Application of artificial neural networks in the power split controller for a series hydraulic hybrid vehicle

Chao Cheng

The University of Toledo

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A Thesis

entitled

Application of Artificial Neural Networks in the Power Split Controller

For a Series Hydraulic Hybrid Vehicle

By

Chao Cheng

Submitted to the Graduate Faculty as partial fulfillment of the requirements

for the Master of Science Degree in Mechanical Engineering

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Yong Gan, Ph.D., Committee Member

________________________________________________________________________

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College of Graduate Studies

The University of Toledo

August 2010
An Abstract of

Application of Artificial Neural Networks in the Power Split Controller
For a Series Hydraulic Hybrid Vehicle

Chao Cheng

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The University of Toledo
August 2010

Hybridization of vehicles has been proven a good way to reduce fuel consumption significantly. Working prototypes of a series hydraulic hybrid vehicle (SHHV) are already under testing. The power split strategy for those prototypes is a rule-based controller, or called a “bang-bang” controller. The controller is designed based on engineer’s intuition, to keep the engine working in the region with high efficiency and low fuel consumption rate. One of the problems of that design is that it only takes one component of the hydraulic hybrid system, the internal combustion engine, into account. It is a device centered rather than system centered design. As a result, the potential of the hydraulic hybrid system is not fully realized.
A more efficient power split strategy is conducted based on the Deterministic Dynamic Programming (DDP), which has been proved a powerful tool for optimal control. However, the DDP is a looking-forward tool, which means it uses the future driving conditions to split the power between the two sources for optimization. Successful applications of DDP used standard driving cycles as the known driving conditions. However, DDP is not applicable where the driving cycle is unknown. This means that the DDP could not be applied in real-time, unless the future driving conditions could be found.

The driving conditions in our everyday commute are extremely different with the typical driving cycles. And different drivers have different driving habits. However, a specific driver has a certain “driving cycle” for a certain commute, although which is not a standard one. As long as the certain “driving cycle” is known, The DDP algorithm could be applied for optimization. Artificial neural network (ANN) has the ability to “learn” the “driving cycle” from a certain driver and then to “predict” the driving conditions before its happening. The “prediction” method is the “time-series forecasting” method. ANN is a good tool for time series forecasting and has also been shown a better way for long term prediction. The ANN is conducted using the software MATLAB/Simulink. A three-layer feed-forward static ANN is built up in the Simulink environment.

The ANN model was able to predict the driving conditions with a twenty seconds window size which has been proven a tradeoff between the forecasting accuracy and the time consumed. The error between the predicted value and the desired value is within an
accepted range. The network is tested based on three different driving cycles: federal urban driving schedule, city urban dynamometer driving schedule and highway urban dynamometer driving schedule respectively.
ACKNOWLEDGEMENTS

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Chapter 1 INTRODUCTION

For hydraulic hybrid vehicles, a proper power split control strategy is used to balance power flow from the internal combustion engine and the storage system in order to maximize the fuel economy. An intelligent controller combined with artificial neural networks and dynamic programming is currently one of the best approaches. The dynamic programming algorithm is powerful in solving sequential problems. In this research, the fuel consumption at each second constructs a sequence and the global minimum of the fuel consumption is the objective of optimization.

However, real time driving conditions vary a lot from the standard driving schedules used in testing. In this case, the dynamic programming algorithm could not be applied for optimization. A way to predict the future driving conditions must be found in order to implement the optimal control strategy.

Artificial neural network is able to predict the future events after several training processes. The predict method is called “time-series forecasting” which uses several past data to forecast the value of the same event in the future. In other words, the ANN serves as a predictor which forecasts and constructs a new non-standard driving schedule.
As long as the driving conditions are known, the DP algorithm could be used to split the power flow between the two power sources: the internal combustion engine and the hydraulic accumulator.

1.1 Background of the research

Hybridization with engine off technologies of large or medium size delivery trucks has been proved to be a very effective way to improve the fuel economy as well as reduce emission. The large mass associated with trucks enables capturing the braking energy when decelerating and reusing it for launching or assisting aggressive acceleration. The hydraulic energy storage system is characterized by high power density compared to the hybrid electric batteries with high energy density [13]. As the energy storage device, a hydraulic accumulator has the ability to accept high rates and high frequencies of charging/discharging, both of which could not be achieved for batteries in a hybrid electric vehicle [1].

There are several power management strategies for series hybrid hydraulic vehicles (SHHV), including the rule-based and the optimal control strategies. In order to fully maximize the fuel economy, a careful design in the control strategy is needed due to the relative low energy density of the hydraulic accumulator. Dynamic programming is a numerical methodology developed for solving sequential or multi-stage decision problems. The algorithm searches for optimal decisions at discrete points in a time sequence.
The deterministic dynamic programming algorithm has been shown to be a powerful tool for optimal control on fixed driving cycles. However, DDP is forward-looking algorithm, i.e., it uses the knowledge of the future driving conditions to determine optimal engine speed for the series hydraulic hybrid vehicle [1]. DDP is not applicable unless the future driving conditions are known. However, if future driving conditions can be predicted, then DDP is the most efficient algorithm to determine the optimal control parameters.

In statistics, signal processing, and many other fields, a time series is a sequence of data points, measured typically at successive times, spaced at (often uniform) time intervals. Time series analysis comprises methods that attempt to understand such time series, often either to understand the underlying context of the data points (Where did they come from? What generated them?), or to make forecasts (predictions). Time series forecasting is the use of a model to forecast future events based on known past events: to forecast future data points before they are measured. While there are many methods for performing time series prediction, including exponential method [33], ARIMA method, etc. neural networks have been shown effective.

A neural network is a tool falling within the domain of control of complex industrial and robotic systems with reasoning, learning, and adaptive abilities. An artificial neural network (ANN) is a mathematical model or computational model that tries to simulate the structure and/or functional aspects of biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system
that changes its structure based on external or internal information that flows through the network during the learning phase. Neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. It is also a tool for investigating time-series data for a supervisory controller, which learns from the known signals, and “predicts” the future output.

1.2 Problem Statement

The problem this thesis attempts to solve is to build an optimal controller for a hydraulic hybrid vehicle using deterministic dynamic programming algorithm and neural network predictor for non-standard driving cycles. A time-series ANN is chosen as an appropriate approach to provide the possible driving conditions based on the past driving conditions, and then being used for the dynamic programming to optimize the energy management for a series hydraulic hybrid vehicle.

