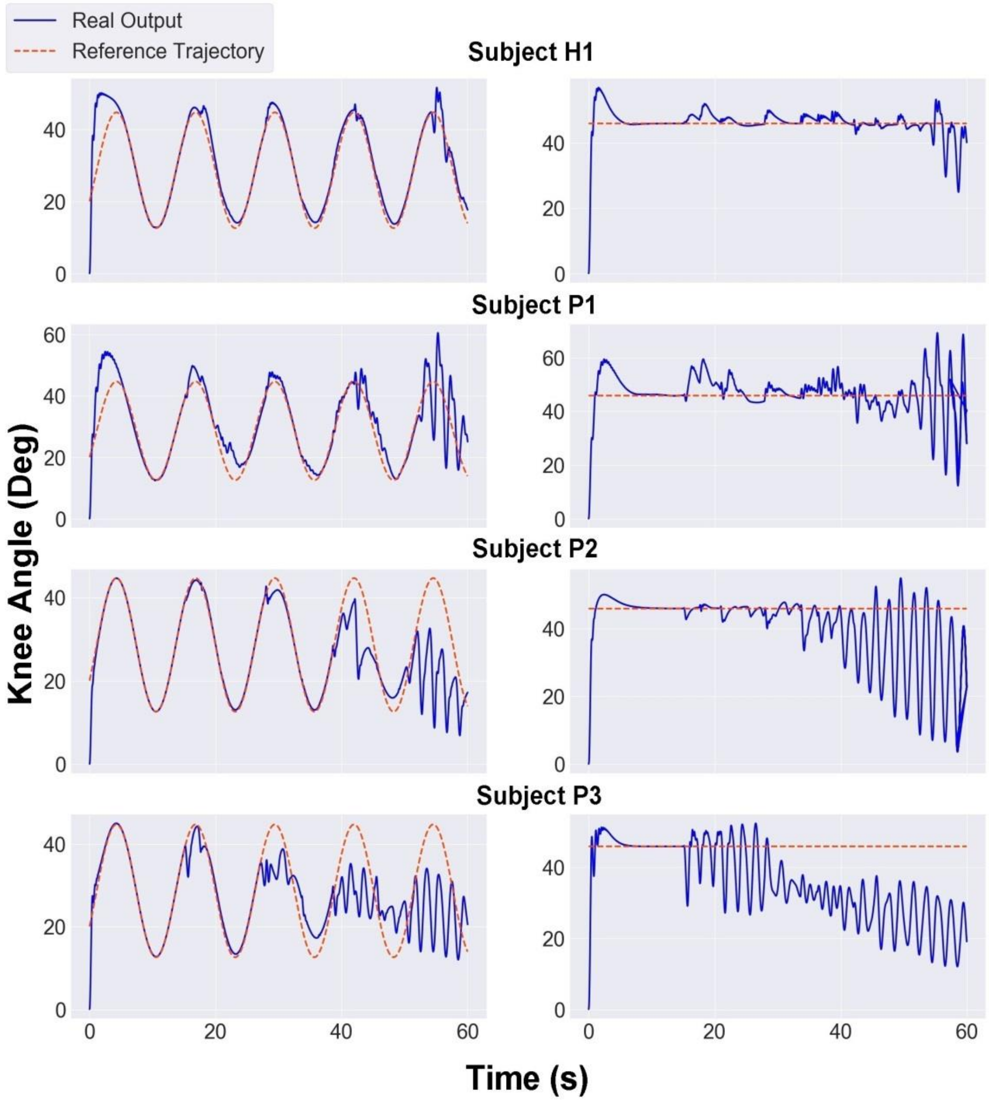
- Empiric gains can also lead to stability. However, as gains selection are immense it is likely to one choose combinations that would not guarantee the best performance.

Simulation results (mathematical model)

- ## Results and discussion

Responses of healthy and paraplegic subjects with IGA tuning (critical nonideal conditions)

- In all cases, transient response presented interesting results, where stronger muscles result in bigger overshoot.
- However, strong muscles demonstrate less sensitivity to external disturbances modeled in this research.



Simulation results (mathematical model)

- **Results and discussion**

Simulation responses are according to real-world applications.

- **Healthy subjects even in spite of non-idealities could track and regulate very well.**
- **An SCI patient with strong muscles (P1) also presented good results, but not as well as a healthy one.**
- **SCI patients with weak muscles do not reach well tracking and regulation results with non-idealities in the model.**

Simulation systems provide a lot of information about human identified behavior to NMES/FES, permitting to save time and resources.

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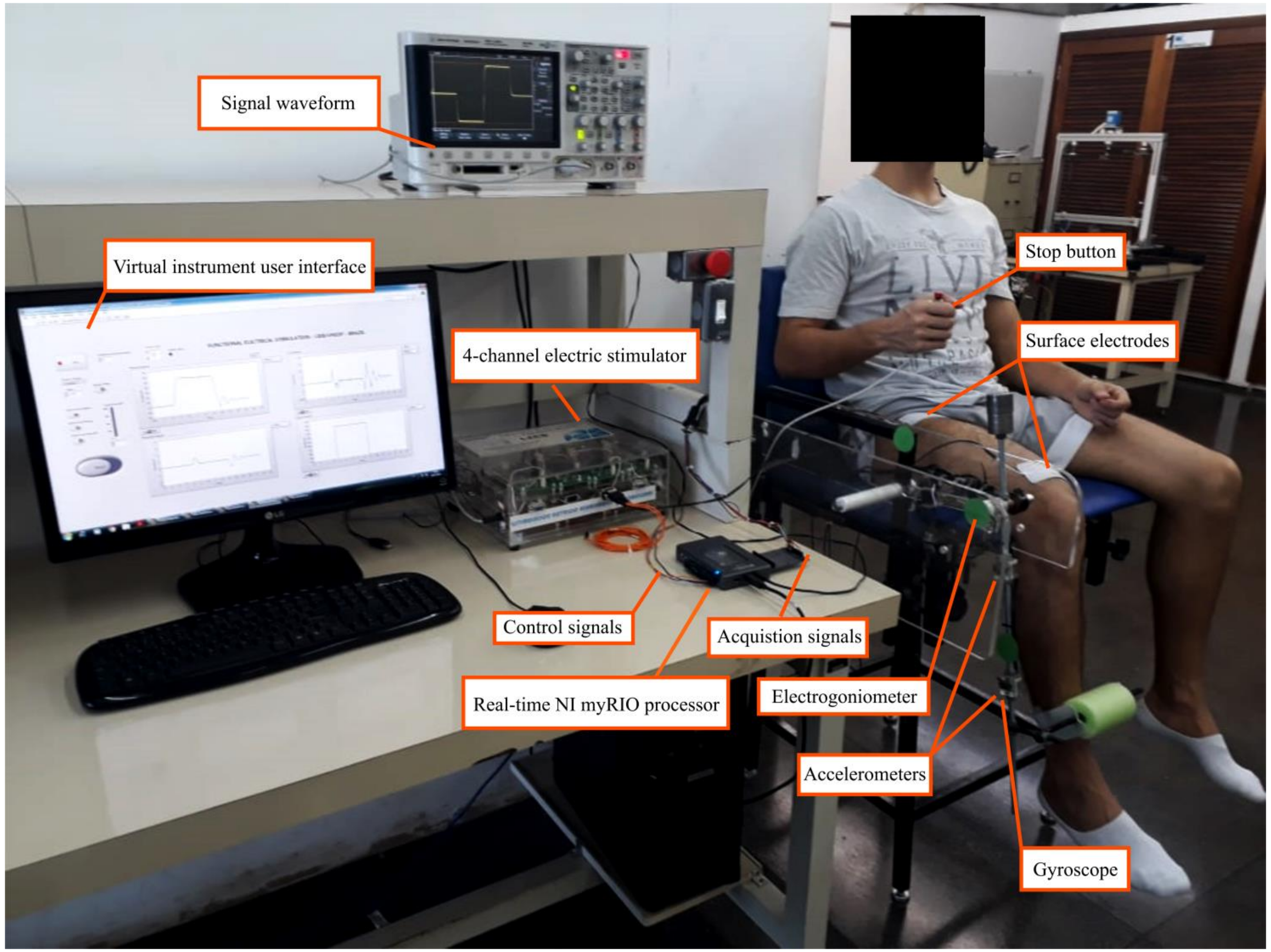
Experimental results (NN models)

- ## Instrumentation

- Neuromuscular electrical stimulator allows a control adjustment of PW in a range of 0–400μs.

- Stimulus frequency was fixed in 50 Hz and the pulse amplitude in 80 mA (healthy subjects) or 120 mA (paraplegic patients).

- Surface electrodes with rectangular self-adhesive CARCI 50 mm x 90 mm.



Experimental results (NN models)

- Analyzed individuals

The study with volunteers was authorized through a research ethics committee (CAAE 79219317.2.1001.5402) at UNESP and before the participation, written informed consent was obtained from all participants.

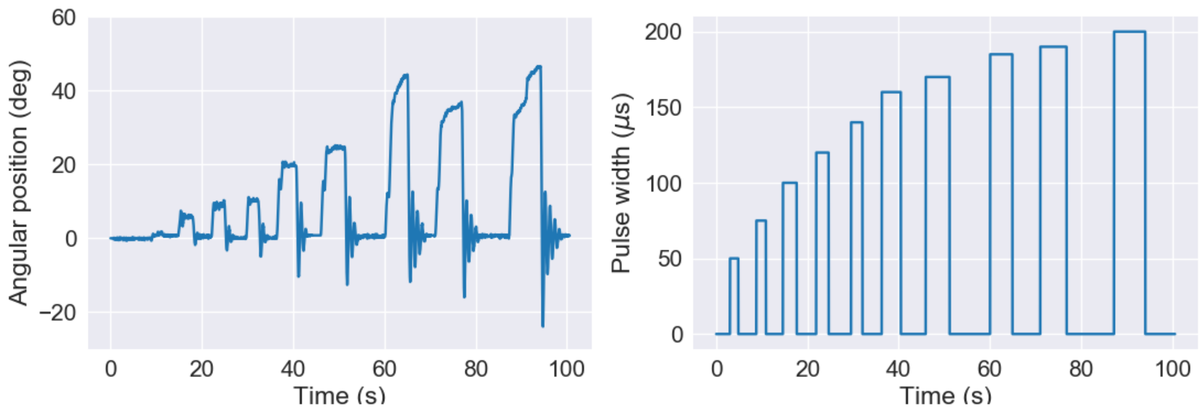
Specific data on analyzed individuals.

	H1	H2	H3	H4	H5	H6	H7	P1	P2
Age (years)	24	28	27	22	22	28	25	32	43
Weight (kg)	74.1	70.4	75	94.3	73	68.8	78.3	70.0	96.0
Height (cm)	174	167	180	186	175	170	165	170	183
Injury level	-	-	-	-	-	-	-	L4, L5	C5, C6
Injury time	-	-	-	-	-	-	-	9 years	17 years

Experimental results (NN models)

- ## Experimental set-up

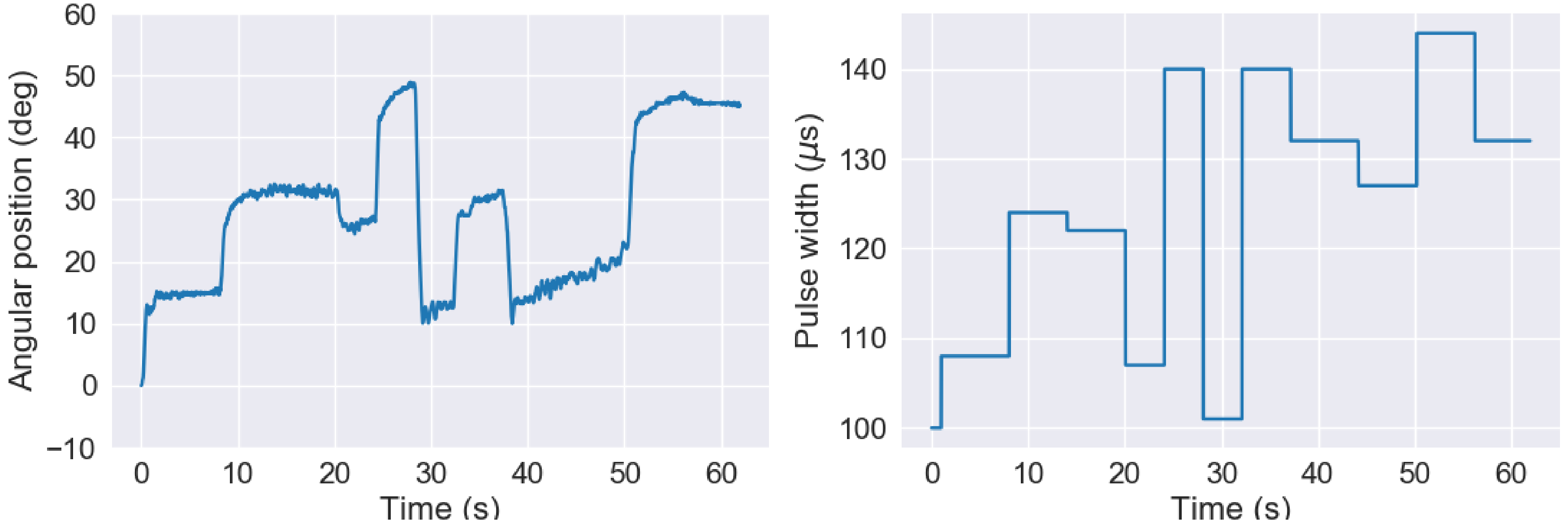
- The chair backrest and the knee joint position are adjusted for each volunteer to ensure patients comfort.
- Muscle analysis to determine the motor point.
- A few open loop tests applying a step-type signal.
  - ❑ Determine a bounded pulse width band ρ_{min} to ρ_{max}, concerning to $\theta_{min} = 10°$ and $\theta_{max} = 40°$.



