

# Forecasting Gait Kinetics and Kinematics for Biological Joint Impedance Estimation Using Machine Learning

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## Abstract

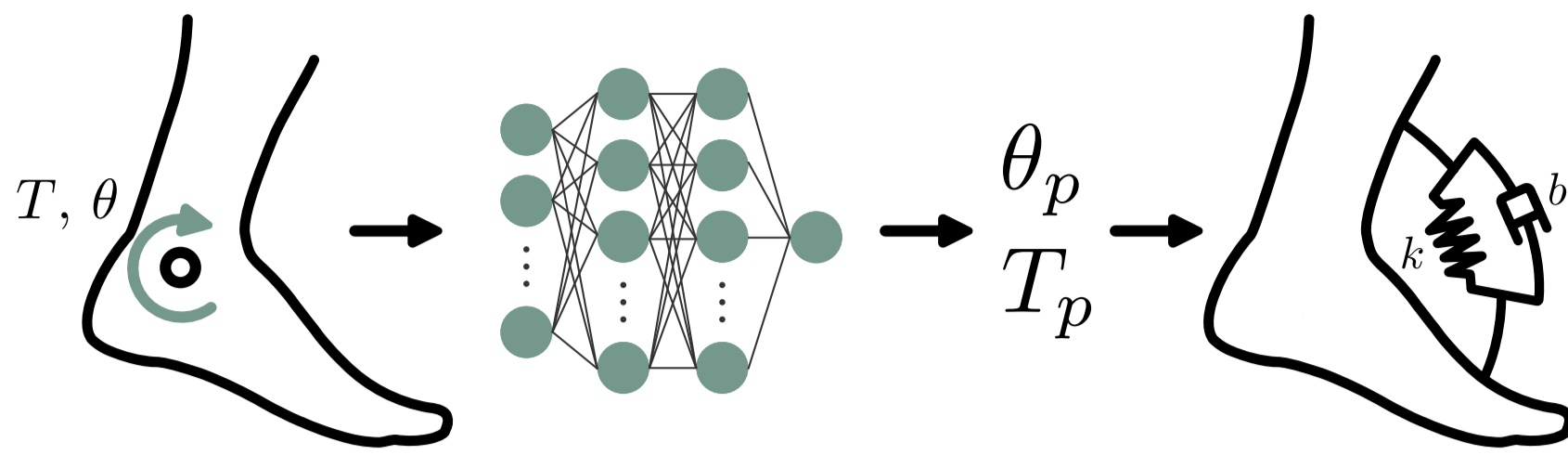


Figure 1: Neural network forecasting method using torque and angle inputs to predict reactions to perturbation for estimating joint impedance parameters.

- State of the art of impedance estimation is **experimentally intensive** [1]
- We propose a method of impedance estimation that **minimizes the data needed for reliable estimates** using machine learning
- Impedance parameter estimates show similar trends across the gait cycle to previously published values with different means

## Background

- Impedance is useful tool in understanding hypertonia, spasticity, and paresis. [3]
- Impedance is **task and phase dependent** [2]
- Current method is a **bootstrap sampling method**

$$\begin{aligned} \sum \theta(t) - \sum \theta_p(t) &= \theta_p(t) \\ \sum T(t) - \sum T_p(t) &= T_p(t) \end{aligned} \rightarrow T_p = I\ddot{\theta}_p + b\dot{\theta}_p + k\theta_p$$

Figure 2: Bootstrap sampling method comparing perturbed and unperturbed trials to measure reaction to perturbation for impedance estimation.