1.3 Work Outline

Chapter Two will present a literature review of the development of the hydraulic hybrid vehicles, the power management strategies as long as the artificial neural networks applications. The configuration of parallel, series hybrid hydraulic vehicles and hydro-mechanical hydraulic hybrid configuration will be presented, and also the key components for them: the high pressure accumulator and lower counterpart, the engine pump and driving pump/motor. The chapter will also cover the control strategies for hybrid vehicles, including the rule based controller, and intelligent controller. Another
main part of this chapter will be the review of the application of the Neural Network for
time-series forecasting.

Chapter Three considers in details the algorithm of deterministic dynamic
programming; the theoretical model of the static feed-forward neural networks and the
time series forecasting method; as well as the choice of neural network prediction
window size.

Chapter Four shows the simulation of the mathematical model using
Matlab/Simulink software.

Chapter Five gives the simulation results, including the vehicle speed prediction
results of the neural networks and the fuel economy results based on the intelligent
controller.

Chapter Six gives the conclusions and the future works.
Chapter 2 LITERATURE REVIEW

2.1. Hybrid Hydraulic Vehicles

A hybrid vehicle is defined as one with two sources of power [26]. In the past, a traditional vehicle featured an internal combustion engine fueled by a petroleum product, with the power transmitted to the driving wheels using a mechanical drivetrain. Thus, when an additional power source was added to a traditional vehicle, it was termed hybrid. The additional power source can be electrical, chemical, hydraulic, fly wheel, or any other form of power storage and production [2]. EPA has pioneered the research efforts on HHVs in the US [12]. A hydraulic hybrid vehicle is a hybrid vehicle that uses hydraulic energy storage system as an additional or alternative power source to the internal combustion engine [14]. One major benefit of the hydraulic hybrid vehicle is it can capture the energy lost to friction braking as heat, store the energy in the hydraulic accumulators, and reuse it when accelerating [16,17]. With this hydraulic assistance, the engine could idle or even be shut down when decelerating and launching. Engine shut-off ability is a major improvement in the fuel economy and emissions. The fuel economy improvement really depends on the driving cycle. There will always be a larger improvement for those vehicles with frequent stop-and-start driving processes. Therefore,
hydraulic hybrid technology has perhaps the greatest commercial potential for a wide range of medium-duty vehicles such as urban delivery trucks [3].

Hydraulic hybrid vehicles could be mainly classified into two categories: parallel hybrid hydraulic vehicles and series hybrid hydraulic vehicles [18]. There are also some other configurations including the hydro-mechanical hydraulic hybrid drive train [21,23] with its own benefits.

i. **Parallel Hybrid Hydraulic Vehicles (PHHV)**

In a parallel hybrid hydraulic system in Figure 2-1, the engine and the hydraulic pump/motor are mechanically coupled to the same drive shaft. The parallel systems are easier to implement, but limited with regards to flexibility of engine and propulsion system control [4]. This system has the potential to decrease the fuel consumption in the range of 20% to 40%. Efficiencies are limited because the engine must follow the speed of the tires through the transmission [5].

![Figure 2-1 Parallel hydraulic hybrid vehicle configuration](image)
The torque converter (TC), transmission (Trns), propeller shaft (PS), differential (D) and driving shaft (DS) are the same as those in the conventional trucks. The assistant power source is an axial piston pump/motor (P/M) with variable displacement. The hydraulic displacement per revolution can be adjusted to absorb or to produce desired torque. When pumping, hydraulic fluid flows from the low pressure reservoir to the high pressure accumulator [22]; when motoring, hydraulic fluid flows in the reverse direction. The accumulator contains the hydraulic fluid, and inert gas such as nitrogen (N₂), separated by a piston. When hydraulic fluid flows in, the gas is compressed and its internal energy increases. When discharging, fluid flows out through the motor and into the reservoir.

ii. Series Hybrid Hydraulic Vehicles (SHHV)

In a series hydraulic hybrid system (Figure 2-2), the IC engine is totally decoupled from the driving shaft. The series system is harder to implement compared with the parallel system, since the conventional powertrain needs to be replaced. But on the other hand, the series system is more flexible for the engine and propulsion system control. The engine can be controlled to operate at more efficient range regardless of the driving condition of the vehicle. In this case the potential to reduce the fuel consumption of this system is approximately 70%, which is much higher than the parallel configuration.
In this configuration, there is no drive shaft; instead, it is connected through hydraulic lines. An engine pump transfers the power from the IC engine to the hydraulic system. In some applications, the engine pump is not only a pump but also serves as a motor to start the engine. In the series configuration, the control parameters are the state of charge (SOC) of the accumulators, the engine speed and the driving pump/motor yoke angle. The SOC could be defined as the instantaneous fluid volume in the accumulator over the maximum fluid capacity or the instantaneous gas pressure over the maximum pressure. The engine speed is determined by the SOC to maintain the SOC at a certain range, avoiding too low or too high SOC values. If the SOC is too low and the vehicle needs enough power to accelerate or maintain a certain speed, the hydraulic system could work in the “hydraulic static” transmission condition, which should be avoided since the low efficiency on the system level. On the other hand, too high SOC should also be avoided to make sure there is enough space in the accumulator to capture the energy.
when braking. The series configuration decouples the engine from the wheel. The engine operation conditions are no longer determined by the wheel, but by the SOC. This is one of the main reasons that the fuel economy of the SHHV is much higher than that of the parallel counterpart.

**2.2. Power Management Strategies**

A proper power management strategy is essential for the vehicle design when considering the fuel economy. For the SHHV, decoupling the engine from the wheels provides an easier way to operate the engine at the more efficient range, but at the same time, it also brings a question “how to manage the power flow between the two power sources?” In order to reduce the fuel consumption and follow the driver’s demand without any safety issues, researchers have developed different strategies to lower the fuel consumption by controlling the hybrid system. Once system configuration, component design and driving cycle are fixed, the fuel economy depends only on strategy for splitting propulsion power between two power sources and gear shifting logic [1], that is to say in which condition the IC engine should be operated to charge the hydraulic accumulator; while in other conditions, the hydraulic energy storage system would provide the power for propulsion and the IC engine is shut down. Currently, there are two major control strategies, and each with their advantages and deficiencies.
i. **Rule Based Control Strategy**

The rule based controller is a “bang-bang” controller that has some pre-set rules to follow. Because of the easy handling switching characteristic, this kind of controller is more reliable and applicable for the SHHV’s; and currently most of the hybrid electric vehicles have rule based controllers [24].

The symbols used as the control parameters are listed and defined as follows:

- **Pedal = [-1, 0, 1]**. Here, Pedal is a discrete variable. -1 means a braking input and 1 means acceleration input. 0 corresponds to a coasting input, where neither the gas nor brake pedal is pressed. But the system is recognized as an energy capture mode.