Experimental results (NN models)

- **Experimental set-up: 1st session**

➢ **A stimulation test is carried out consisting of one minute of randomly selected PW in the predetermined range (ρ_{min}, ρ_{max}) per individual, being each value applied during minimum four and maximum seven seconds (also random).**



Experimental results (NN models)

- **Experimental set-up: 1st session**

➢ **The identification data is read and manipulated for feeding up an MLP feedforward NN with one hidden layer.**

Example of how datasets are encoded.

Features		Target
Angular_Position $(k-1)$	**Pulse_Width** $(k-1)$	**Angular_Position** (k)
13.348546°	215μs	13.399383°
13.399383°	215μs	13.382377°
13.382377°	215μs	13.325167°
13.325167°	215μs	13.306247°
13.306247°	215μs	13.347835°
13.347835°	248μs	13.387653°
13.387653°	248μs	13.357460°
13.357460°	248μs	13.256510°
13.256510°	248μs	13.131691°
13.131691°	248μs	13.016152°

Experimental results (NN models)

- Experimental set-up: 1st session

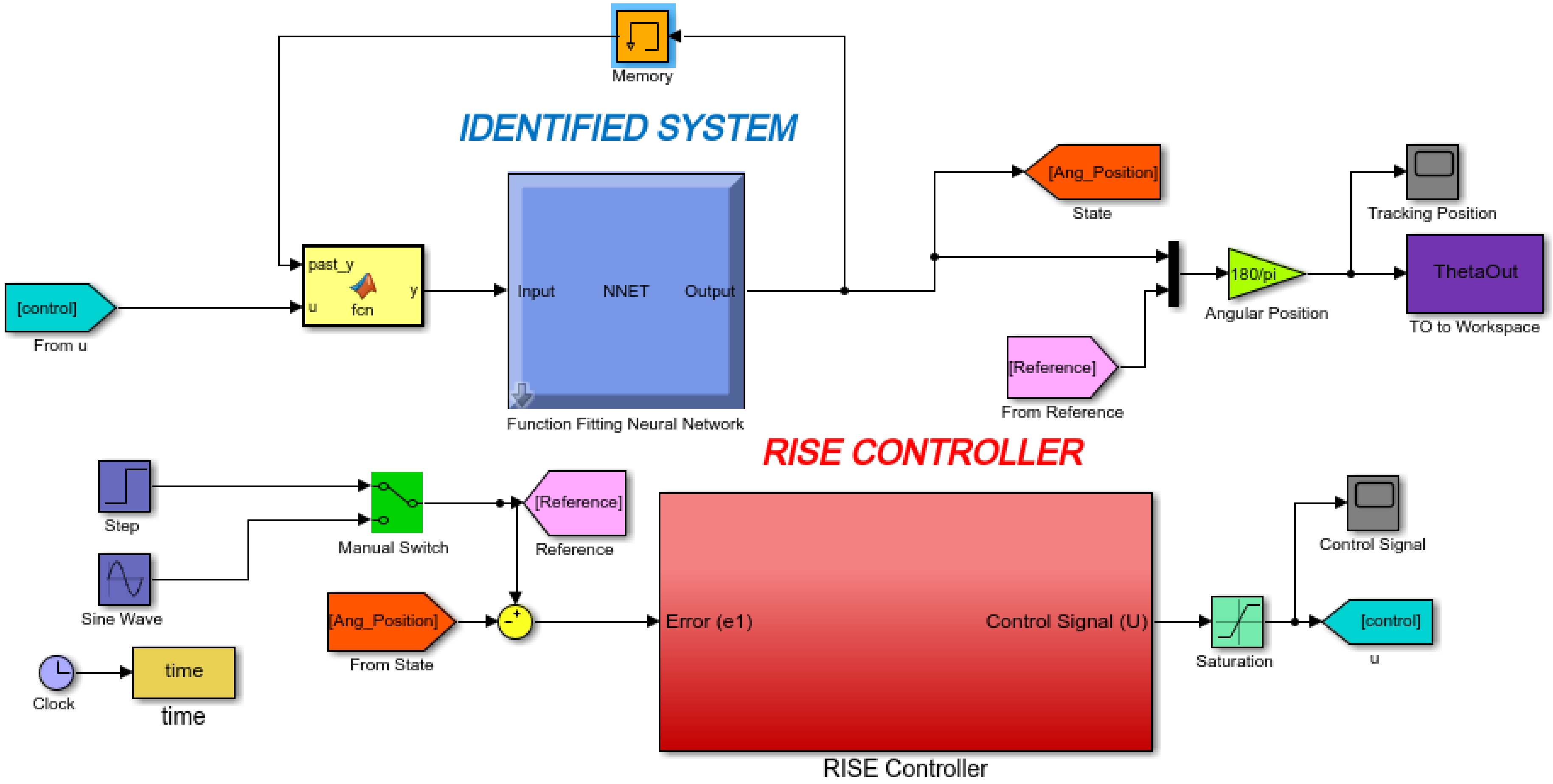
➢ Optimization procedure based on the proposed IGA to find the best gains combination for two reference trajectories.

  - ❑ Sinusoidal trajectory (10º to 40º) to mimic an isotonic contraction.
  - ❑ Step trajectory (40º) replicating an isometric contraction.

➢ Lastly, using empiric gains and then IGA gains, the controlling procedure is implemented for both trajectories.

Experimental results (NN models)

- Experimental set-up: 1st session



simulink model

Experimental results (NN models)

- **Experimental set-up: two up to five sessions**

➢ **For all individuals, data from previous rehabilitation sessions are used for training a NN model in an offline scheme.**

➢ **IGA optimization to find the best gains combination for both sine and step trajectories.**

➢ **Electrodes are positioned at the motor-point identified in the first session, and similar open-loop tests are made.**

❑ **Determine (ρ_{min}, ρ_{max}) concerning to $\theta_{min} = 10°$ and $\theta_{max} = 40°$.**

➢ **Knowing fine-tuned gains for each individual, the controlling procedure is made for both references, and then with empiric gains.**

Experimental results (NN models)

- **Results and discussion: Individual P1**

➤ **Patient P1 participated in one session.**

Technical information on experiments for individual P1.

Identification		Empiric		Sine IGA		Step IGA	
$\rho_{min};\rho_{max}$	$\theta_{min};\theta_{max}$	$\rho 0;sat$	$\alpha_1;\alpha_2;ks;\beta$	$\rho 0;sat$	$\alpha_1;\alpha_2;ks;\beta$	$\rho 0;sat$	$\alpha_1;\alpha_2;ks;\beta$
200;250	18;50	200;350	1;2;30;5	180;300	2.61;3.34;48.94;1.78	180;300	2.72;3.57;47.12;1.54

Identification results for individual P1.

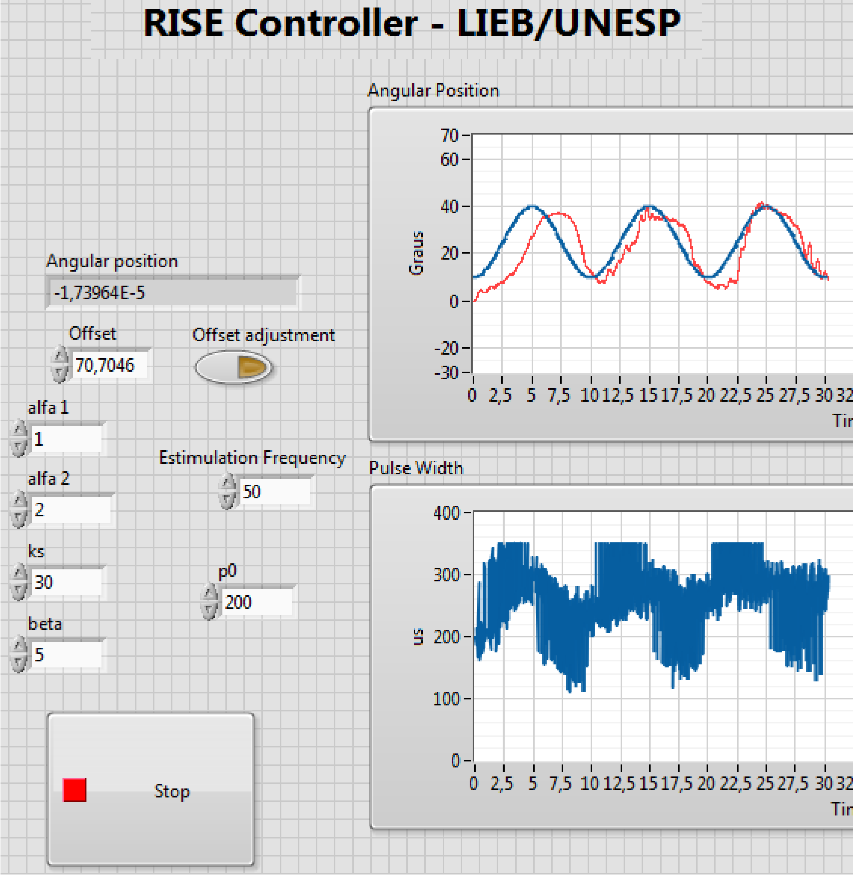
Session	TT	Corr	MSE
1st	28(s)	0.836	0.0019

Metrics on experimental results for individual P1.

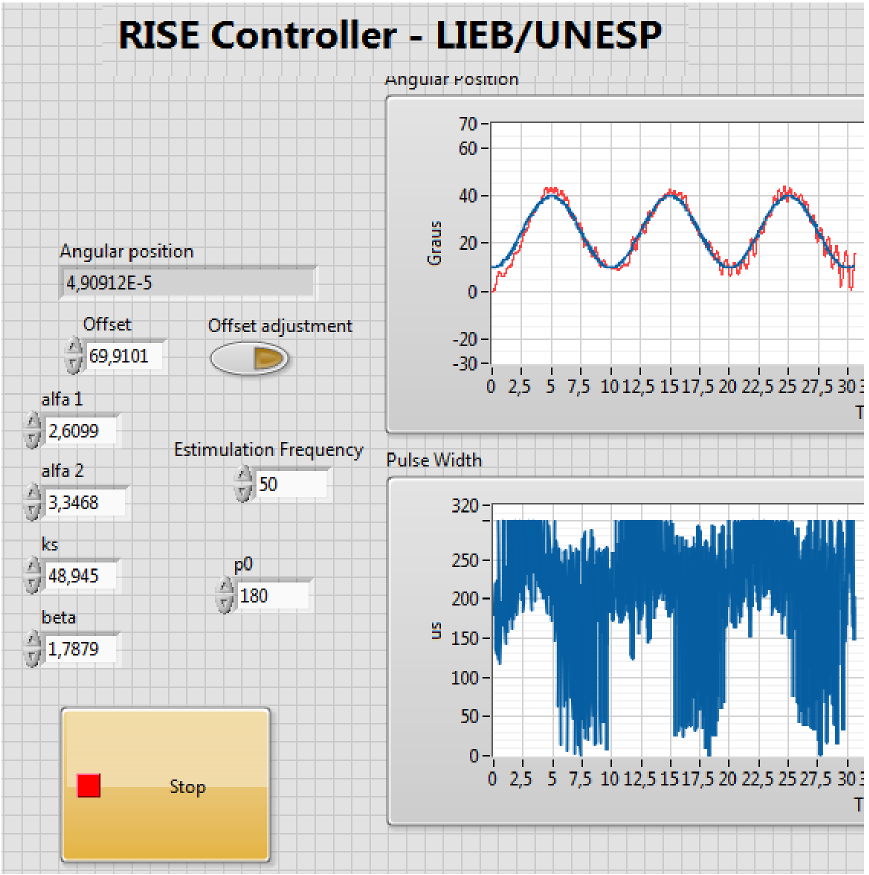
	Sine				Step			
	Empiric		IGA		Empiric		IGA	
Session	RMSE	TEC	RMSE	TEC	RMSE	TEC	RMSE	TEC
1st	9.1471°	30(s)	2.9842°	30(s)	10.9950°	30(s)	5.9786°	25(s)

