 PID vs. Artificial Neural Network Control of an H-Bridge Voltage Source Converter

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Abstract

An H bridge voltage source converter connected to a supercapacitor, knee motor, and ideal gear ratio is simulated with both a PID controller and an artificial neural network. The performance of the two controllers are compared to each other based upon their ability to track a reference knee angle trajectory and to harness energy inside the supercapacitor. The PID controller was able to match the trajectory with an RMS tracking error of 5.1 degrees while the ANN controller had and RMS error of 103.97 degrees. The PID controller was not able to harness as much energy as the ANN controller with 578.9 joules lost over the gait cycle compared to 53.62 joules lost for the ANN controller.

1. Introduction

Active leg prostheses have shown the capability to restore a normal gait pattern for transfemoral amputees [1], [3], [4]. Due to the large amount of energy consumed by the active prostheses, study has been expanded to include the possibility of regenerative braking due to research that showed that energy is dissipated while braking during normal walking [3], [4], [9]. Power electronics are required by regenerative prostheses due to the different forms of power required by the prosthesis motors (knee and ankle) and the energy storage system (capacitor bank). Previous research in prosthesis power electronics has focused on incorporating an H bridge voltage source converter into a prosthesis with an impedance-based controller [4]. Our research evaluates the same H bridge circuit for a transfemoral prosthesis simulation that uses supercapacitors to harness energy from braking. PID and artificial neural network (ANN) controllers are implemented to this circuit simulation, which can then be combined with the prosthesis simulation. The PID controller was selected since it is a standard controller used in systems. The ANN controller was selected for comparison to the PID controller.

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since it has more degrees of freedom than the PID controller, including nonlinearity and requires fewer tuning parameters than the PID controller.

Our research goal is to integrate the H bridge circuit into a simplified prosthesis model along with a PID and ANN controller to determine which of the two control methods would provide better results when combined with a more developed prosthesis simulation. The two controllers are compared based upon their ability to track a reference knee angle trajectory and their ability to capture energy from regenerative braking into a supercapacitor.

The next section of this paper shows the system model of the H bridge voltage source converter. After the model is introduced, the PID and ANN controllers are described, which leads to discussion of optimization of the system and control parameters. The results will be presented, and then ideas to expand this research will be proposed.

2. Simulation schematic

The model used to simulate the H bridge circuit with the simplified prostheses model is shown in Figure 1. The knee is connected to an ideal gear ratio transformer of ratio 1:n. The transmission is then connected to the knee motor, which acts as a gyrator between the mechanical system and the electrical system. The H bridge circuit is then connected between the motor and supercapacitor to convert the power flow between the two devices.
The H bridge voltage source converter, as seen connected to the motor and supercapacitor in Figure 2, contains a set of four switches to control the current flow in the prosthesis. The H bridge allows for the prosthesis to operate in four modes: motoring+, motoring−, generating+, and generating−. Motoring mode refers to the situation in which the knee motor requires power from the supercapacitor to drive the prosthesis while generating mode refers to the situation when the knee is braking and the energy should be stored inside the supercapacitor. The signs on the motoring and generating modes describe the direction of the knee angle motion.
The control signals sent to the circuit determine which mode the circuit operates. Once a mode is selected by the direction of the knee's torque and velocity, according to Table I, the circuit operates by controlling the MOSFETs through a duty cycle determined by the PID or ANN controller. The duty cycle allows for the voltage seen across the capacitor to be modulated for control of the motor position. Table II summarizes which circuit elements are used in each mode.

**Table I: The direction of the knee torque and velocity determine which mode the prosthesis should operate**

<table>
<thead>
<tr>
<th>Mode</th>
<th>Torque</th>
<th>Velocity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motor+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Motor–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Generator+</td>
<td>–</td>
<td>+</td>
</tr>
<tr>
<td>Generator–</td>
<td>+</td>
<td>–</td>
</tr>
</tbody>
</table>
Table II: Circuit elements used in each mode

<table>
<thead>
<tr>
<th>Mode</th>
<th>MOSFETs on</th>
<th>Switching MOSFET</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motor+</td>
<td>Q1, Q4</td>
<td>Q1</td>
</tr>
<tr>
<td>Motor−</td>
<td>Q2, Q4</td>
<td>Q3</td>
</tr>
<tr>
<td>Generator+</td>
<td>Q1, Q4</td>
<td>Q2</td>
</tr>
<tr>
<td>Generator−</td>
<td>Q2, Q3</td>
<td>Q4</td>
</tr>
</tbody>
</table>

