# PREDICTIVE SIMULATION OF ROWING EXERCISE USING GPOPS II

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## INTRODUCTION

An exercise machine presents a specific geometrical and mechanical environment to the user. The design parameters affect how the user performs the exercise and which forces are generated in musculoskeletal tissues. If we are able to predict these effects during the design process, exercise outcomes can be improved. Current approaches aim at presenting simple conditions such as constant load or constant speed, or replicate existing sports-related exercise conditions such as rowing, weightlifting and bicycling. There is, however, much more design freedom which remained unexplored.

To predict human execution and optimize machine parameters, human musculoskeletal dynamics and adaptive neuromuscular control should be taken to account. Here we will use a computational method based on musculoskeletal modeling and optimal control to predict how mechanical parameters alter human performance [1]. The specific purpose of this research is to investigate the effects of resistance parameters on movements and forces generated by the arm during periodic arm flexion exercise.

## METHODS

*System dynamics*

We will consider a one-degree of freedom arm flexion exercise, where resistance is similar to that found in a rowing machine. The rowing machine model has two phases in which there are different dynamics. In the first phase (power phase), resistance is provided by a spring ($k_1$), a damper ($b$) and a mass, which is the total effective mass of the user ($m_h$) and the rowing machine ($m_r$) (Fig 1). In the second (recovery) phase, the resistance mechanism is disengaged, except for a weak spring ($k_2$) which winds up the cable (Fig 2). The user's action is represented by a force ($F_{arm}$) which is generated by the arm.

The rowing machine inertia was assumed to be 40 kg and the human inertia was assumed to be 10 kg. Also $k_1$, $k_2$ and $b$ were set to 120 N/m, 10 N/m and 20 Ns/m, respectively.

A Hill-based muscle model (Fig 3) was used to model the dynamics of muscle contraction in which contractile element (CE) represents the muscle fibers, the series elastic element represents the tendon that transfers force from muscle fibers to the skeleton [2]. A small amount of parallel damping was added to the contractile element for numerical reasons. The connection between muscle and the machine was a simple lever where $d$ is moment arm at elbow is and $L$ is the total length of forearm and hand.

Muscle properties and other model parameters were obtained from both heads of the biceps brachii muscle in an existing arm model, and combined into one equivalent muscle [3].

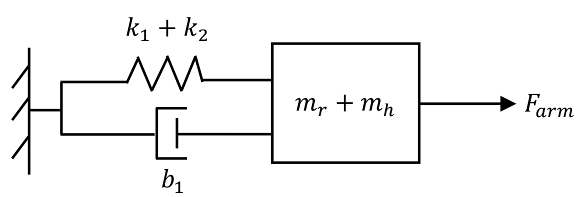


**Figure 1**: Dynamic model for the power phase.

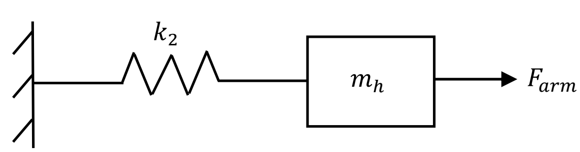


**Figure 2**: Dynamic model for the recovery phase.

*Simulation*

The predictive simulation was formulated as an optimal control problem, to find the force profile that produces a periodic movement with an amplitude of 0.2 $m$ with minimal effort. Effort was defined as the integral of the squared neural control. Duration of the entire movement fixed at 4 seconds; however the duration of each of two phases (power phase and recovery phase) was predicted.

GPOPS II [4] (MATLAB optimal control software) was used to solve the two-phase optimal control problem.

Preliminary results will be presented with a simplified static muscle model in which there was no series elastic element and no length or velocity dependence in muscle force generation. In this model, the muscle force was directly controlled by the neural control signal $u$.

$$F_{muscle} = uF_{max} \tag{1}$$

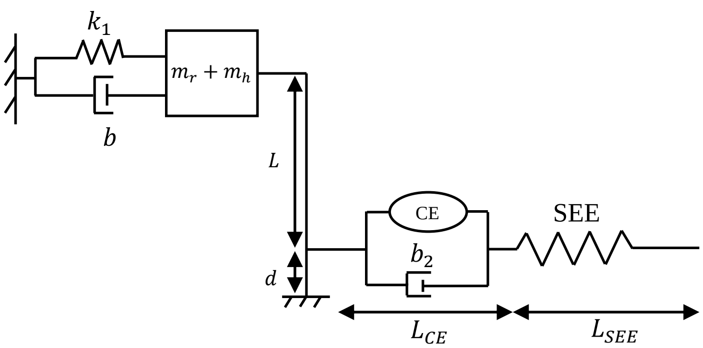


**Figure 3**: Dynamic model for the muscle model in power phase .

## RESULTS AND DISCUSSION

GPOPS II required about 10 seconds of computation time to solve the problem. The optimal phase 1 occurred in 1.84 *s* and phase 2 had a duration of 2.16 *s* (Fig 3). As expected, the model starts from the initial position and moves towards the final position with positive velocity in first phase. In the second phase, the model goes back to the initial position with a negative velocity.

The optimal control profile for the phase one shows that the muscle applies about 70% of its maximal force during the power phase. During the return phase, the mass-spring dynamics rewinds the system and muscle controls the system with a small force to avoid overshooting the starting point.

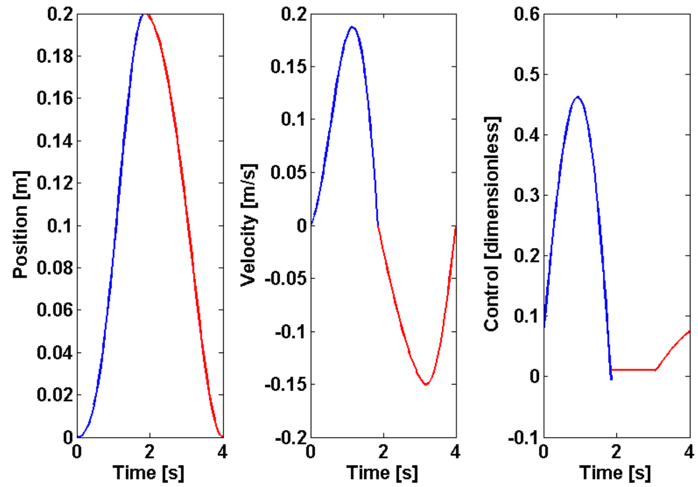


**Figure 4**: Predicted movement, velocity and control.

## CONCLUSIONS AND FUTURE WORK

GPOPS II was able to solve the optimal control problem quickly and accurately. The predicted motions and forces seem realistic. A non-linear dynamic muscle model will be added to the model to examine how it affects the results.

## REFERENCES


1. van den Bogert, AJ, et al. *Proc Inst Mech Eng, Part P: J Sports Eng Technol* 226, 123-133, 2012.
2. van den Bogert, AJ et al. Procedia IUTAM 2, 297-316, 2011.
3. Chadwick, EK, et al. *IEEE Trans Biomed Eng* 61, 1947-1956, 2014.
4. Patterson, MA, et al. A general-purpose MATLAB software for solving multi-phase optimal control problems, University of Florida (http://www.gpops2.com), 2014.