Experimental results (NN models)

- **Results and discussion: Individual P1**



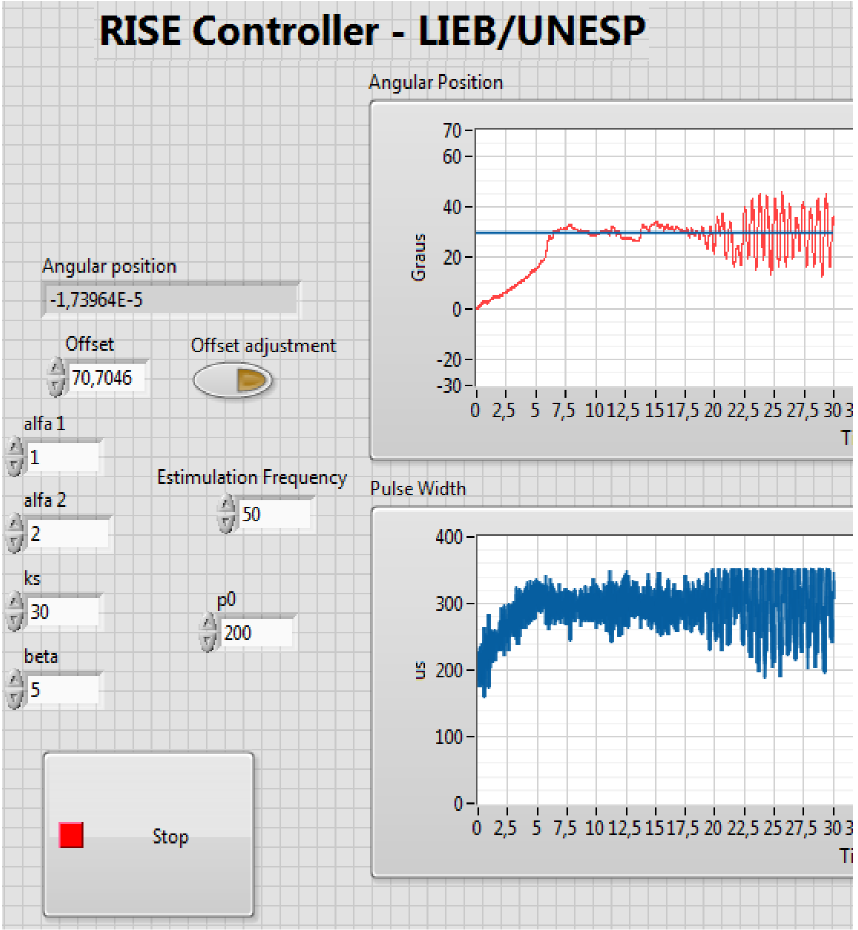
empiric gains



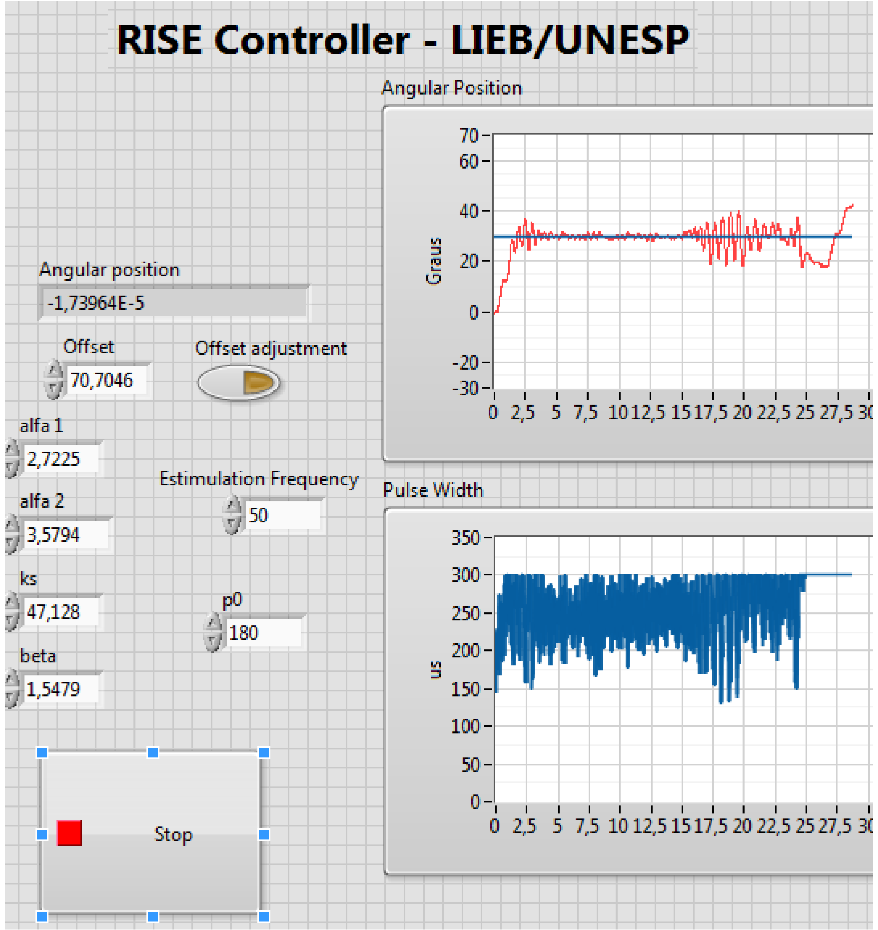
IGA gains

Experimental results (NN models)

- **Results and discussion: Individual P1**



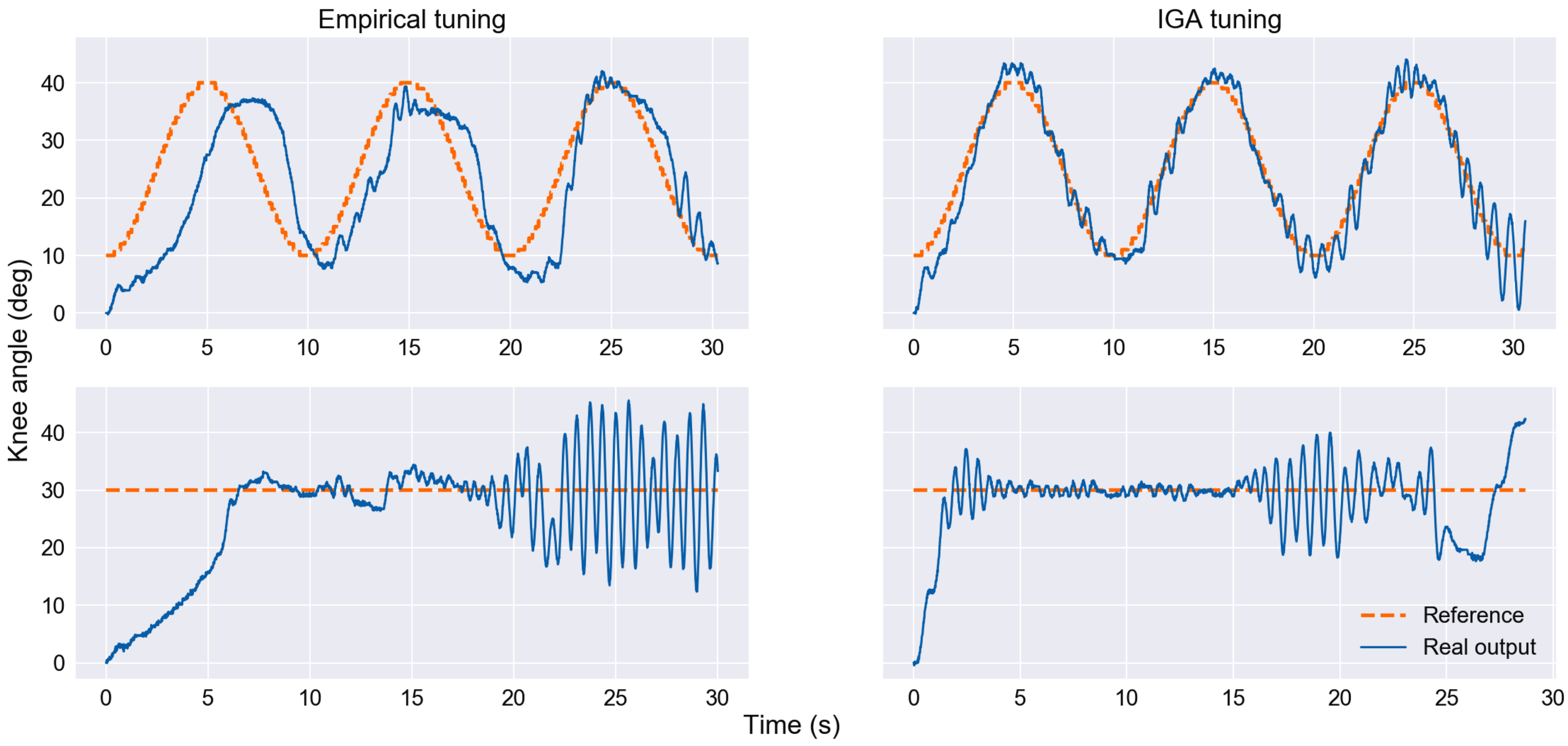
empiric gains



IGA gains

Experimental results (NN models)

- **Results and discussion: Individual P1**



Experimental results (NN models)

- **Results and discussion: Individual P2**

➢ **Patient P2 participated in one session.**

Technical information on experiments for individual P2.

Identification		Empiric		Sine IGA		Step IGA	
ρ_{min};ρ_{max}	θ_{min};θ_{max}	$\rho 0$;sat	α_1;α_2;ks;β	$\rho 0$;sat	α_1;α_2;ks;β	$\rho 0$;sat	α_1;α_2;ks;β
150;250	8;38	200;370	1;2;30;5	185;310	2.22;3.54;39.50;1.40	190;360	3.01;1.91;48.34;2.65

Identification results for individual P2.

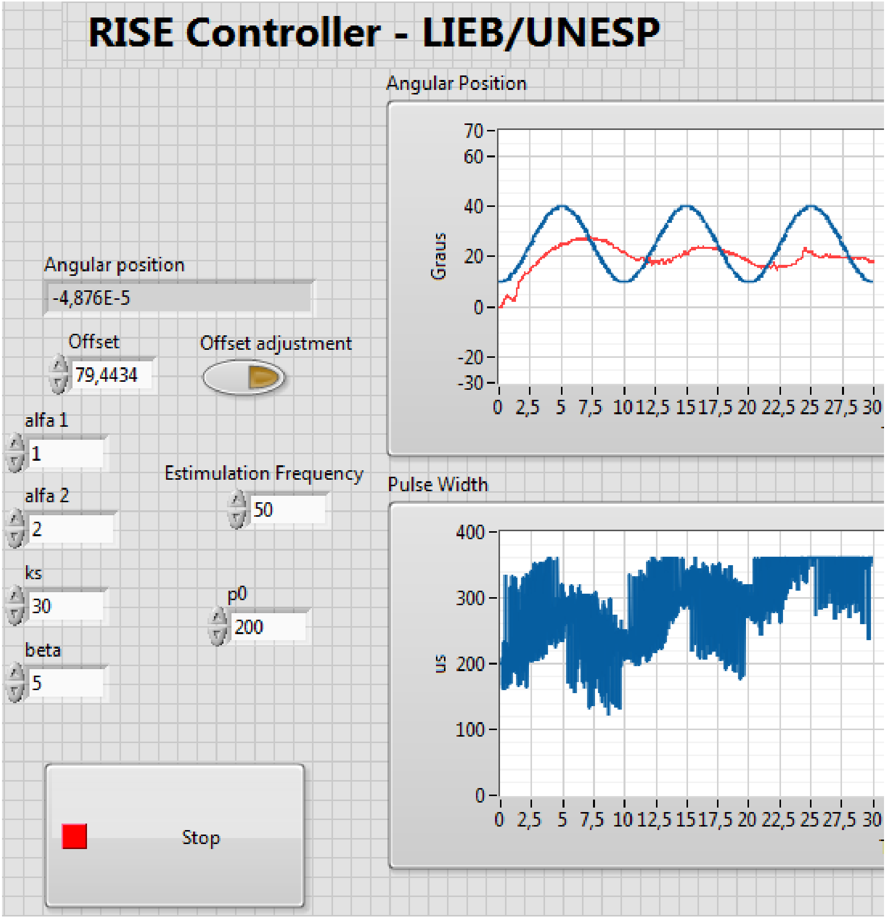
Session	TT	Corr	MSE
1st	33(s)	0.796	0.0032

Metrics on experimental results for individual P2.