## Methods

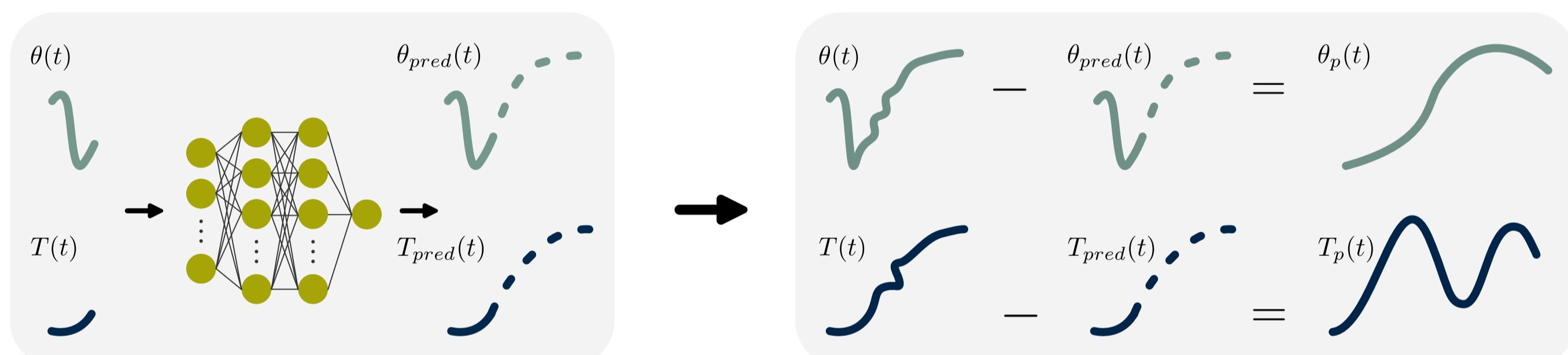


Figure 3: Feed-forward neural network using pre-perturbation data to forecast unperturbed trajectories for impedance parameter estimation.

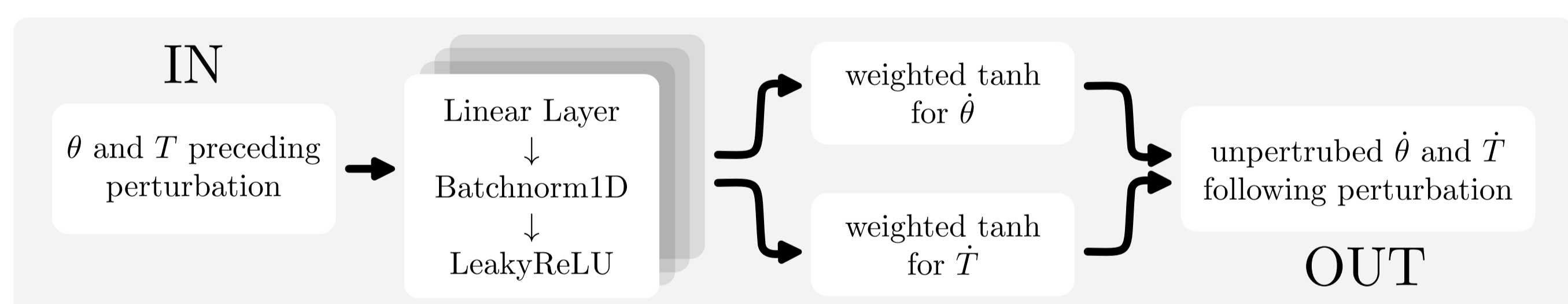


Figure 4: Model architecture with four linear layers processing 100ms pre-perturbation angle and torque data, using batch normalization and Leaky ReLU activations, with tanh output constraining predictions to realistic values.

- Models trained on **data from previous studies** [2,3]
- Simple **feed-forward neural network** structure
- Predict first derivative for **vertical shift invariance**
- Residual of actual perturbed data and predicted nominal data gives reaction to perturbation