- **SOC**: The state of charge, which is defined as the ratio of the instantaneous gas pressure in the high pressure accumulator over the maximum pressure capacity, $\text{SOC} = \frac{p_{ha}}{p_{ha,\text{max}}}$. SOC is a continuous variable, $0 \leq \text{SOC} \leq 1$ (more realistically $0.1 \leq \text{SOC} \leq 0.9$). 0 means the minimum pressure in the high pressure accumulator, corresponding to the status of minimum fluid in the high pressure accumulator. 1 means the allowable maximum pressure in the high pressure accumulator.

- **SOC\text{start}**: The value below which the engine will start. $\text{SOC}_{\text{start}}$ is a little bit greater value than 0.

- **SOC\text{min}**: The minimum pressure value to which the high pressure accumulator should be pressurized to. If this value is set too high, there will not be enough room to capture the energy in braking process. If this value is
set too low, there will not be sufficient energy to propel the vehicle for the next run cycle. $\text{SOC}_{\text{min}}$ is always greater than $\text{SOC}_{\text{start}}$.

The rule based controller for a SHHV always has 5 working modes:

- **“Accumulator Propulsion”**.
  In this mode, Pedal $\geq 0$. Engine is off and SOC drops until reaches $\text{SOC}_{\text{start}}$, the vehicle is propelled only by accumulator.

- **“Engine Propulsion and SOC regulation”**.
  In this mode, Pedal $\geq 0$. Engine propels vehicle through the hydraulic line. At the same time, engine also pumps fluid from the reservoir to the high pressure accumulator until SOC reaches $\text{SOC}_{\text{min}}$.

- **“Flow Mode”**.
  In this mode, Pedal $> 0$. No energy is transferred to/from the accumulators, therefore SOC is held at the current value, which is a very small value. Engine propels vehicle using engine pump and driving pump/motor. The system is running in the hydrostatic mode.

- **“Energy Capture”**.
  In this mode, Pedal $\leq 0$. The vehicle is braking and engine is shut off (or in some other designs, the engine idles instead of shuts off). Energy is captured by driving pump/motor (here, it serves as a pump). Then the energy is stored in high pressure accumulator as SOC rises until to the maximum allowed value. The “$\leq$” here means if the accelerator pedal is not pressed, the vehicle is recognized as decelerating.
“Friction Braking”.

In this mode, Pedal < 0 and the engine is shut off. Once the SOC reaches the maximum value, the accumulators are disconnected from hydraulic line in order to guarantee the safety of the hydraulic system. Thus energy capture is terminated and the standard friction brakes must be engaged. The friction braking mode is also activated when the brake pedal is stepped down quickly and deeply. The reason is that the regenerating braking system’s response time is above 100ms generally. For the sake of personal and vehicle safety, the standard brakes are used.

The flow mode should be avoided since in this mode, the hydraulic hybrid system works as a hydrostatic transmission and the engine operation points depend on the driving wheel, which means the IC engine is not decoupled from the wheels.

Figure 2-3 Rule-based control algorithm for positive power
Figure 2-4 Rule-based control algorithm for negative power

Figure 2-4 and Figure 2-5 give us the algorithm of the rule based controller for a SHHV. Figure 2-4 represents the condition when the power demand is positive (propelling the vehicle) while Figure 2-5 represents that of the negative power condition (decelerating the vehicle).

Kim and Filipi at the University of Michigan provided a control strategy for a SHHV based on the SOC solely [6]. Four parameters are used to fully define the thermostatic control strategy, namely threshold SOC, the threshold power, the dead band, and the SOC at which power command becomes 100%. This kind of control strategy is a “bang-bang” controller, or we could say it is a rule-based one.
As long as the SOC is above the threshold value (e.g. 0.4), the engine shuts off or idles (depends on the pre-setup). When SOC drops below the threshold value, the engine starts charging the accumulator until the SOC reaches the upper threshold (about 0.5 for a threshold SOC 0.4 with a dead band of 0.1). If the power required for propulsion exceeds the threshold level, the SOC will instantaneously drop below the lower limit and the engine power will be progressively increased [20]. Further increase in demand essentially keeps the system operating in the hydrostatic drive mode. The threshold SOC should be relatively low for enough spare capacity for regeneration braking energy capture. However, the limit should also be high enough to provide a buffer during a transition to full-load hydrostatic mode. The controller attempts to operate the engine at the “sweet spot” value at the brake specific fuel consumption (BSFC) map since they believed that the global minimum in fuel consumption could be reached through this strategy. However, the simulation results indicate a much better result with $P_{\text{threshold}} = 60$ kW rather than the “sweet spot” value of 100 kW @ 1800 rpm [15]. This is because very rapid load
transients come with a penalty, as there is an energy loss associated with rapid engine acceleration.

![Figure 2-6 Engine brake specific fuel consumption map](image)

Figure 2-6 Engine brake specific fuel consumption map

Figure 2-7 is the illustration of the BSFC map [15].

**ii. Intelligent Control**

Dynamic programming (DP) is a useful mathematical technique for making a sequence of interrelated decisions. It provides a systematic procedure for determining the optimal combination of decisions [7]. The DP is a method of solving complex problems by breaking them down into simpler steps. The algorithm searches for optimal decisions at discrete points in a time sequence. And it has been shown to be a powerful tool for optimal control in various application areas. There are two types of dynamic programming:

- Deterministic Dynamic Programming (DDP)
If the state at the next stage is completely determined by the state and policy at the current stage, it is called a deterministic dynamic programming. The DDP method was used by Wu in a parallel hydraulic hybrid delivery truck [1]. The DDP was formulated as:

$$\min J = \min_u \sum_{k=0}^{k=N-1} L(x(k), u(k)) + G = \min_u \sum_{k=0}^{k=N-1} L(x(k), u(k)) + \alpha (SOC(N) - SOC(0))^2$$  \hspace{1cm} (2.1)

Where $L$ is fuel consumption over a time segment, $N$ is driving cycle length, $x$ and $u$ are the vectors of state variables and control signals respectively, and $G$ is a penalty term to match the final SOC.