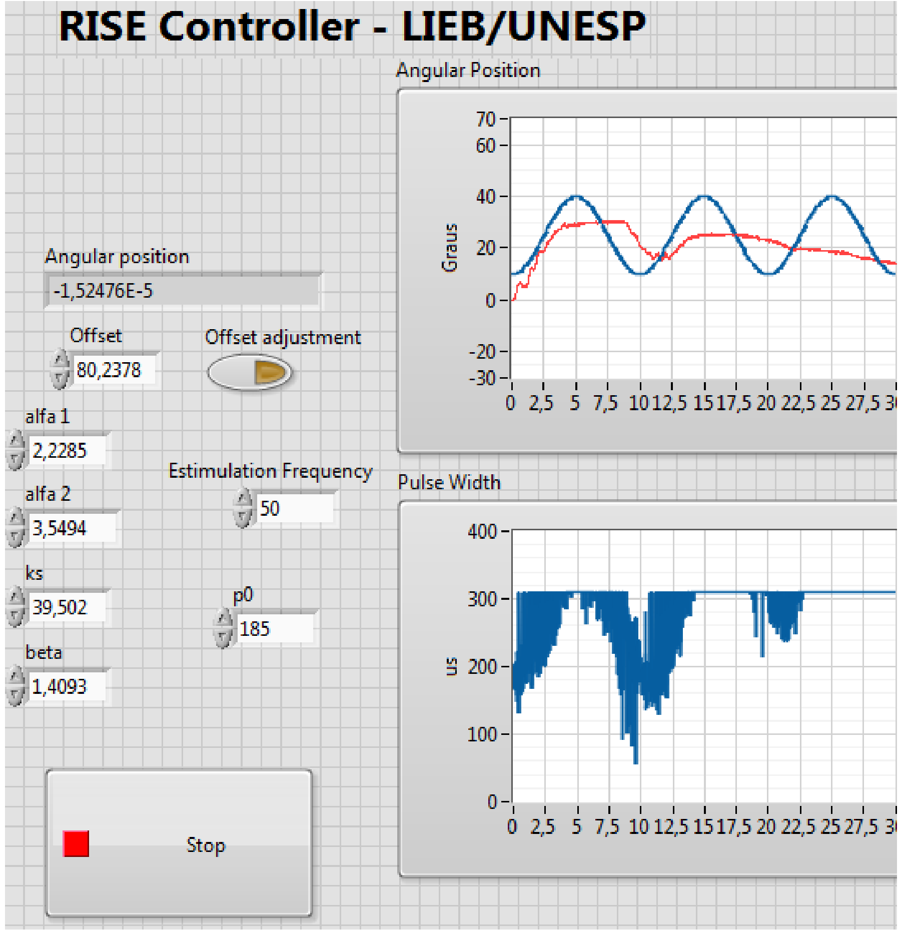
	Sine				Step			
	Empiric		IGA		Empiric		IGA	
Session	RMSE	TEC	RMSE	TEC	RMSE	TEC	RMSE	TEC
1st	11.2966°	30(s)	10.7306°	30(s)	10.1067°	23(s)	6.6134°	21(s)

Experimental results (NN models)

- Results and discussion: Individual P2



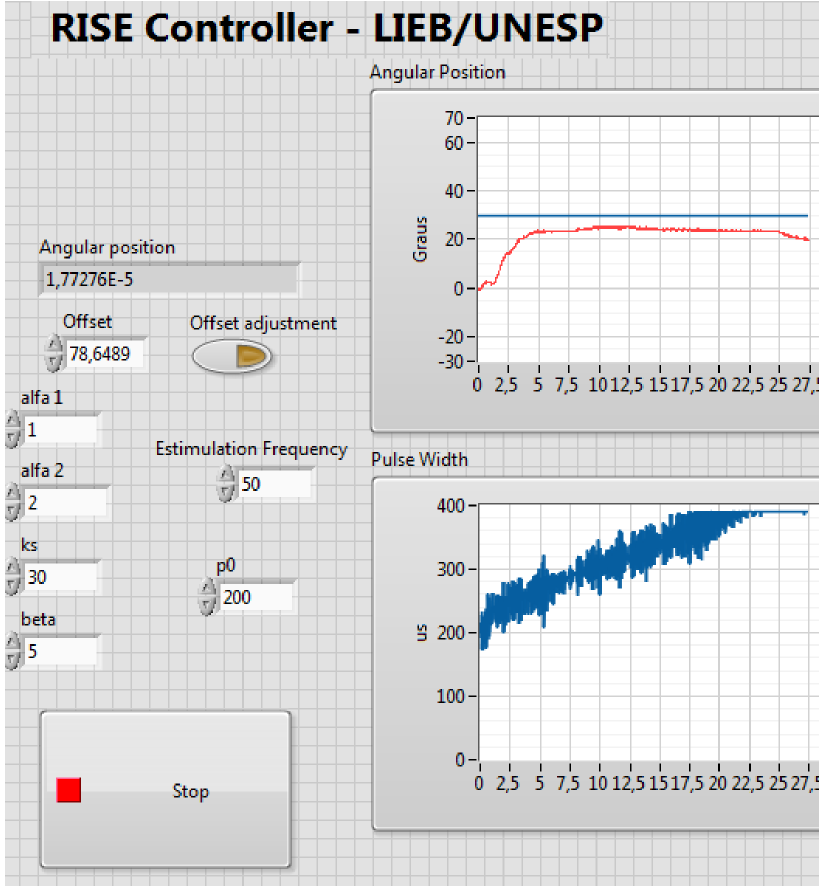
empiric gains



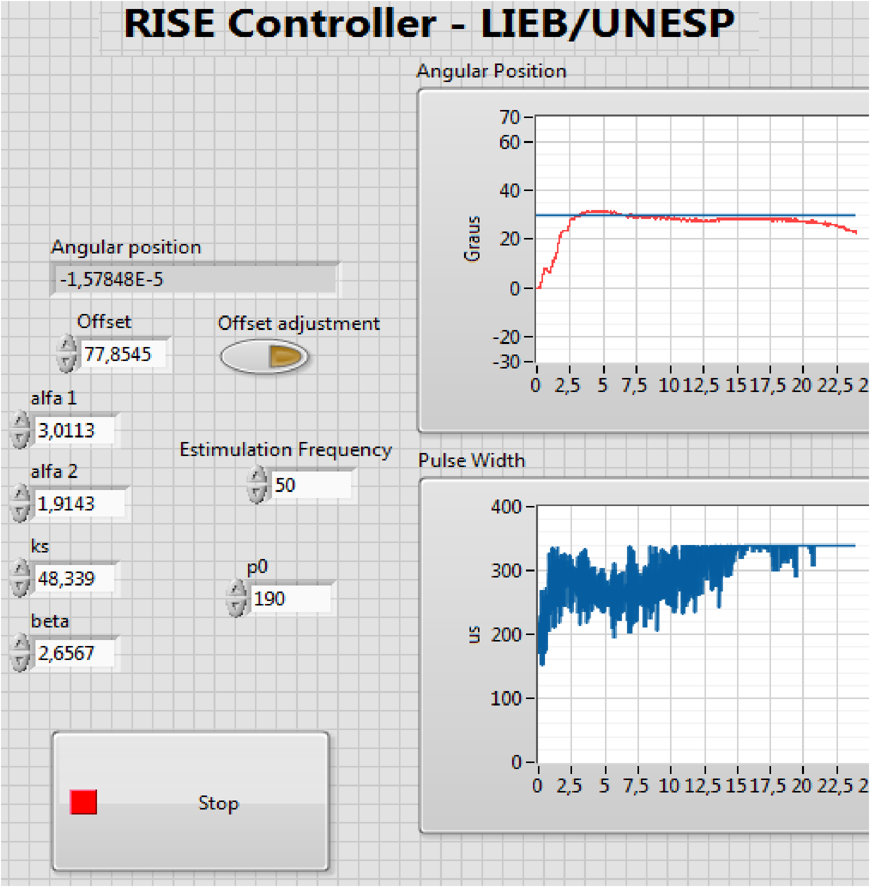
IGA gains

Experimental results (NN models)

- **Results and discussion: Individual P2**



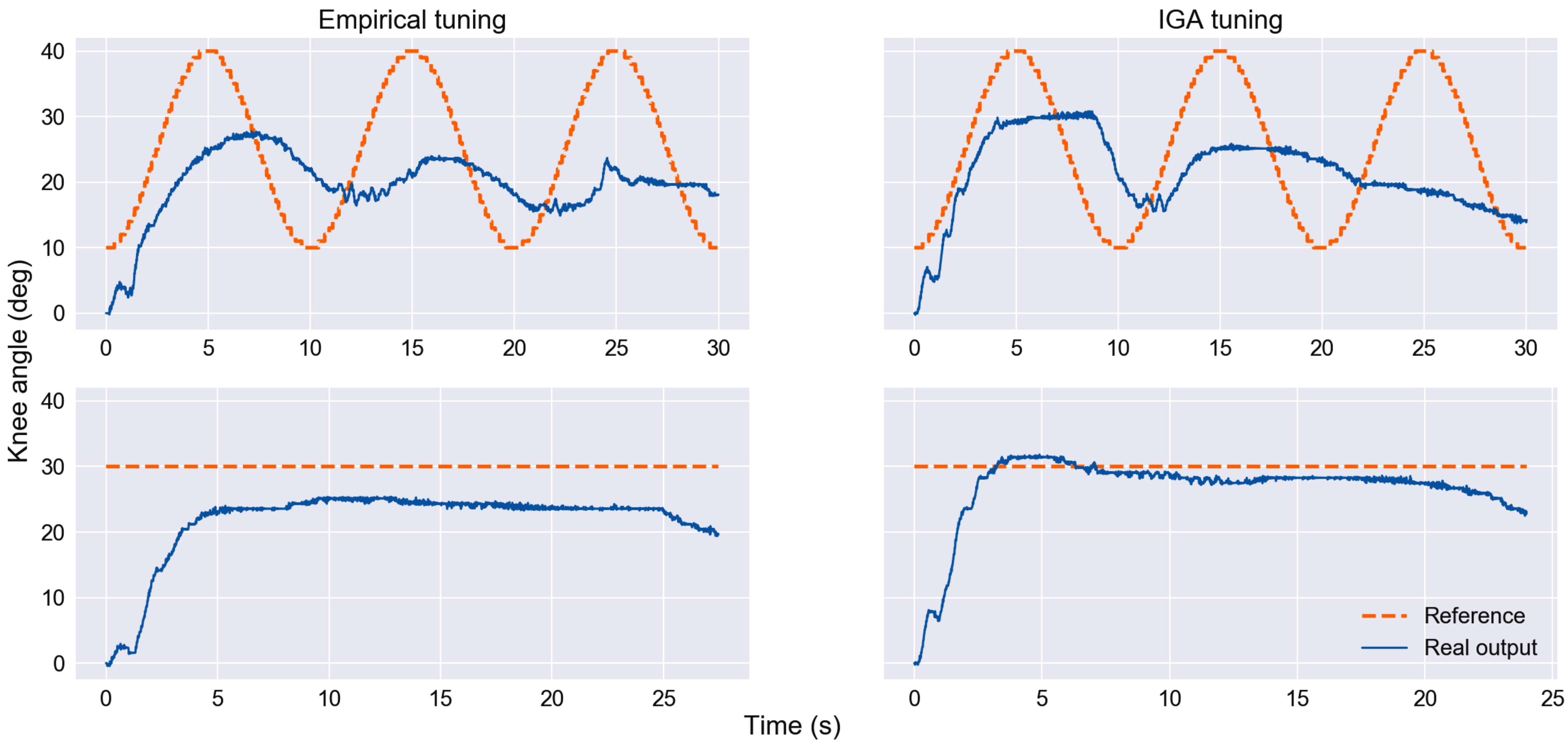
empiric gains



IGA gains

Experimental results (NN models)

- **Results and discussion: Individual P2**



Experimental results (NN models)

- Results and discussion: SCI patients

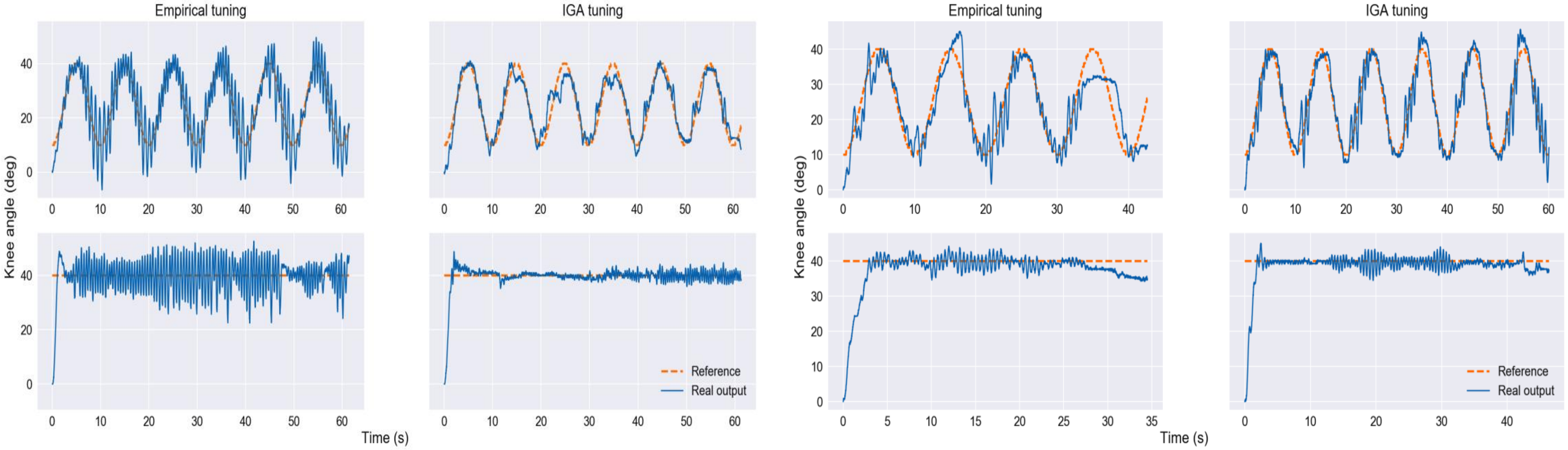
- ➢ The proposed methodology could be effectively applied to clinical procedures for treating SCI patients via NMES/FES.
- ➢ The RMSE for the sine wave from P1 is the best result achieved in all experiments made during this research.
- ➢ It is notable premature fatigue for paraplegic patients (less than 30 seconds) due to electrical stimulus.
- ➢ Results from P1 and P2 validate the first hypothesis.