Depending on which mode the voltage source converter is operating in, a different set of equations are used to describe the electrical states of the prosthesis model. The equations are derived using Kirchoff's voltage law around the loop for each mode. Due to the switching MOSFETs in each mode, every mode that the voltage source converter has requires two equations: one for the case when the capacitor is connected and one for the case when the capacitor is disconnected. Following the loop in Figure 2 for the generator+ mode the voltage loops

\[ 0 = \varepsilon - v_{RA} - v_L - v_c - v_{Q4} \]  \hspace{1cm} (1)

\[ 0 = \varepsilon - v_{RA} - v_L - v_{Q2} - v_{Q4} \]  \hspace{1cm} (2)

are found for the cases when the capacitor is connected and disconnected, respectively where \( \varepsilon \) is the back emf of the motor, \( V_{RA} \) is the voltage drop across the motor's resistance, \( v_L \) is the voltage drop across the motor's inductance, \( V_c \) is the voltage drop across the capacitor, and \( V_Q \) is the voltage drop across the MOSFET resistance.
3. Control methods

To achieve proper knee angle tracking, a control system is required to provide the correct amount of braking to the knee during a generating mode and must provide the correct amount of power from the supercapacitor during a motoring mode. The H bridge voltage source converter is able to modulate the power flow by switching the supercapacitor in and out of the circuit in both generating and motoring modes by switching the respective MOSFETs according to Table II. During motoring modes, the stored energy in the supercapacitor causes the knee angle to increase (motor+ mode) or decrease (motor– mode) based upon when the switching MOSFETs cause the supercapacitor to be included in the circuit. When the prosthesis is running in generating mode, the supercapacitor acts as a brake because of the extra impedance it puts into the circuit. To be able to determine when to switch the supercapacitor in and out of the circuit, a control system (PID or ANN) generates a control signal that is compared to a triangular waveform at 10 kHz to generate a pulse-width modulated (PWM) switch signal. When the prosthesis is in a generating mode, the PWM signal modulates the voltage across the capacitor, while in motoring mode the PWM signal modulates the voltage across the motor.

3.1 PID controller

The simulation with the PID controller works by comparing the simulated knee angle to a reference knee angle trajectory provided by the Cleveland Clinic Foundation [5]. The difference between the two trajectories creates the error signal that is sent to the PID controller. Eight sets of control parameters are used with this controller. The first set of four gains are given to each mode in Table II. The second set of four gains are also given to each mode in Table II, but are
used when the prosthesis is in swing phase (not touching the ground) instead of stance phase (touching the ground). The equation

$$\Delta U = K_p e(t) + K_i \int e(t) dt + K_d \frac{d}{dt} e(t)$$

(3)

is used to determine a delta control signal, $U$, that then creates a PWM signal by being compared to a triangular carrier signal at 10 kHz. The control parameters, $K_p$, $K_i$, and $K_d$ each have eight different values depending on which mode the prosthesis is operating in and whether it is in stance phase or swing phase, requiring a total of 24 control parameters.

3.2 ANN controller

The simulation with the ANN controller works in a manner similar to the PID controller. The simulated knee angle is compared to a reference knee angle trajectory provided by the Cleveland Clinic Foundation [5]. The difference between the two trajectories creates the error signal that is sent to the ANN controller. The neural network used in this system uses the sigmoid function as the activation function and has one input neuron with a bias node, one hidden layer with three neurons and a bias node, and one output neuron. Each node of a layer is connected to each node of the next layer in the network and each of these connections requires a weighting factor, giving the ANN 10 control parameters. Since the input of this controller is used to generate a change in the PWM signal and not a knee angle, the desired output from this controller is not known. Since the output from the controller is unknown, derivative-based training of the neural network is not feasible. An evolutionary algorithm, biogeography-based optimization, is used to tune the control parameters in each simulation.
4. Biogeography-based optimization

For both the PID and ANN controllers, control parameters must be chosen so that the H bridge circuit provides the required modulation of voltages in the prosthesis. The physical parameters, such as the ideal gear ratio, the ON resistance of the MOSFETs, the initial charge on the supercapacitor, and the capacitance of the supercapacitor also need to be optimized to obtain desirable results. To optimize all of these system parameters, biogeography-based optimization was selected due to the resources available for this algorithm from previous studies.

Biogeography-based optimization is an evolutionary algorithm that was motivated by the study of migration of species [6], [7]. This algorithm creates sets of system parameters, which then have the ability to share information with other sets of system parameters through immigration and emigration processes. Immigration is when certain parameters are brought into a set of parameters, and emigration is when a set of parameters sends information to a set of parameters. The relationship between emigration and immigration is assumed to be linear in this research.

The emigration and immigration rates represent how the desirability of a specific set of parameters. When a set of parameters is desirable, its emigration rate will be large because it has information from many different sets. The immigration rate will be low when a set of parameters is desirable because it already contains information from many different sets. A set probabilistically decides whether to share parameter information with another set. If a specific parameter is chosen to emigrate, then the set to which the parameter emigrates is selected from a roulette wheel selection normalized by the emigration rate. Once the parameter emigrates, a

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mutation may randomly occur on each parameter in the parameter set. Biogeography-based optimization repeats this algorithm until a solution is considered to be desirable.