For the step $N-1$:

$$J^*_{N-1}(x(N-1)) = \min_{x(N-1)} [L(x(N-1), u(N-1)) + G(x(N))] \hspace{1cm} (2.2)$$

For step $k$, $0 \leq k < N-1$:

$$J^*_{k}(x(k)) = \min_{u(k)} [L(x(k), u(k)) + J^*_{k+1}(x(k+1))] \hspace{1cm} (2.3)$$

The recursive equation is solved backwards from step $N-1$ to 0. Table 2-1 in is the result from Wu for the comparison of the improvement of the initial rule based power management strategy, the improved rule based method and the dynamic programming strategy.
Table 2-1 Fuel consumption of hydraulic hybrid vehicles with different control strategy compared with the baseline vehicle

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Conventional</th>
<th>Initial Rule</th>
<th>Initial Rule + Improved Shifting</th>
<th>Improved Rule</th>
<th>Dynamic Programming</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM Efficiency</td>
<td>NA</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>mpg</td>
<td>10.39</td>
<td>13.75</td>
<td>12.01</td>
<td>14.08</td>
<td>12.40</td>
</tr>
<tr>
<td>Regen. Energy (kJ)</td>
<td>NA</td>
<td>9748</td>
<td>9700</td>
<td>9652</td>
<td>9736</td>
</tr>
<tr>
<td>Reused / Regen.</td>
<td>NA</td>
<td>6034</td>
<td>3187</td>
<td>5963</td>
<td>3229</td>
</tr>
</tbody>
</table>

From Table 2-1, the fuel economy of the DP is more than double of the initial rule based power management strategy for the environmental protection agency (EPA) federal urban driving schedule (FUDS) driving cycle.

Figure 2-8 shows how the DP splits the power between the engine and the hydraulic accumulator, the SOC varies during the driving cycle and the gear shifting.
Figure 2-7 Dynamic Programming Results Over the Federal Urban Driving Schedule (FUDS) for a Series hydraulic hybrid vehicle [1]

The DP has been proven with great potential for the improvement of the fuel economy for a hydraulic hybrid vehicle power management. However, the dynamic programming algorithm uses forward-looking strategy, which means that it uses the knowledge of the future driving conditions. Based on this characteristic, the DP optimal control signals are not applicable where the driving cycle is unknown.

- Stochastic Dynamic Programming (SDP)

The stochastic dynamic programming (SDP), or called the probabilistic dynamic programming, differs from the DDP in that the state at the next stage is not completely
determined by the state and policy decision at the current stage. Rather, there is a probability distribution for what the next state will be [7]. For the HHV application, SDP is not based on a particular driving cycle (time signal), but rather the statistical characteristics of many driving cycles and hence it is non-cycle-beating [8]. Johri et. al., carried out the application of the SDP in a small size city car.

The driver power demand and wheel speed is discretized into finite values:

\[ P_{\text{dem}} \in \{ P_{\text{dem}}^1, P_{\text{dem}}^2, \ldots, P_{\text{dem}}^{N_p} \} \]

\[ \omega_{wh} = \{ \omega_{wh}^1, \omega_{wh}^2, \ldots, \omega_{wh}^{N_{\omega}} \} \]

The dynamics of driver power demand is assumed to be:

\[ P_{\text{dem},k+1} = w_k \]  

\[ P_{ij,l} = \Pr \left[ w = P_{\text{dem}}^i \mid P_{\text{dem}} = P_{\text{dem}}^j, \omega_{wh} = \omega_{wh}^l \right] \quad i,j = 1,2,\ldots,N_p, l = 1,2,\ldots,N_{\omega} \]  

Figure 2-8 Naturalistic driving cycles during typical commutes in SE Michigan
Figure 2-9 shows some of the driving cycles Johri used for generating the transition probability matrix given in Figure 2-10.

\[
J_\pi(x_0) = \lim_{N \to \infty} E \left\{ \sum_{k=0}^{N-1} \gamma^k g(x_k, \pi(x_k), w_k) \right\}
\]

(2.6)

Where the \( J_\pi \) is the total cost over an infinite horizon, \( \pi \) is the optimal control policy, \( g \) is the instantaneous cost incurred, and \( 0 < \gamma < 1 \) is the discount factor.

\[
g = FC(\omega_e, \alpha, SOC) + \mu \cdot (SOC - SOC_{ref})^2 \cdot (SOC < SOC_{ref})
\]

(2.7)

Where the \( FC \) is the fuel consumption of the engine for an engine speed \( \omega_e \), engine command \( \alpha \) and \( SOC \).

After making some approximation and improvement, the author found the improved policy as:
In SDP control, the engine is not restrained to run along the best BSFC line, on the contrary, it operates in a range away from the BSFC line. The reason is that it focuses on the system-level optimization.

\[
\pi'(x') = \arg \min_{u \in U(x')} \left[ g(x', u, w') + E_w \gamma J_\pi(x') \right]
\]  

(2.8)

Figure 2-10 shows that the SDP policy operates the engine to maximize the system efficiency rather than just the engine efficiency. And Figure 2-12 gives how the SDP maintains the SOC and controls the engine operation.
From Figure 2-12, we can see that the SDP seems to keep the SOC at about 0.2 for the FUDS, which means that the SOC allows enough room for energy capture during the braking process.

The SDP is carried out for a city car which is much lighter than the delivery truck. The fuel economy is impressing with around 93.5 without engine shut down and 107.5
with engine shut down for the FUDS driving cycle; and 86.4 without engine shut down and 87.3 with engine shut down for the HWFET driving cycle. The vehicle mass is 723 kg with all the electric components replaced with the hydraulic counterparts for a baseline Honda Insight hybrid electric vehicle. There is great potential in the fuel economy for small size cars.

2.3. Artificial Neural Networks

An artificial neural network (ANN) is a mathematical model that simulates the structure and the function of the biological neural networks. It consists of a number of interconnected artificial neurons, the basic element of neural networks, to process information. The ANNs are non-linear statistical data modeling tools that can be used to model complex relationships between inputs and outputs [25].

![Figure 2-12 Schematic illustration of artificial neural network](image)
The ANNs always contain an input layer, an output layer, and one or multiple hidden layers (Figure 2-13). The hidden layers are defined as all the layers between the input layer and the output layer. All these layers are constructed with neurons.

Biological neural networks are made up of real biological neurons that are connected or functionally related in the peripheral nervous system or the central nervous system. Artificial neural networks are made up of interconnecting artificial neurons (programming constructs that mimic the properties of biological neurons). Artificial neural networks may either be used to gain an understanding of biological neural networks, or for solving artificial intelligence problems without necessarily creating a model of a real biological system. The real, biological nervous system is highly complex and includes some features that may seem real, biological based on an understanding of artificial networks.