Experimental results (NN models)

- ## Results and discussion: healthy patients

➢ Time of stimulation greater than presented in the literature (at most 45 seconds), getting to 60 seconds in many stimulation sessions.

➢ Took more time to fatigue due to NMES/FES.



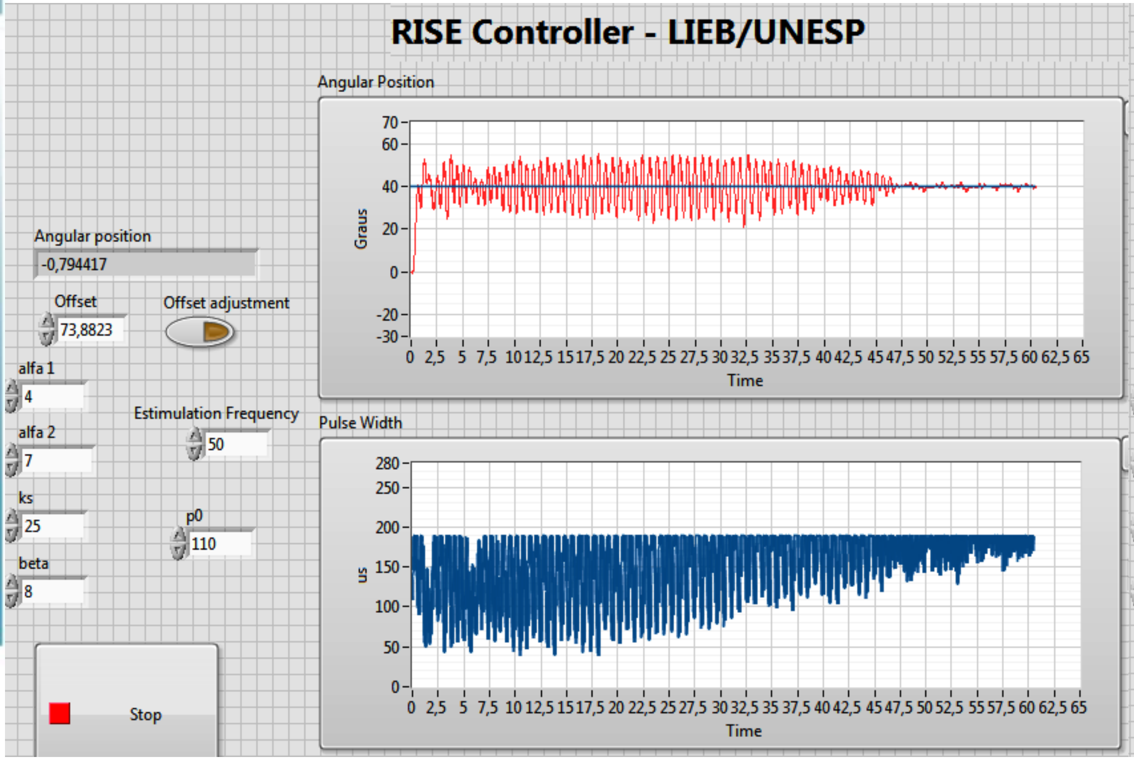
Experimental results (NN models)

- **Conclusion**

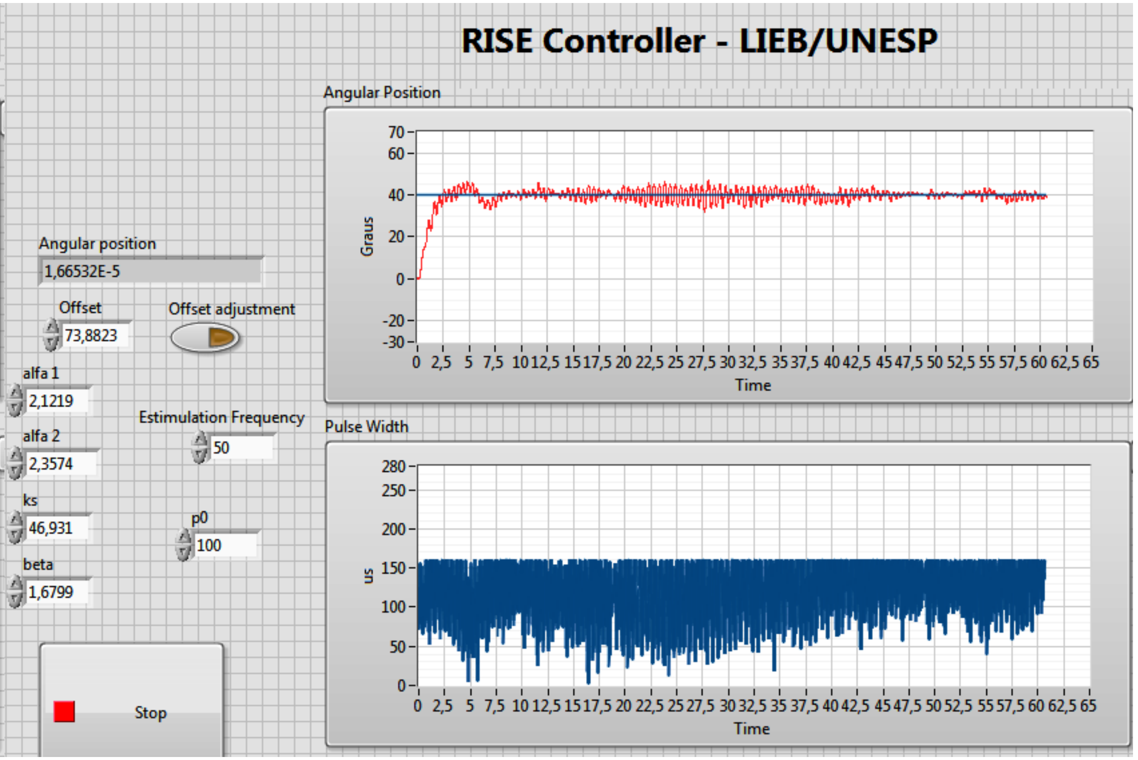
- The use of an empirical approach on clinical procedures presents several poor performances, wherein most of the tests, the control stimulated lower limb did not track the reference angle.
- Alternatively, by using the proposed methodology, for all patients, satisfactory and suitable tracking results were acquired for both situations.
- Additionally, as sessions passed by, it was noticed an improvement of tracking results for some individuals.

Experimental results (NN models)

- Conclusion



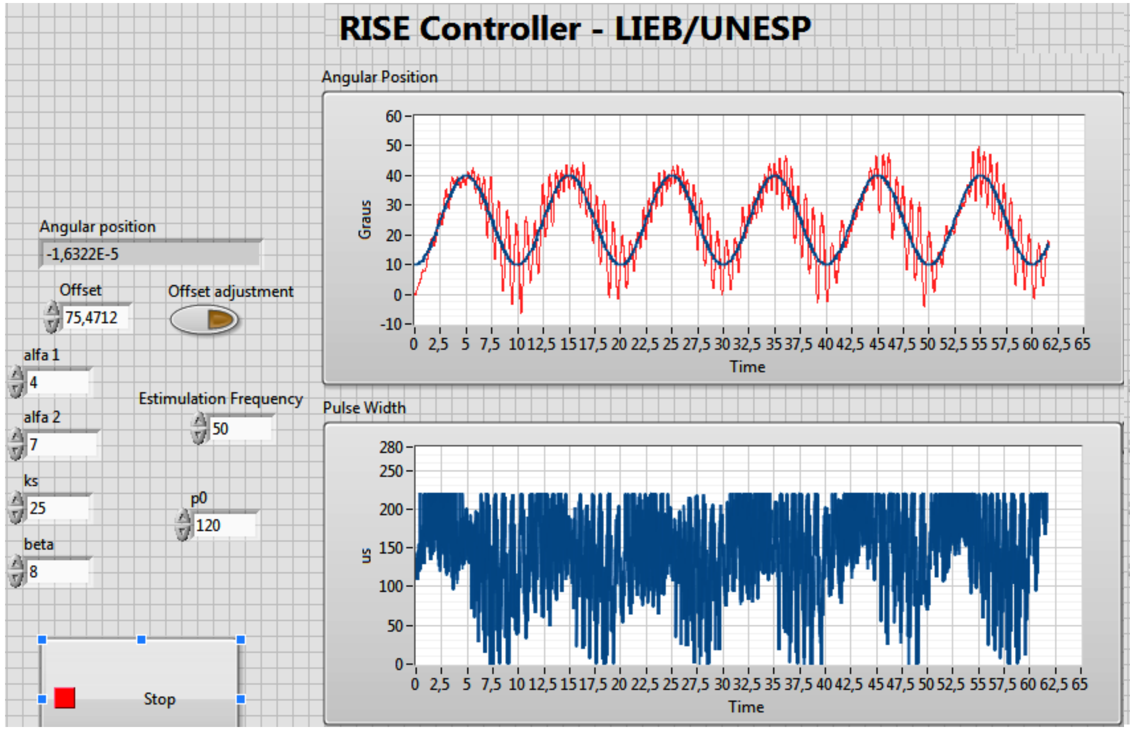
empiric gains



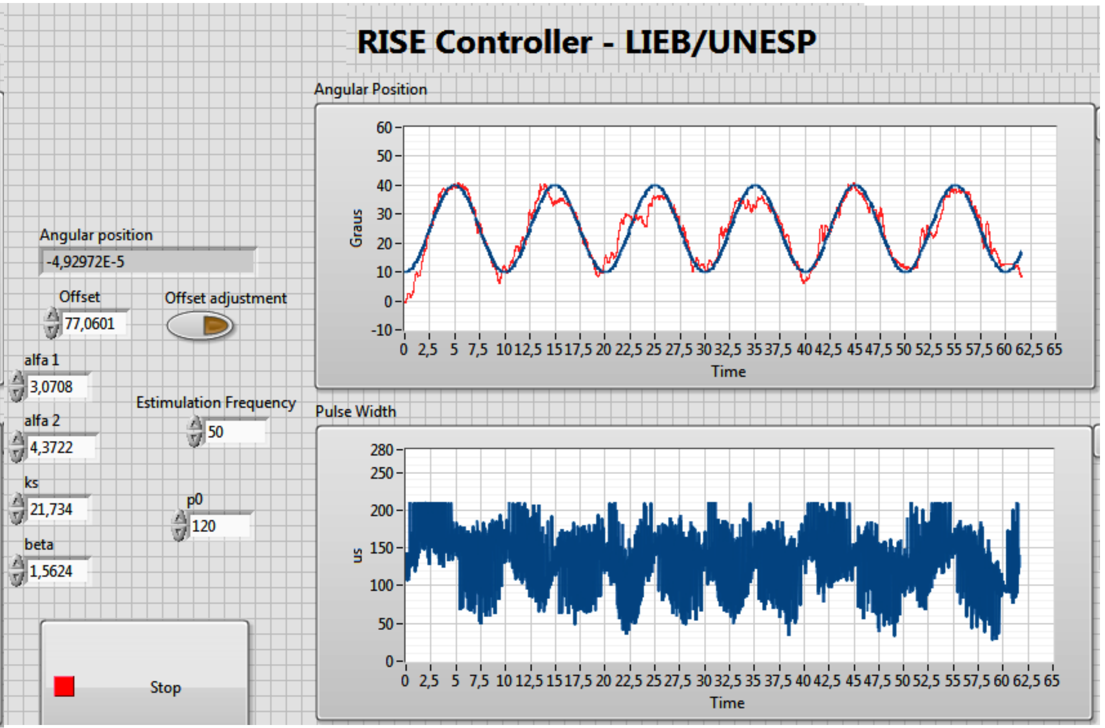
IGA gains

Experimental results (NN models)