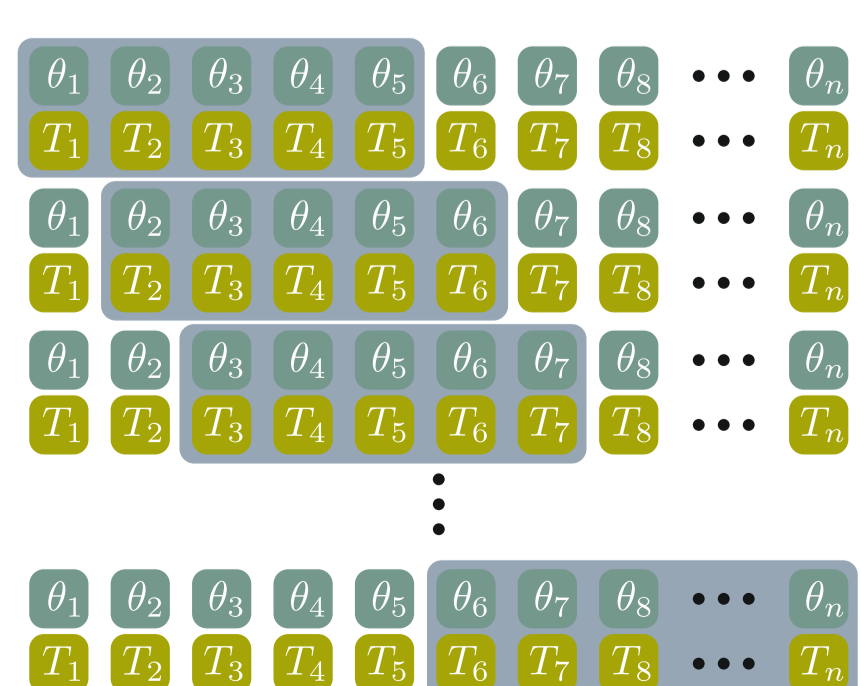


Figure 5: Windowing method



Figure 6: Vertical shift invariance.