In the artificial intelligence field, artificial neural networks have been applied successfully to speech recognition, image analysis and adaptive control. The application for this research here is a supervisory control.

i. **Neuron**

Artificial neurons are constructive units of an artificial neural network. There could be multiple input signals for each neuron with multiple weights. The neuron receives the inputs, multiplies the weights and then transfers the result as an output for
other neurons’ use. There are always $m+1$ inputs with signals $x_0$ through $x_m$ and weights $\omega_0$ through $\omega_m$.

![Schematic illustration of a neuron unit](image)

Figure 2-13 Schematic illustration of a neuron unit

Usually, the $x_0$ is assigned the value $+1$, which makes it a bias input with $w_{k0} = b_k$. This leaves only $m$ actual inputs to the neuron: from $x_1$ to $x_m$. The output of the $k$th neuron is:

$$y_k = f \left( \sum_{j=0}^{m} \omega_{kj} x_j \right)$$  \hspace{1cm} (2.9)

Here $f()$ is the transfer function and will change the linear relationship to a non-linear one.

ii. **Adaptation and Learning**

The objective of training the network is to adapt the weights and finally to minimize the residual. And the application of an ANN depends upon the successful
implementation of a training procedure which will establish the number of hidden neurons necessary to balance the often conflicting requirements of accuracy in training and out-of-sample generalization [31]. We need to correct the weight each time-step until the error is small enough to be neglected. The modification of the weight for the next time-step is:

$$\omega_a(k+1) = \omega_a(k) - \mu \nabla \omega_a \cdot e^2(k)$$

$$= \omega_a(k) + 2 \mu e(k) (1 - \sigma^2(k)) x_a(k) \quad (2.10)$$

The relationship above is easier to understand based on the schematic in Figure 2-15.

![Figure 2-14 Schematic representation of the backpropagation algorithm for a sigmoid adaline](image)

The backpropagation relationship between two neuron units could be expanded and deduced for multilayered feedforward neural networks (MFNNs).
Time series forecasting is to use a model to forecast the future events based on the past events: to predict the data points before they are measured [19].

A time series is a sequence of vectors, $x(t)$, $t=0, 1, 2, \ldots$, where $t$ is the representation of the elapsed time. The time-series forecasting method is the prediction of the value we are interested in future time steps before their happening using the knowledge of the past values. Acturally, the value of $x$ will be sampled to give a series of discrete data points, equally spaced in time [30].

\[
\delta \omega_a^{(i)} = \eta e_j^{(i)} \sigma'(S_j^{(i)})(x_a^{(i-1)})
\]  

(2.11)

\[
i = 1, 2, \ldots, M; j = 1, 2, \ldots, n_i
\]

The basic expression for the time-series forecasting could be represented as the following:

\[
x_{(t+1)} = f(x_{(t-n)}, x_{(t-(n-1))}, \ldots, x_t)
\]  

(2.12)
Here, $x_{(t+1)}$ is the value which we are interested in at time $t + 1$. The current time is $t$ and $n + 1$ known values are used to form the relationship.

The ANN has been shown a good tool for the time series forecasting because they are easily built up for multiple-step-ahead forecasting. The $x$ values in different past time points would be used as the inputs to the network and the outputs are the values predicted. The output is not limited to only one time-step ahead. Actually multiple time-steps ahead could be achieved.

From Tang and Fishwick [9], neural networks could be easily built for multiple-step-ahead forecasting, and the result in the long term forecasting is better compared with the Box-Jenkins method.
Chapter 3 THEORETICAL ANALYSIS

The additional power source for the series hydraulic hybrid vehicle not only brings the potential of increasing the fuel economy significantly, but it also brings a critical difficulty: how to split the power most efficiently between the hydraulic source and the traditional one to achieve the greatest fuel economy. The previous chapter discussed rule-based power management strategies which could help reduce the fuel consumption to some extent. However, they are not the optimal strategies. Those power split strategies were developed based on engineers’ intuition. The controller monitors the internal combustion engine operating conditions rather than considering the entire hydraulic hybrid system. In other words, it is a component-centered controller rather than a system centered one [1]. In this condition the hydraulic components (accumulator, pumps and motors) work in the low-efficiency range.

In this chapter, an intelligent power split control strategy combining an artificial neural network and dynamic programming algorithm applied on the SHHV is proposed. The formulation of the dynamic programming algorithm is presented. Also, the time series forecasting method using neural network is discussed. The network is able to predict 20 steps ahead of the vehicle speed through time series prediction method. Then the choice of the 20 seconds window size is analyzed.
3.1. Dynamic Programming for Power Split Optimization

Dynamic programming (DP) is a useful mathematic method to solve complex problems by breaking them down into simpler sequences or steps. As the configurations of the hybrid system could not be changed, the only thing that affects the fuel consumption is the power management strategy. DP has been shown to be a powerful tool for optimal control in various application areas and is also chosen to split the power between the two power sources.

Dynamic programming algorithm deals with the problem having multiple stages. Or the problem can be divided into stages. And each stage has a number of states associated with the beginning of that stage [7]. For the fuel consumption problem this thesis attempts to solve, the objective is to minimize the fuel consumption. The stage is defined as each time step, which is one second. The state variable is the state of charge (SOC) in the accumulator, which is defined as:

\[
SOC = \frac{P - P_{\text{min}}}{P_{\text{max}} - P_{\text{min}}} \quad (3.1)
\]

where, \(P\) is the instantaneous pressure inside the high pressure accumulator; \(P_{\text{min}}\) and \(P_{\text{max}}\) are the preset allowed minimum and maximum pressures, respectively at the high pressure side. The SOC is a continuous variable between 0 and 1. 0 corresponds to the empty status (pressure as low as the low pressure side); and 1 is corresponding to the fully charged condition.
The control variables are the engine speed, the displacement of the driving pump/motor, which can be converted to the yoke angle, and the gear ratio. The IC engine is monitored concerning the SOC condition as mentioned in previous chapters, without respect to the driving condition. And the yoke angle of the driving pump/motor is determined by the torque needed from the driving wheels.

![Dynamic Programming Diagram](image)

**Figure 3-1 Schematic representation for dynamic programming**

Figure 3-1 is the representation of the DP. Between `stage_i` and `stage_i+1`, we could find an optimal way between them since it is critical that reaching any state at `stage_i+1` has to start from one of the state at `stage_i`. In this case, we only need to consider each optimal decision ending at each state at `stage_i+1` rather than taking all possibilities from the `stage_1` to `stage_i+1`. This would definitely save time and resources for the computer calculation.
It could be formulated as:

$$\min J = \min_{i=0}^{19} f(x(i), u(i))$$

(3.2)

$x$ and $u$ are the vectors of state variables and the control signal respectively.