- Conclusion



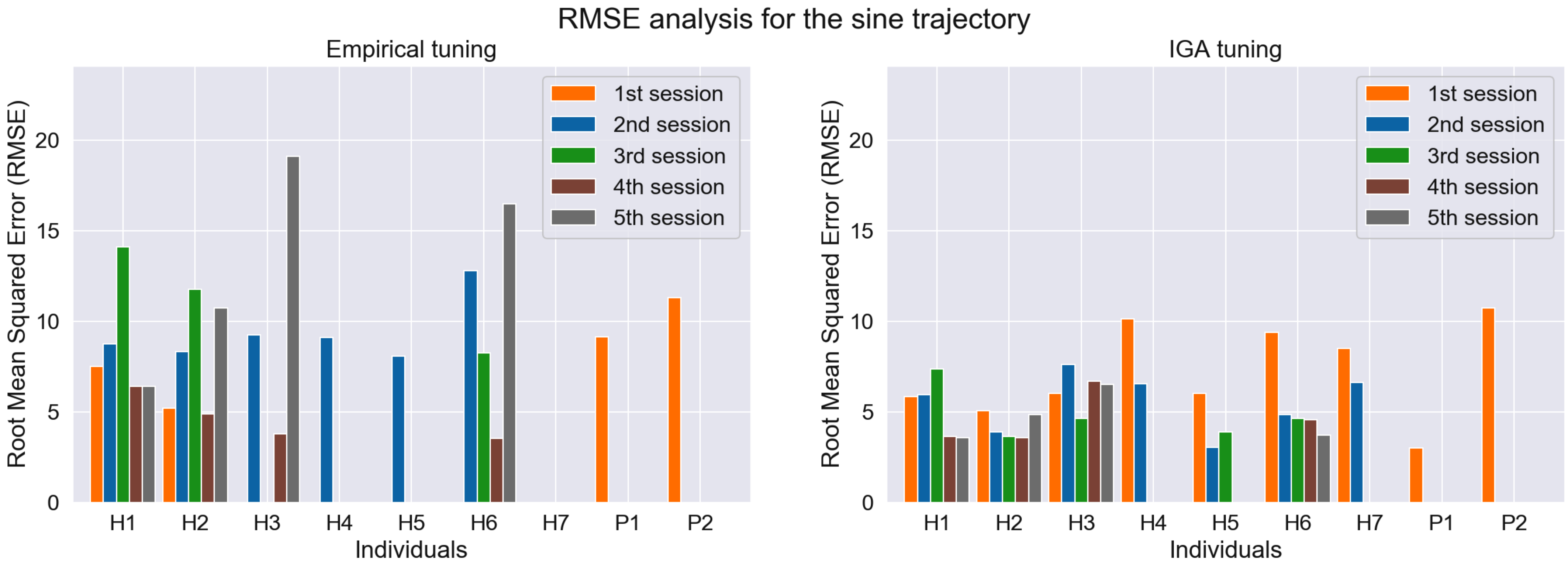
empiric gains



IGA gains

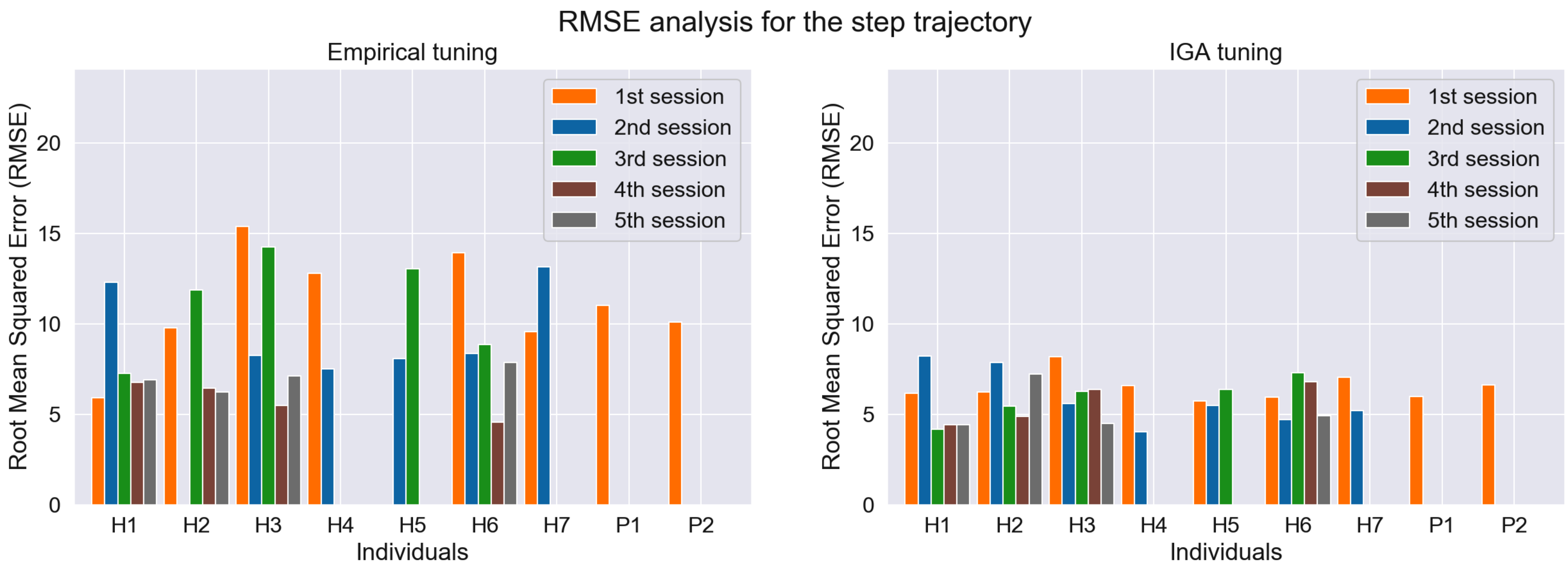
Experimental results (NN models)

- **Conclusion**



Experimental results (NN models)

- **Conclusion**



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Deep and dynamic NNs for sys. ident.

- An **efficient mapping describing the relationship between the muscular model and stimulation parameters.**
- **Investigate more sophisticated neural network architectures to propose better control-oriented models.**
- **Three specific architectures are investigated namely the MLP, a simple RNN, and the LSTM.**

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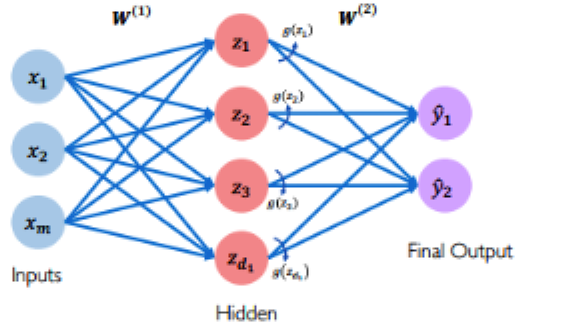
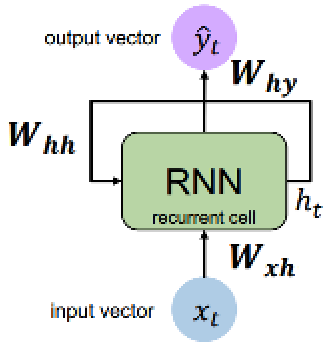
- NN models





Apply a recurrence relation at every time step to process a sequence:

$$h_t = f_W(h_{t-1}, x_t)$$

new state; function parameterized by W; old state; input vector at time step t

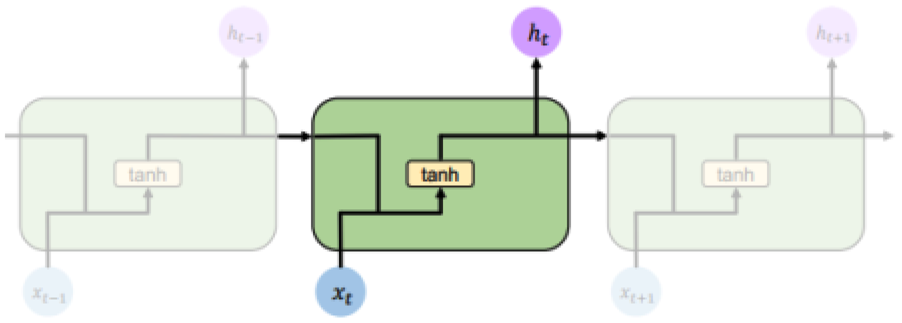
Output Vector

$$\hat{y}_t = W_{hy} h_t$$

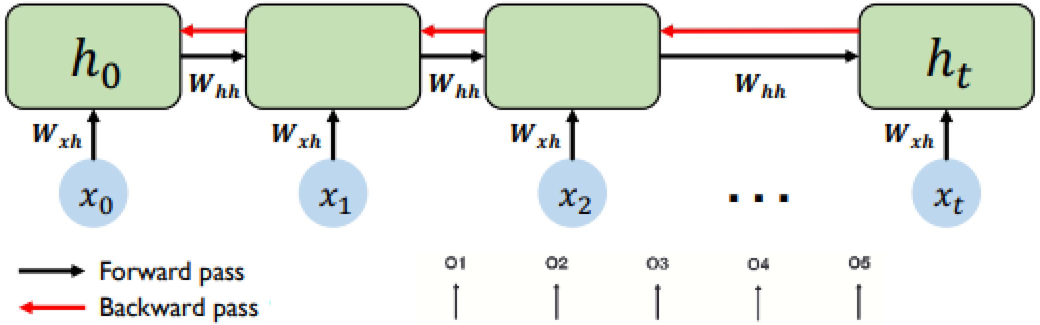
Update Hidden State

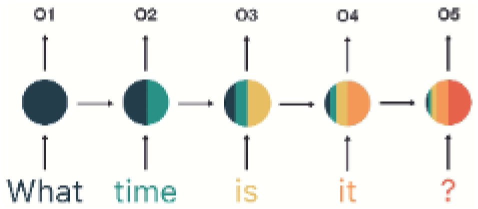
$$h_t = \tanh(W_{hh} h_{t-1} + W_{xh} x_t)$$

Standard RNN: simple computation node



exploding and vanishing gradients





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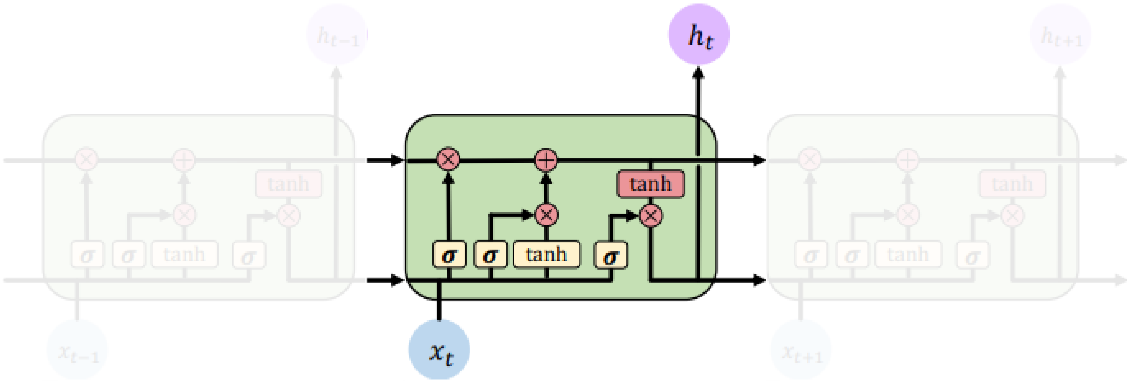
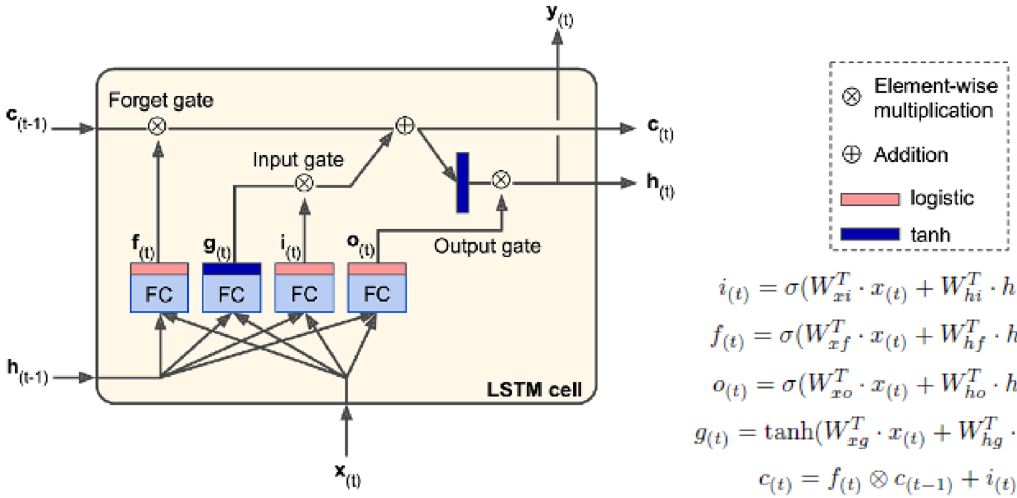
- ## NN models

