# BODY-IN-THE-LOOP OPTIMIZATION FOR THE SELECTION OF PROSTHETIC CONTROL PARAMETERS – A PILOT STUDY

Wyatt Felt, Emily S. Gardinier, Jeffrey Wensman, Deanna H. Gates, C. David Remy

The University of Michigan, Ann Arbor, MI, USA email: cdremy@umich.edu, web: http://ram-lab.engin.umich.edu/

#### INTRODUCTION

Like many assistive devices, the BiOM T2 powered ankle-prosthesis (BiOM, Inc., Bedford, MA) has numerous software settings that need to be tuned. Four basic parameters control stiffness and ankle power, while seven advanced parameters control the timing of push-off and other functionalities [1]. Selecting appropriate values for these parameters or those of similar devices can be a challenge. Evaluating many different device settings can be a slow and fatiguing process for the user and the resulting settings might suffer from a subjective bias of the clinician. Therefore, a faster and more objective method for identifying proper device settings would be a valuable tool. "Body-in-the-Loop" optimization refers to a process of parameter selection that utilizes physiological measures to drive an algorithmic parameter selection process [2]. The purpose of this study was to determine if such a process could be used to accelerate the identification of metabolically optimal device settings for a powered prosthesis.

## **METHODS**

The proposed process relies on real-time measures of metabolic cost acquired while parameters are continuously varied. We estimate the instantaneous metabolic cost, x, using transient metabolic measurements (rather than using "steady-state" measurements [3]). To this end, we represent the relationship between the parameter setting p, and the instantaneous metabolic cost, x, with a fifthorder polynomial of p with a vector of coefficients,  $\lambda$ . Modeling the dynamics of the measured metabolic response, y, as a first-order, linear system with inputs, x, and a time constant,  $\tau$ , yields an estimated series of breath measurements,  $\overline{y}^{i}$ . The dvnamics of breath-to-breath the

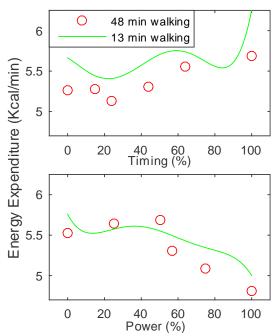
consumption measures can be written in terms of the breath-number, i, and the time between breaths,  $h_i$ :

$$\overline{y}^{i} = \left(1 - \frac{h_{i}}{\tau}\right) \overline{y}^{(i-1)} + \frac{h_{i}}{\tau} x^{i} \left(\boldsymbol{p}^{i}, \boldsymbol{\lambda}\right)$$

The vector of coefficients,  $\lambda$ , is optimized to minimize the error between a set of predicted breath measurements,  $\bar{y}^i$ , and actual measurements,  $\hat{y}^i$ .

$$\min_{\boldsymbol{\lambda}, \overline{y}^{1}} e = (\hat{y}^{1} - \overline{y}^{1})^{2} + \sum_{i=2}^{n} (\hat{y}^{i} - \overline{y}^{i} (x(\boldsymbol{\lambda}, \boldsymbol{p}^{i}), \overline{y}^{i-1}))^{2}$$

In this equation, we recursively propagate an initial measurement,  $\overline{y}^1$ , that is also being estimated.



**Figure 1**: Using continuous measures of metabolic cost, we identified metabolically optimal parameter settings in a fraction of time needed by traditional methods. The red dots are means energy expenditure from steady-state tests. The green line is the fifth-order polynomial,  $x(p, \lambda)$ , that was fit to breath measures taken while the parameters were varied continuously.

We applied this process to approximate the metabolically optimal parameters of the BiOM T2 Ankle System for a 59-year-old male with unilateral transtibial amputation. The device was fit and the settings were adjusted by a manufacturer-certified prosthetist. The subject's BMI and walking speed were 28.9 kg/m<sup>2</sup> and 1.16 m/s respectively. Energy use was measured with a portable respirometer (K4b2, COSMED, Rome, Italy).

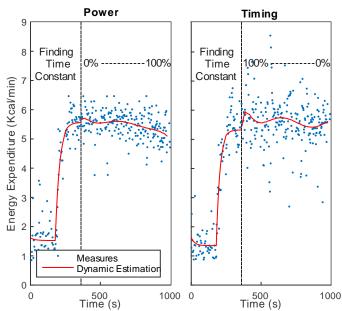
The BiOM manufacturer allows the power and timing parameters to be varied between 0% and 100%. We tested each parameter independently. While varying the timing parameter, the power was fixed at the prosthetist-selected 57%. Similarly, in the power trials, the timing was fixed at 44%. All other device parameters were fixed at prosthetist-selected settings.

We ran two tests to identify the relationship between the energy expenditure and the parameters. The first test evaluated energy expenditure by averaging several minutes of data at steady-state conditions. The total walking time for each parameter was approximately 48 minutes.

The second test applied the methods of "body-in-the-loop" optimization. The walking time required for these trials was approximately 13 minutes per parameter. In these trials, the dynamics of the metabolic response were first identified by asking the subject to stand at rest for three minutes and then walk for three minutes. The parameters were then varied between 0% and 100% (or vice-versa) over the course of ten-and-a-half minutes. A fifth-order polynomial was used as a surrogate function.

## RESULTS AND DISCUSSION

For the power setting, both methods indicated the 100% power setting as the metabolically optimal choice. For timing, the results of the two methods differed slightly. In the "Body-in-the-Loop" optimization, the best-fit 5th-order polynomial predicted the optimal timing parameter to be 22%. A 5th-order polynomial fit to the means of the steady-state measures had a minimum at 28%.



**Figure 2**: Our method enables us to estimate relationships between device parameters and metabolic cost in real-time, using noisy and dynamically changing measures of energetic cost ( $\hat{y}^i$ , blue dots). The first part of the experimental trial was used to identify the time constant of the metabolic response. The red line is the best-fit, predicted metabolic response,  $\bar{y}^i$ .

Though these methods were only tested on a single subject, "Body-in-the-loop" optimization techniques hold promise for improving the selection of parameter settings. They allow for the rapid and objective evaluation of parameter settings without an excessive amount of subject fatigue.

#### REFERENCES

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- 3. Selinger JC and Donelan JM. *J Appl Physiol* **117.11** (2014): 1406-1415

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