The recursive relationship for the entire driving cycle is:

$$J^*_k s(k) = \min_{u(k)} c s(k), u(k) + J^*_{k+1} s(k+1) \quad (1 \leq k \leq N)$$

(3.3)

where $k$ is time index or stage index, $N$ is the prediction window size, $J^*_k s(k)$ is the minimum total fuel consumption from stage $k$ to $N$, and $c s(k), u(k)$ is immediate fuel consumption at stage variables $s(k)$ and control variables $u(k)$ at time stage $k$ [10].

Dynamic programming algorithm is capable to search the optimal trajectory of the engine and driving pump/motor operation conditions. However, the specific driving cycle must be known as mentioned before. That means the DP could not be used in real time control since the driving condition information in the future is unknown. Some way to predict the future driving condition is necessary.

3.2. Artificial Neural Networks for Time Series Forecasting

A multilayered feedforward neural network is designed as a predictor of the vehicle speed in this thesis. The MFNN configuration is the most popular structure for prediction so far. And the Backpropagation (BP) algorithm is used for weights adaptation.
because it has been the most widely implemented learning algorithm for neural network paradigms.

In this section, the time series forecasting formulation is discussed using an artificial neural network. The discussion only focuses on the general idea of prediction. The specific prediction window size is discussed in the next section.

Figure 3-2 is a schematic representation of the neural network in both learning and forecasting modes.

![Figure 3-2 Schematic of the kth independent neuron](image-url)
The output of the neural network can be presented as:

\[ y = F \left( \alpha_0 + \sum_{j=1}^{M} \alpha_j F \left( \sum_{i=1}^{L} \beta_{ij} x_i + \beta_{0j} \right) \right) \]  

(3.4)

where \( L \) is the number of the input layer nodes, \( M \) is the number of hidden layer nodes, and \( F(\cdot) \) is sigmoidal transfer function. \( X = (x_1, x_2, \ldots, x_i) \) is the input layer non-linear output vector, \( \alpha_j \) is the weight of the connection from the \( j \)th hidden layer unit to the output unit, and \( \beta_{ij} \) is the weight of connection from the \( i \)th input layer unit to the \( j \)th hidden layer unit.

\( v(t) \) is the current vehicle speed, and \( v(t-1), v(t-2), \ldots \) are the past vehicle speed series, and \( v^*(t+1), v^*(t+2), \ldots \) are the predicted future vehicle speed series. The non-linear function mapping from the past observations to the future values is:

\[ v^*(t+k) = f(v(t), v(t-1), \ldots, v(t-N)) \]  

(3.5)

Here \( f(\cdot) \) is a function determined by the connection weights and \( N \) is the look-back length.

### 3.3. Forecasting Window Size

The forecasting window size is defined as the number of stages that the DP uses for optimization. It not only affects the DP calculation time, also the ANN prediction accuracy. Having a sufficiently large time delay window is important for a time-series predictor — if the window size is too small then the attractor of the system is being
projected onto a space of insufficient dimension, in which proximity is not a reliable
guide to actual proximity on the original attractor [30]. If the window size is as large as
the entire driving cycle, then the dynamic programming algorithm could come up with
the global minimum for the fuel consumption. However, at the same time, the effort and
time of the DP calculation increases dramatically. With a smaller the window size, it is
possible to find local minimum that is less efficient than the global minimum. This will
affect the optimization result. But an advantage of smaller window size is it will take less
time for the optimization calculation of the DP. The calculation time is an important
factor for the power management controller as it is applied in real time on-line
application. Another concern of the prediction window size is the forecasting accuracy of
the neural networks. Although the ANN has comparable better performance for long
term prediction, it is not to say it could predict as long as a driving cycle.

The forecasting window sizes are evaluated using the normalized mean square
error (NMSE) between the actual and learning/forecasting vehicle speed.

The normalized mean square error is defined as:

\[
NMSE = \frac{\sum_{i=1}^{N} \left( \frac{v_i - \hat{v}_i}{v_{\text{max}}} \right)^2}{N}
\]  

(3.6)

where, \(v_{\text{max}}\) is the maximum value of the selected vehicle speed profile and \(N\) is the
number of the length of the selected driving schedule.
Table 3-1 Normalized mean square error over FUDS.

<table>
<thead>
<tr>
<th>Prediction Length [sec]</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>NMSE [%]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forecasting</td>
<td>0.06</td>
<td>0.22</td>
<td>0.49</td>
<td>0.84</td>
<td>1.25</td>
<td>1.68</td>
<td>2.12</td>
<td>2.54</td>
<td>2.94</td>
<td>3.33</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Prediction Length [sec]</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td>NMSE [%]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forecasting</td>
<td>3.72</td>
<td>4.10</td>
<td>4.48</td>
<td>4.84</td>
<td>5.21</td>
<td>5.57</td>
<td>5.94</td>
<td>6.31</td>
<td>6.68</td>
<td>7.04</td>
</tr>
</tbody>
</table>

A proper window size must be with the consideration of both the forecasting accuracy and the dimension sufficiency. The mean square errors with different forecasting window sizes are listed in Table 3-1.

Figure 3-3 represents how the NMSE varies with the variation of the window size. It is easy to find that the NMSE increases significantly as increasing the prediction window size. However, a 7% NMSE is accepted for our research since the maximum speed over the entire FUDS cycle is less than 60 mph. So the maximum speed error is around 4 mph. And for most of the time, the error is less than that which could be found in the next chapter.
Figure 3-3 NMSE wrt different window size for the forecasting process over FUDS

Very similar to the speed mean square error data table, Table 3-2 gives the fuel economy data over FUDS with different prediction window sizes.

Table 3-2 Fuel economies with different forecasting window sizes over FUDS

<table>
<thead>
<tr>
<th>FUDS</th>
<th>Prediction Window size [sec]</th>
<th>5</th>
<th>10</th>
<th>20</th>
<th>21</th>
<th>42</th>
<th>85</th>
<th>171</th>
<th>342</th>
<th>684</th>
<th>1369</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>FE [mpg]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>9.46</td>
</tr>
</tbody>
</table>
Figure 3-4 is a representation of the fuel economy value comparing with the baseline vehicle fuel consumption over the same driving schedule.
Chapter 4 SIMULATION OF MATHEMATICAL MODEL

In this chapter, parameters of the simulation, the mathematical model of neural network are presented.

Figure 4-1 is a scheme of the series hydraulic hybrid vehicle. The solid line in the scheme represents the “solid” mechanical connection between the components; while the dashed line is the “soft” hydraulic connection between components.