LSTMs: contain **interacting layers** that **control information flow**



LSTMs: key concepts

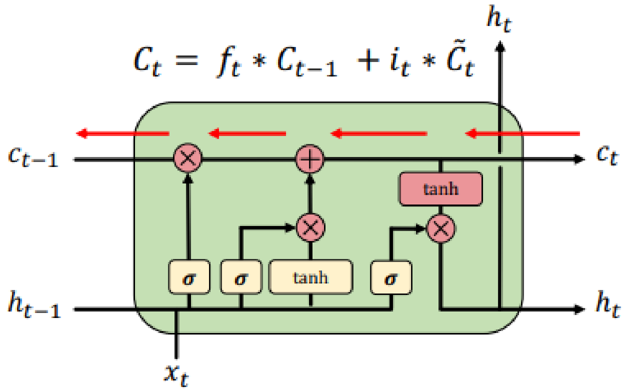
- Maintain a **separate cell state** from what is outputted
- Use **gates** to control the **flow of information**
- Backpropagation from c_t to c_{t-1} doesn't require matrix multiplication: **uninterrupted gradient flow**



$$i_{(t)} = \sigma(W_{xi}^T \cdot x_{(t)} + W_{hi}^T \cdot h_{(t-1)} + b_i)$$
$$f_{(t)} = \sigma(W_{xf}^T \cdot x_{(t)} + W_{hf}^T \cdot h_{(t-1)} + b_f)$$
$$o_{(t)} = \sigma(W_{xo}^T \cdot x_{(t)} + W_{ho}^T \cdot h_{(t-1)} + b_o)$$
$$g_{(t)} = \tanh(W_{xg}^T \cdot x_{(t)} + W_{hg}^T \cdot h_{(t-1)} + b_g)$$
$$c_{(t)} = f_{(t)} \otimes c_{(t-1)} + i_{(t)} \otimes g_{(t)}$$
$$y_{(t)} = h_{(t)} = o_{(t)} \otimes \tanh(c_{(t)})$$

LSTM gradient flow

Backpropagation from C_t to C_{t-1} requires only elementwise multiplication!
No matrix multiplication → avoid vanishing gradient problem.



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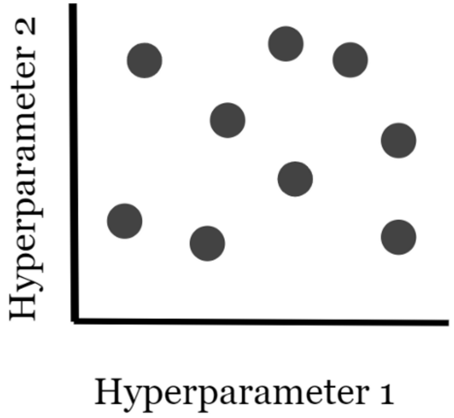
- ## Model selection

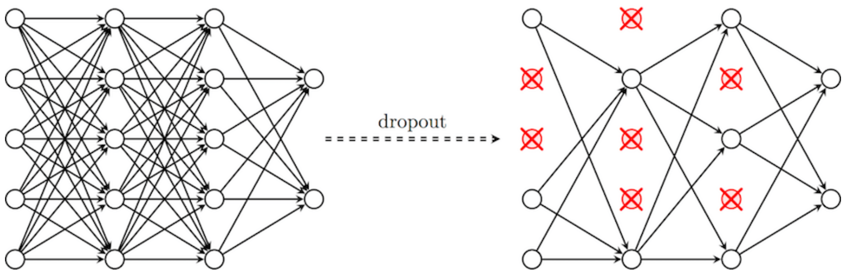
Random Search

Pseudocode

```
Hyperparameter_One = random.num(range)
Hyperparameter_Two = random.num(range)
```



Regularization (avoid overfitting)



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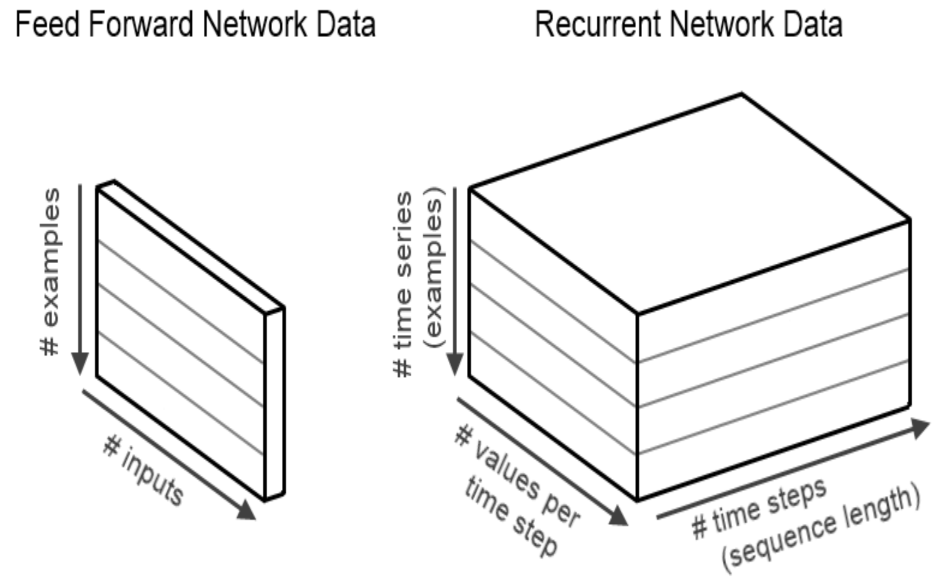
- ## Feature extraction and data encoding

➢ **The StandardScaler method from the scikit-learn library was applied to re-scale the distribution of values to zero mean and unit variance.**

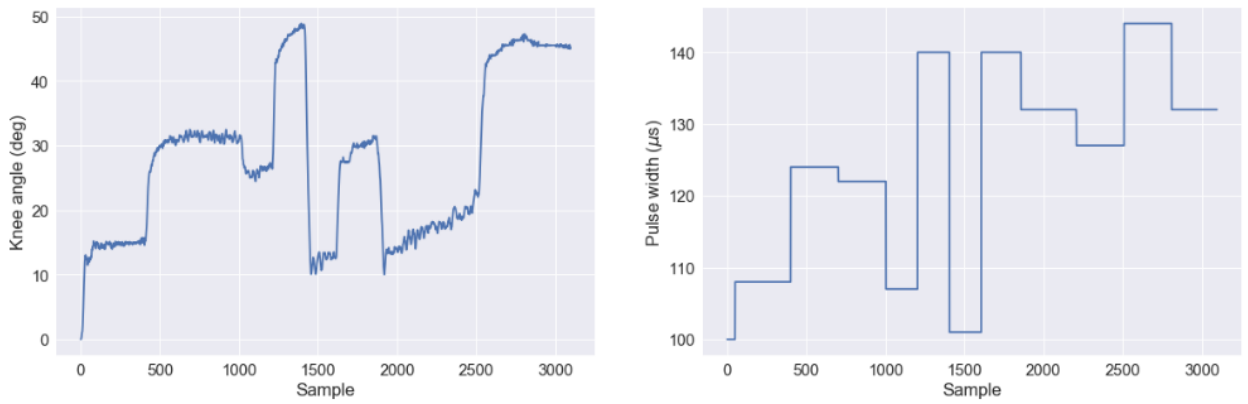
	Angular_Position(t-1)	Pulse_Width(t-1)	Angular_Position(t)
1	-2.078177	-1.628839	-2.078177
2	-2.078177	-1.628839	-2.077933
3	-2.077933	-1.628839	-2.076678
4	-2.076678	-1.628839	-2.073245
5	-2.073245	-1.628839	-2.066889
6	-2.066889	-1.628839	-2.058281
7	-2.058281	-1.628839	-2.049395
8	-2.049395	-1.628839	-2.041484
9	-2.041484	-1.628839	-2.032742
10	-2.032742	-1.628839	-2.018480

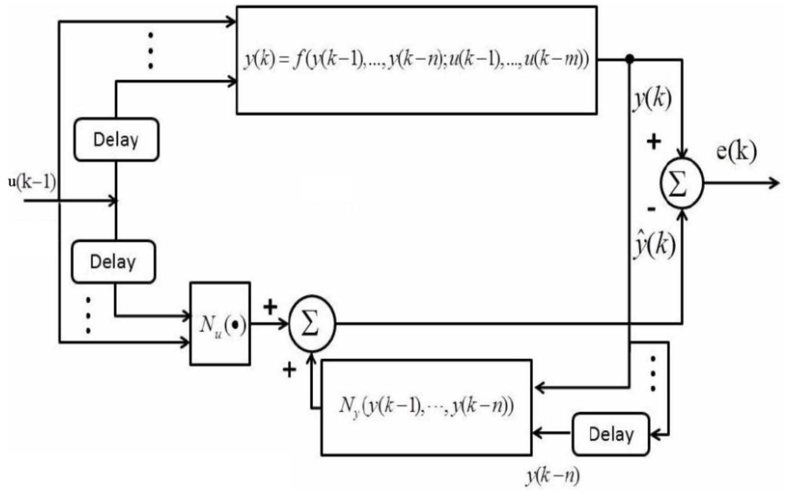


Deep and dynamic NNs for sys. ident.