To determine how desirable a parameter set is, biogeography-based optimization calculates a cost function of each parameter set. In this simulation, the cost is calculated by the two objectives of the system: to track a reference knee angle trajectory and to harness energy into a supercapacitor. To determine the ability to track a reference knee angle trajectory, the RMS error value between the simulated and reference data is used. To determine the ability to harness energy, the change in energy stored in the capacitor from the beginning to the end of the simulation is used. These two objectives are combined with a weighting factor since RMS degrees and energy cannot be directly added. The weighting factor also allows biogeography-based optimization to put a higher importance on tracking the knee angle over the ability to store charge. The equation

$$\text{Cost} = \int [\phi^d_k(t) - \phi_k(t)]^2 dt - W \Delta C \quad (4)$$

gives the optimization algorithm a quantitative value for how desirable a parameter set is where \(\phi^d_k\) is the reference knee angle, \(\phi_k\) is the simulated knee angle, \(\Delta C\) is the change in energy stored in the supercapacitor, and \(W\) is the weighting factor. The weighting factor was selected to have a value of .05 so that more emphasis would be placed on knee trajectory tracking than energy storage.

5. Results

The H bridge circuit and simplified prosthesis model is currently being simulated with two separate systems. Both systems were optimized with BBO. The simulation with the PID
controller was optimized with a population size of 20 and a generation size of 20. The results of this optimization can be seen in Figure 3. An RMS error of 5.15 degrees is present throughout one cycle of gait. The capacitor was able to harness energy at some points during the stride, as seen with positive current through the capacitor in Figure 4, but had an overall loss of energy during the stride. The capacitor lost 648.74 joules of energy during this cycle.

Figure 3: The simulated and reference knee angle trajectories after the first round of BBO for the PID controller. An RMS tracking error of 5.15 degrees occurred along with a loss of 648.74 joules of energy from the supercapacitor.
Figure 4: The current through the supercapacitor during a single stride. Positive current relates to a charging capacitor while negative current shows that the capacitor is discharging.

To improve the amount of energy that the capacitor could harness during regenerative braking, BBO was used again with the same generation and population parameters, but more emphasis was placed on energy harvesting by changing the weighting factor in Equation (4) from .05 to .1. The tracking error increased to 5.35 degrees (.2 degrees worse) while the amount of energy lost decreased to 578.92 joules, a decrease of over 100 joules. If BBO were to run again, it is likely that a similar trend would happen. This multi-objective problem could be solved by using a multiple objective BBO algorithm that can find a Pareto front.

The simulation with the ANN controller was originally optimized with a generation size of 20 and a population size of 20 with a weighting factor of .05. The initial results from this optimization loop gave an RMS tracking error of 116.05 degrees and loss of 39.26 joules. To improve these results, BBO was run again with the same optimization parameters and yielded an
RMS tracking error of 103.97 degrees and loss of 53.615 joules. The trajectory that this controller was able to provide is shown in Figure 5.

![Diagram showing simulated and reference knee angle trajectories after the second round of BBO for the ANN controller. An RMS tracking error of 103.97 degrees occurred along with a loss of 53.615 joules of energy from the supercapacitor.]

The ANN controller did not provide desirable results, but it is possible that if more iterations of the optimization algorithm were to occur, then the controller would find neural weights that provide decent results. It is also possible that having different neural networks for stance and swing phases or generator and motor modes would improve performance.
6. Conclusion and Future work

A modulated voltage source converter circuit was modeled with a regenerative active transfemoral prosthesis. Simulations of both a PID and ANN controller were developed into the model of the simplified prosthesis with an H bridge voltage source converter. Biogeography-based optimization was used to find system and controller parameters that allowed the two systems to match a reference trajectory and harness energy through regenerative braking. The PID controller matched the reference data with an RMS error of 5.15 degrees while the ANN controller was only able to achieve an RMS error 103.97 degrees with the same optimization parameters that were used with the PID controller. The PID controller was able to recover enough energy during one cycle of gait to lose 578.92 joules when averaged over the whole cycle while the ANN controller only lost 53.62 joules when averaged over the whole cycle.

More work is required to determine which controller would be better suited for use in the higher-fidelity simulation. As it stands now, the PID controller would be better to use since it is able to track the reference data. A multiple objective BBO algorithm could be used for both controllers so that the two systems could be compared by their Pareto fronts. Once the two controllers are compared, one of the controllers could be inserted into a higher-fidelity prosthesis simulation.

Once a controller is combined into the higher-fidelity simulation, this research could be pursued even further by being implemented in a hardware prototype. Once a prototype is built with the use of microprocessors or tools such as the DSpace system, the hardware can be tested with Cleveland State University's hip robot to ensure desirable operation [8].
References