Figure 4-1 Schematic of the series hydraulic hybrid vehicle with key components
In the scheme, the HPA and LPA represent the high pressure and low pressure accumulators respectively; FD is the final drive combining a 2-speed transmission. More details about the vehicle specification can be found in Appendix A.

4.1 Parameters of the Simulation

i. Sizing of the Diesel Engine

Since there are two power sources for a hybrid vehicle, the IC engine does not need to provide all the power required by the driver. In addition, for the series configuration, the hydraulic accumulator is used as the primary power source while the IC engine just provides additional power at some certain conditions, e.g. the heavy acceleration. With the additional power source, the engine of the SHHV could be downsized, which is one way for the improvement of the fuel economy of the SHHV.

The engine used in the conventional medium truck is a V8 6L direct injection (DI) diesel engine. When changing the size of the engine, it is hypothetic that the downsized engine has the capability of meeting all the requirement of the driver. Since the 0-60 mph acceleration time is the common ground for all the configurations, a SHHV with a downsized V6 4.5L DI diesel engine is tested for comparison with the conventional vehicle with a V8 6.0L engine. Figure 4-2 shows the comparison of the 0-60 mph acceleration time between conventional medium truck and the SHHV with a rule-based controller after downsizing the engine. It could be found that the acceleration performance of the SHHV overshadows the conventional one and meet all the requirements for the 0-60 acceleration.
Figure 4-2 SHHV \((SOC_{in} = 1)\) vs. CONV in comparison of 0-60 mph acceleration time

ii. **Sizing of Hydraulic Pump/Motor**

Two driving pump/motors are coupled to the integrated two-speed transmission and differential in order to maximize the hydraulic machine efficiency. One of the motors operates as a primary motor which providing most of the torque for the propulsion. The other one, with a gear ratio of 1.5, runs only as an assistant motor during hard acceleration and/or grade requirement. Once the primary motor itself could fulfill all the requirement of the driving demand, the assistant one is set to idle immediately. The reason of the operation of the two motors is to run the primary motor in the high load range, which would result in high efficiency of the motor [8].
The engine pump/motor is sized to have the ability to transferring the power from the engine efficiently. Actually the engine pump/motor only works in the pump mode, in which the engine power is used to pump the fluid back into the high pressure accumulator from the low pressure accumulator. The system pressure remains above 1000 psi most of the time, that requires resizing the engine pump/motor.

- The maximum displacement of the primary drive pump/motor: 175 cc/rev
- The maximum displacement of the assistant drive pump/motor: 150 cc/rev
- The maximum displacement of the engine pump: 265 cc/rev

The pump/motor inertias can be found in the Appendix A.

iii. **Sizing of Hydraulic Accumulator**

The sizes of the low pressure accumulator and the high pressure accumulator are critical for the energy regeneration system. The pressure in the reservoir is in the range of 50 psi to 250 psi; while the pressure in the high pressure one is between 1000 psi to 5000 psi. The reason for maintaining the pressure in the low pressure accumulator is to avoid cavitations. The size of the accumulator is configured to absorb sufficient required regenerative braking energy and serve as a buffer for the engine ON/OFF operation, when the engine shut-down strategy is applied [10]. Generally speaking, the larger the size of the accumulators, the better the hybrid system would perform. This is mainly because larger accumulator space means it could capture more energy during the regenerative braking process; and there would also be more energy used to launch the vehicle in the next propulsion process. A smaller accumulator would result in more
frequent engine start-and-stop events and much shorter engine operation time. Both of the
two points could drop down the engine efficiency.

For the SHHV in this thesis, the capacity of each accumulator is designed to be 100 liters. The maximum fluid capacity is 68.3 liters which the remaining is compressed inertial gas. The high pressure accumulator has the capacity of 1007 kJ energy at the maximum operation pressure, 5000 psi.

The dynamic law for the high pressure accumulator is:

\[
\frac{\partial P}{\partial t} = -\frac{1.4P \frac{\partial V}{\partial t}}{V}
\]  

(4.1)

where \( P \) is the instantaneous pressure and \( V \) is the instantaneous volume of the inertial gas.

The relationship of the SOC and the fluid volume and pressure is shown in Figure 4-3 with the solid line represents the fluid volume while the dashed line represents the pressure.
Figure 4-3 Fluid volume and pressure as a function of SOC

4.2. Model of Artificial Neural Networks (ANNs)

The model of neural unit [27,28] is based on the mathematical structure. The Figure 4-4 shows the structure on the single neuron.
Part 1 is the network input, which is a certain driving cycle in discrete time series.

Part 2 is the output of this specific neuron. As we see, there are two outputs; the upper one is the linear combination of the input signals; while the lower one is the non-linear result after the signumal function. Part 3 is the process of weights updating, which represents the relationship:

$$
\omega_{aj}^{(2)}(k+1) = \omega_{aj}^{(2)}(k) - \eta \nabla \omega_{aj}^{(2)}(E(k))
$$

$$
= \omega_{aj}^{(2)}(k) + \eta \sigma_j^{(2)}(k)z_a(k)
$$

$$
= \omega_{aj}^{(2)}(k) + \eta e_j(k)\sigma'(s_j^{(2)}(k))z_a(k)
$$

(4.2)
And then, the weight value after updating is ready for next step calculation. Part 4 is the error outputs. The number of error signals is the same as that of the input signals minus one (the threshold $x_0$).

Figure 4-5 is the Simulink model of the input with multiple steps delays.

![Figure 4-5 Input block for the neural network simulation](image)

The Part 1 in Figure 4-5 is the data from certain driving schedule. When the simulation starts, the signal is normalized first, and then goes through a “zero-order hold” block. After that, the signal goes through multiple “unit delay” blocks since the signal we need is a sequence of data rather than only one. As we need a 20-step-ahead forecasting, so we also choose a 20 input window size. Generally speaking, the number of input window size is always chosen the same as the number of steps ahead. But there are also
other structures with difference between them. In addition, Part 2 in this diagram is the threshold $x_0$.

For the input, the data series are normalized in the range of $[0, 1]$ before feeding into the neural network. The main reason of the normalization is we need the signals within a useful range. Otherwise, if the normalization is removed, there would always be saturation so we cannot find the correct results. Some other researchers also normalize the data series into different range like $[0.2, 0.8]$ to facilitate the neural network with better training results. But here, the $[0, 1]$ works fine for this model.