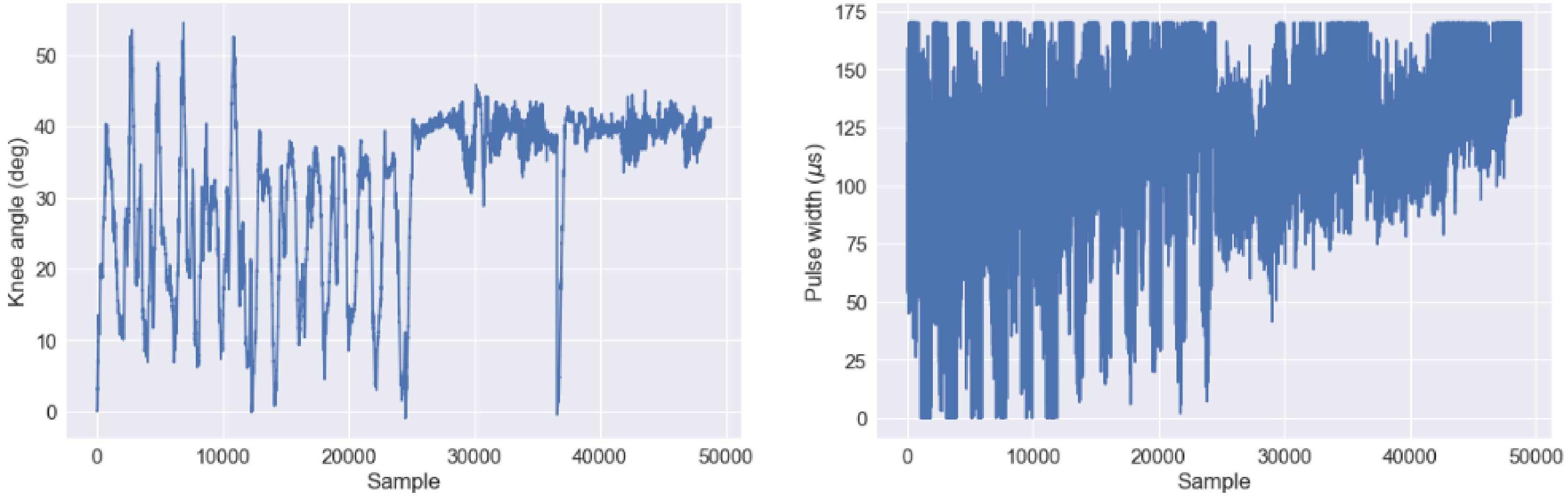
- **Results and discussion**

Training data



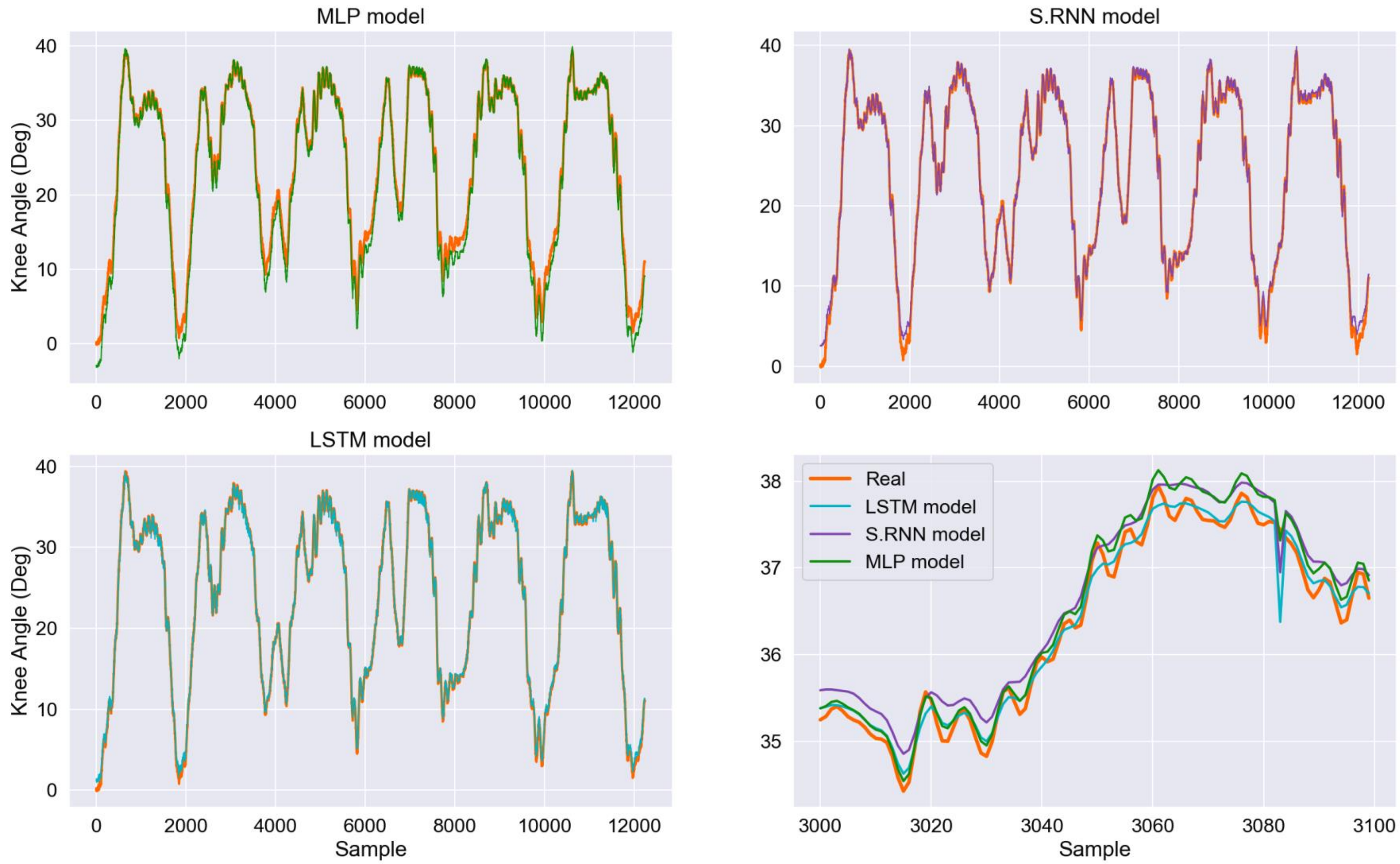


Testing data



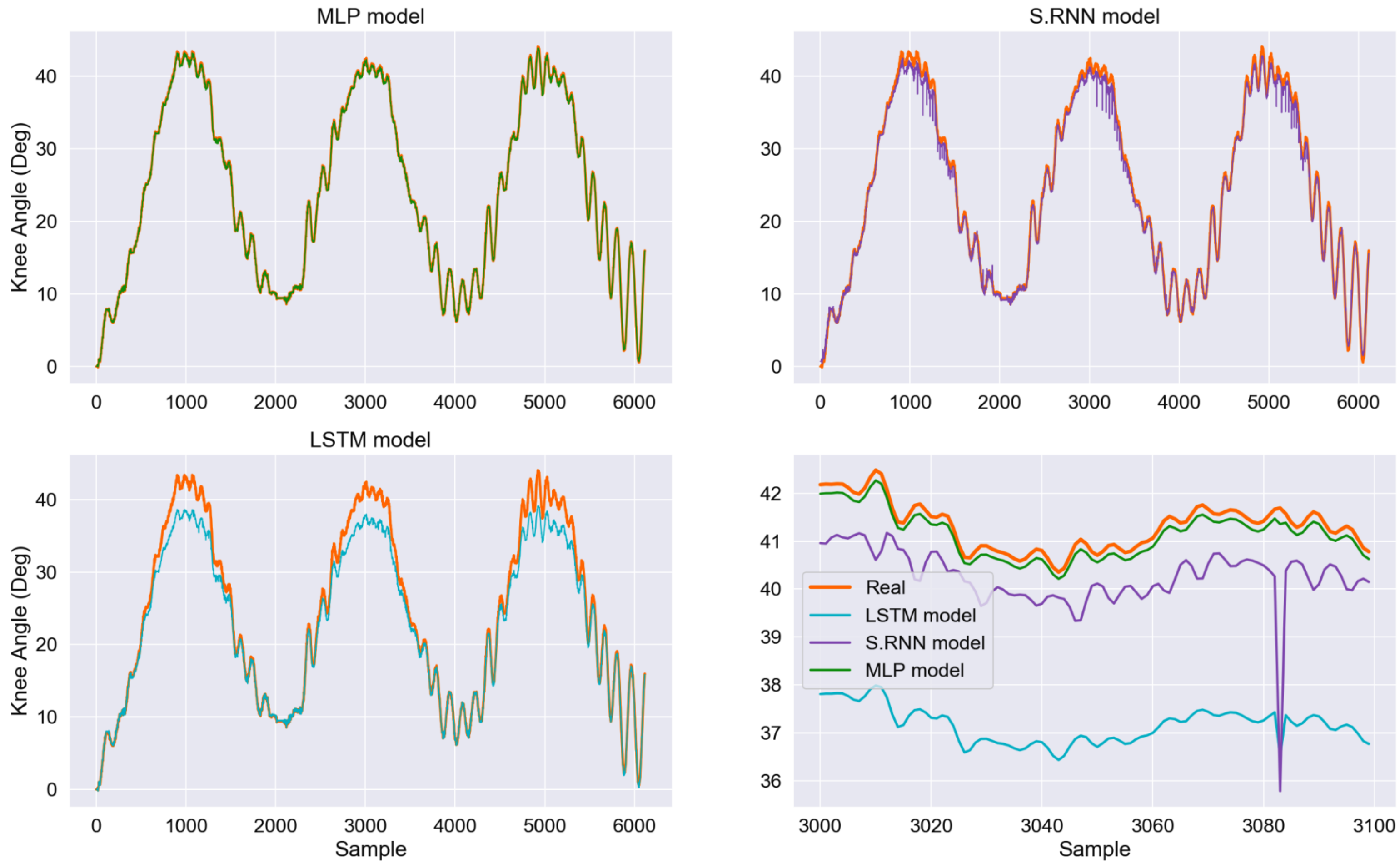
Deep and dynamic NNs for sys. ident.

- Results and discussion



Deep and dynamic NNs for sys. ident.

- **Results and discussion**



Deep and dynamic NNs for sys. ident.

- Results and discussion

- The identified models indicate good fitting to data and very low RMSE metric for all individuals.
- The proposed methodology (based on an offline controller optimizer) using a better model will provide more realistic simulation.
- Consequently, better tuning of the RISE controller for each SCI patient in clinical procedures will be acquired.
- Saving every rehabilitation data from a patient, such deep and dynamic NNs can improve the mapping for each patient with the electrical stimulus as sessions pass by.

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General Conclusions

- The proposed methodology was experimentally implemented with seven healthy individuals and two paraplegic patients.
- For the first time, real experiments are made with SCI patients using the RISE controller.
- Models approximate of real applications with nonideal conditions (fatigue, tremors, and spasms) using past rehabilitation data.
- The proposed simulation system allows liberty of studying the system's response using more sophisticated control-oriented NN models, and to improve/test different control laws.

General Conclusions

- **Future works**

➢ **Deeper validation using the proposed methodology with SCI patients during more sessions.**

➢ **Implement the proposed deep and dynamic neural networks as control-orient models for simulations.**

➢ **Investigate combinations of deeper and dynamic NNs (recurrent and convolutional) and implement it.**

➢ **Investigate fundamentally similar control laws or improvements to the RISE control law.**

General Conclusions

- ## Publications

➢ ARCOLEZI, H. H.; NUNES, W. R. B. M.; ÑAHUIS, S. L. C.; SANCHES, M. A. A.; TEIXEIRA, M. C. M.; CARVALHO, A. A. de. A RISE-based Controller Fine-tuned by an Improved Genetic Algorithm for Human Lower Limb Rehabilitation via Neuromuscular Electrical Stimulation. In: 6th International Conference on Control, Decision and Information Technologies (CODIT). CoDiT, 2019.

Extended versions of this research are planned to be submitted on the "Advanced Engineering Informatics" Journal (Elsevier, Impact Factor: 3.358) with preceding publications at a brazilian conference as:

➢ ARCOLEZI, H. H.; NUNES, W. R. B. M.; ARAUJO, R. A. de; SANCHES, M. A. A.; TEIXEIRA, M. C. M.; CARVALHO, A. A. de. A Robust and Intelligent RISE-based Control for Human Lower Limb Tracking via Electrical Stimulation. In: XIV Conferência Brasileira de Dinâmica, Controle e Aplicações (DINCON). DINCON, 2019.

➢ ARCOLEZI, H. H.; NUNES, W. R. B. M.; CERNA, S.; ARAUJO, R. A. de; SANCHES, M. A. A.; TEIXEIRA, M. C. M.; CARVALHO, A. A. de. On the Ability to Identify the Knee Joint Position Under Neuromuscular Electrical Stimulation Using Long Short-Term Memory Neural Networks. In: XIV Conferência Brasileira de Dinâmica, Controle e Aplicações (DINCON). DINCON, 2019.

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SHARMA, N.; GREGORY, C. M.; JOHNSON, M.; DIXON, W. E. Closed-loop neural network-based NMES control for human limb tracking. *IEEE Transactions on Control Systems Technology*, Institute of Electrical and Electronics Engineers (IEEE), v. 20, n. 3, p. 712–725, may 2012. Available in: <https://doi.org/10.1109/tcst.2011.2125792>.

SHARMA, N.; STEGATH, K.; GREGORY, C.; DIXON, W. Nonlinear neuromuscular electrical stimulation tracking control of a human limb. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Institute of Electrical and Electronics Engineers (IEEE), v. 17, n. 6, p. 576–584, dec 2009. Available in: <https://doi.org/10.1109/tnsre.2009.2023294>.

STEGATH, K.; SHARMA, N.; GREGORY, C. M.; DIXON, W. E. Experimental demonstration of RISE-based NMES of human quadriceps muscle. In: *2007 IEEE/NIH Life Science Systems and Applications Workshop*. IEEE, 2007. Available in: <https://doi.org/10.1109/lssa.2007.4400880>.

XIAN, B.; DAWSON, D.; QUEIROZ, M. de; CHEN, J. A continuous asymptotic tracking control strategy for uncertain multi-input nonlinear systems. In: *Proceedings of the 2003 IEEE International Symposium on Intelligent Control ISIC-03*. IEEE, 2003. Available in: <https://doi.org/10.1109/isic.2003.1253913>.

XIAN, B.; QUEIROZ, M. S.; DAWSON, D. M. A continuous control mechanism for uncertain nonlinear systems. In: *Optimal Control, Stabilization and Nonsmooth Analysis*. Springer Berlin Heidelberg, 2004. p. 251–264. Available in: <https://doi.org/10.1007/978-3-540-39983-4$_1$6>.

SpinalCure AUSTRALIA https://www.spinalcure.org.au/research/sci-facts/

World Health Organization https://www.who.int/news-room/fact-sheets/detail/spinal-cord-injury

SCIRE Professional — Spinal Cord Injury Research Evidence https://scireproject.com/evidence/rehabilitation-evidence/lower-limb/electrical-stimulation-to-enhance-lower-limb-muscle-function/func/

Thank you for your attention!!!

Student: Héber Hwang Arcolezi
Advisor: Prof. Dr. Aparecido Augusto de Carvalho
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