## Preliminary Results

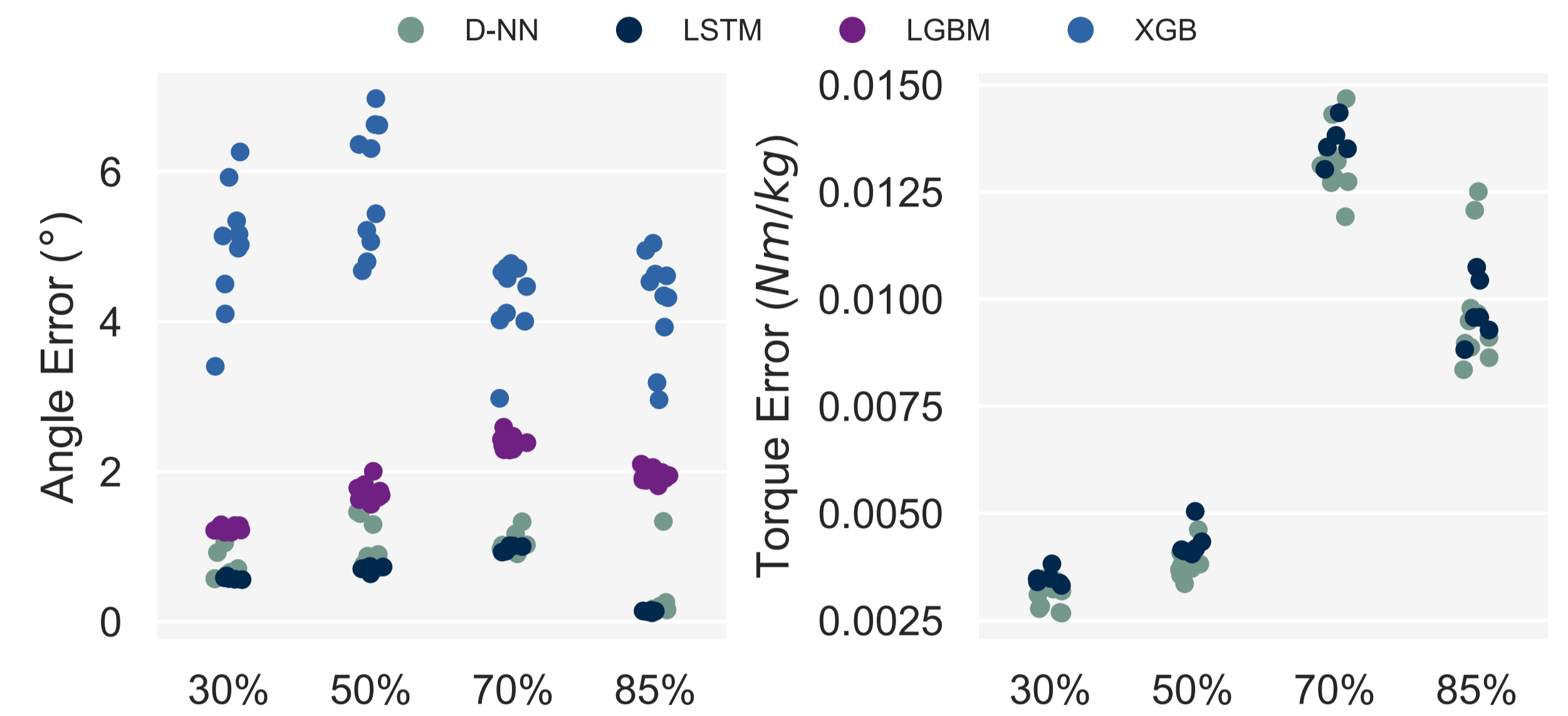


Figure 7: Validation of different model types by percent of stance

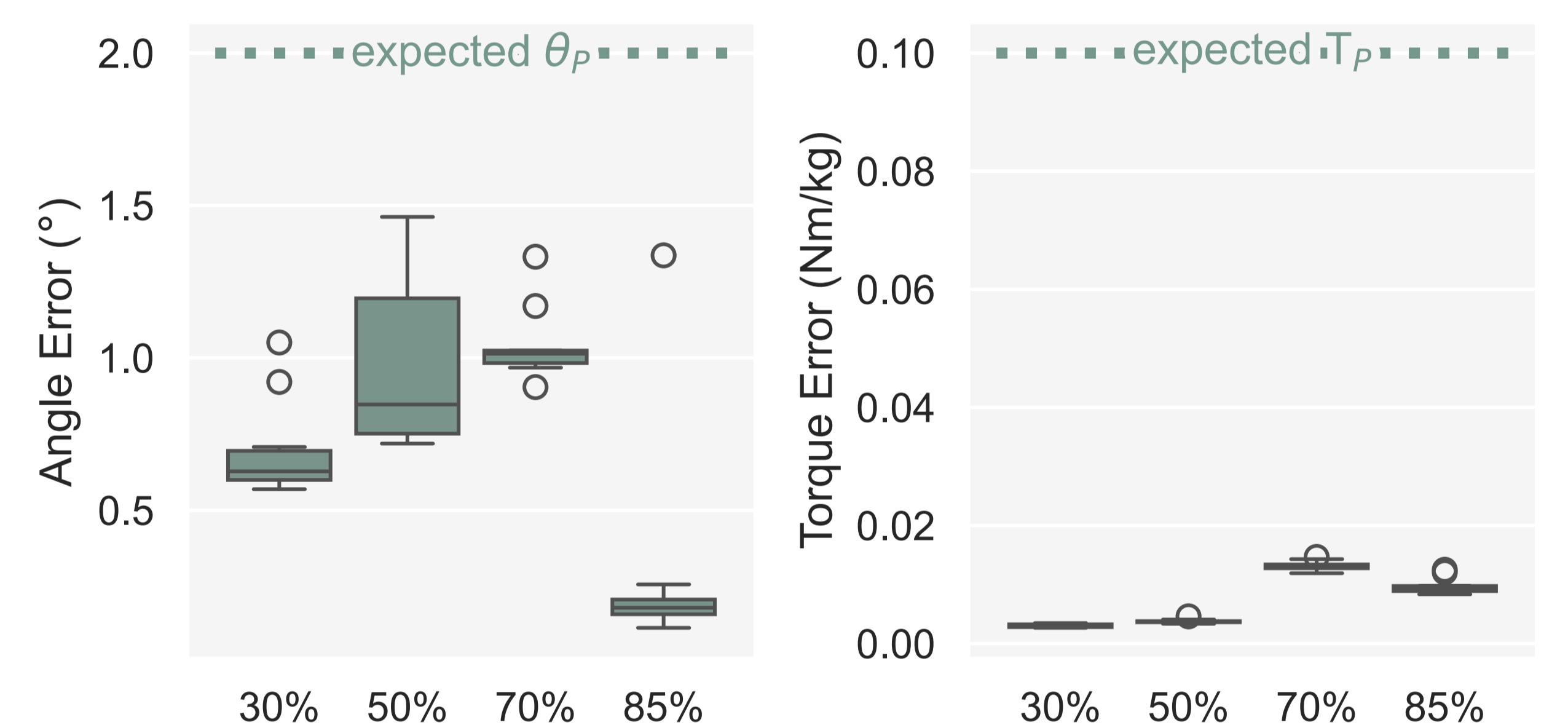


Figure 8: K-fold cross validation of D-NN by percent of stance phase compared to expected magnitude of  $\theta_p$  and  $T_p$

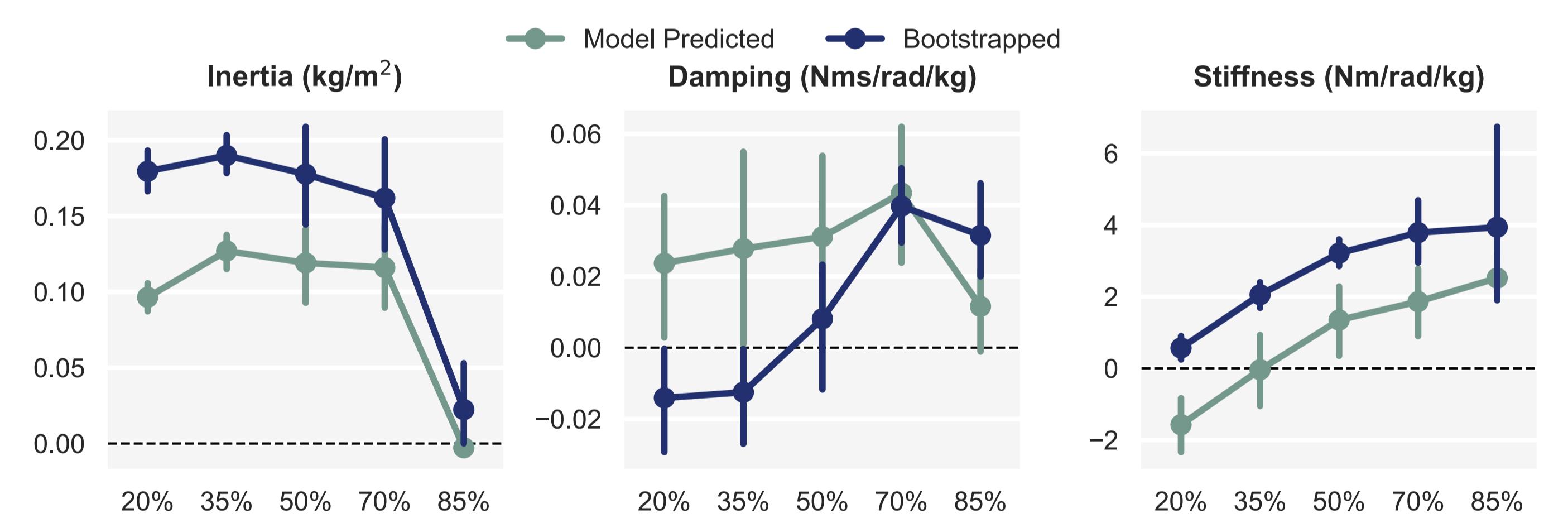


Figure 9: Estimates of impedance parameters by percent of stance phase

## Conclusions

- Torque predictions are much better than angle predictions compared to perturbation magnitude
- Estimates from proposed method show **similar trends to published estimates** [2]
- Future work will **include data from stroke patients** in the training data
- Subject independent model would **cut data collection in half**

## References

- [1] E. J. Rouse, L. J. Hargrove, E. J. Perreault, M. A. Peshkin, and T. A. Kuiken, "Development of a mechatronic platform and validation of methods for estimating ankle stiffness during the stance phase of walking," *J Biomech Eng*, vol. 135, no. 8, p. 81009, Aug. 2013, doi: [10.1115/1.4024286](https://doi.org/10.1115/1.4024286).
- [2] E. J. Rouse, L. J. Hargrove, E. J. Perreault, and T. A. Kuiken, "Estimation of Human Ankle Impedance During the Stance Phase of Walking," *IEEE Trans Neural Syst Rehabil Eng*, vol. 22, no. 4, pp. 870–878, Jul. 2014, doi: [10.1109/TNSRE.2014.2307266](https://doi.org/10.1109/TNSRE.2014.2307266).
- [3] A. L. Shorter, J. K. Richardson, S. B. Finucane, V. Joshi, K. Gordon, and E. J. Rouse, "Characterization and clinical implications of ankle impedance during walking in chronic stroke," *Sci Rep*, vol. 11, no. 1, p. 16726, Aug. 2021, doi: [10.1038/s41538-021-95737-6](https://doi.org/10.1038/s41538-021-95737-6).