As mentioned before, there are 20 input signals in each layer (not including the threshold). Besides the input, the error signals are also important for the network. In Figure 4-6, Part 1 is the input signal vector which is the same for each neural unit. For the input layer, the signal is directly from the input. However, for the hidden layer and the output layer, the inputs signals are the output of the input layer and the hidden layer respectively. Part 2 is the error signal for the first neuron in the current layer. Part 3 is the learning ratio $\eta$. If the learning ratio is set small, the network will adapt slowly; on the other hand, if the learning ratio is comparably large, the network is trained quickly but probably will not converge. A tradeoff between the learning speed and the convergence should be considered. And Part 4 is the neuron unit, while Part 5 is the neuron unit non-linear output, which would constitute the input vector for the next layer together with the outputs from other neurons in this layer.
There are two ways to conduct a long term forecasting using neural networks; one is to directly build a multiple-step-ahead forecast model, the other is to do stepwise forecast and then the forecast output is feedback as input again for next stepwise prediction. For the former method, it could be easily implemented with neural networks by simply adding more output units [9]. For the latter method, there would be more “loops” depending on the number of steps ahead.
Figure 4-7 Simulation model of the artificial neural network with three layers

Figure 4-7 is the diagram of the entire ANN model. In this neural network model, there are three layers, one input layer, one hidden layer and one output layer. The effect of the number of hidden layers in a neural network performance is not the same and strongly depends on the input series with different natures.
Chapter 5 SIMULATION RESULTS

In this chapter, the simulation results are presented including the forecasting vehicle speed values as well as the overall fuel consumption results.

5.1. Simulation Test of Different Driving Cycles

In this section, the simulation of the artificial neural networks with time-series forecasting performance is presented. There are three driving cycles: federal urban driving schedule (FUDS), city urban dynamometer driving schedule (city_UDDS) and the highway urban dynamometer driving schedule (hwy_UDDS) respectively.

As is the characteristic of neural networks, in most conditions the driving cycle should be feed into the network several times to train the weights, until the error would converge to an acceptable range. This may require different training times depending on the nature of the network as well as the driving schedule. According to the above, we repeat each driving cycle six times. In the five times, the objective is to train the neural net and adapt the weights while the remaining one is used for time series forecasting.
i. **FUDS Test**

![Image of FUDS schedule](image)

**Figure 5-1 FUDS schedule**

Figure 5-1 is the FUDS test cycle while Figure 5-2 is output of the speed value with the last cycle of the predicted speed.
Figure 5-2 Six time repeat FUDS for simulation

Figure 5-3 shows the comparison of the forecasted speed (red line) with the desired one (blue line) in the last cycle of the six-time simulation. It is easy to find that the speed predicted in this cycle is very close to that desire for the FUDS. The main difference between them is in the sharp deceleration condition which happens around 250 sec.
Figure 5-3 Comparison between the forecasted speed and the desired speed for FUDS

Figure 5-4 is the error diagram between the predicted value and the desired speed. At the very beginning the error is very large since the high slope of the speed profile and the random selection of the weight values. After several adaptation of the weights, the result becomes much better.
Figure 5-4 Errors during the entire simulation for FUDS

From Figure 5-4, it can be found that the error converges well and quickly. We also tried the network with different learning ratio $\eta$ and it gave us different results. For example, if the learning ratio is too large, the error would not converge, the speed predicted deviated from the desired value a lot and even maintain at a certain value, which is incorrect since the actual speed varies with time. From the project, it seems the result would be better if the $\eta$ is relatively small. The results are found with the value of $\eta$ as 0.05.

For the result, the maximum error is less than $4 \ km/h$, which means the error percentage is less than 7% for the FUDS.
Figure 5-5 Errors in the first 50 time steps and the last 50 time steps for FUDS

Figure 5-5 is the representation of the errors in the first 50 time steps and the last 50 time steps. The dash line represents the former while the circled one represents the latter. From this we could see that at the beginning the errors are much larger than the error in the last several seconds, which is the same as we expect.

Then the weight adaptation is shown for a certain weight (one weight in the first neuron in the output layer).
Figure 5-6 Weight adaptation for a certain neuron for FUDS

Figure 5-6 is the weight adaptation diagram which gives us how this weight changes during the whole learning and forecasting process. At the very beginning, the weight is a random number generated by MATLAB. In this diagram, the weight varies a lot and has somehow periodic character. That is because the range in the y-axis is really small, [0.58, 0.65]. And it could also be found that the weight varies a little bit more for the first several seconds than for the other seconds.

ii. UDDS Test

Figure 5-7 gives the city-UDDS test cycle.
For the city UDDS cycle, we find the time period of this schedule is less than the FUDS. And the acceleration is milder than the FUDS. There are two main accelerations as well as two sharp decelerations following.

Figure 5-8 is the output values of the network including the training processes as well as the forecasting process.
There is a large error happening at the end of the first cycle besides those errors at the very beginning, which is most because the sharp change in speed.

Figure 5-9 Comparison between the forecasted speed and the desired speed for city-UDDS
Figure 5-9 gives the predicted speed (circled line) and the desired speed (non-circled line). There seems to be a “lag” for the predicted result.

Figure 5-10 Errors during the entire simulation for city-UDDS

Figure 5-10 gives how the error changes during the entire test. The error seems also comparably small except the beginning and the end of the first cycle. The value of error is small but since the speed profile is less than that of the FUDS, the percentage error is higher, which is less than 10%.
Figure 5-11 Errors in the first 50 time steps and the last 50 time steps for city-UDDS

Figure 5-11 shows the errors in the first 50 seconds (dash line) and the last 50 seconds (circled line) of the entire driving cycle. From that, the first 50-time-step error oscillates until falling into a convergence zone after around 15 seconds. On the other hand, the last 50-time-step error is much more smooth and close to zero.
Figure 5-12 Weight adaptation for a certain neuron for city-UDDS

The weight adaptation of an arbitrary neuron is shown in Figure 5-12. Excepting some periodical peaks, the weights adapts from around 0.04 to 0.036.

iii. HWY_UDDS Test

Figure 5-13 gives the highway-UDDS test cycle, for which the vehicle speed changes less than other two test cycles.
Figure 5-13 Hwy-UDDS schedule

Figure 5-14 is the output of the network for the entire test cycle, which including the weight training process and the forecasting process.

Figure 5-14 Output of the neural network for hwy-UDDS
Figure 5-15 Comparison between the forecasted speed and the desired speed for hwy-UDDS

Figure 5-15 is the comparison between the predicted speed and the desired speed. The predicted speeds almost match the desired speed profile. The only issue here is during the sharp acceleration and deceleration conditions. The speed error between the desired one and the actual one is very small.
Figure 5-16 Errors during the entire simulation for hwy-UDDS

Figure 5-16 shows the error for the hwy_UDDS.

Figure 5-17 Errors in the first 50 time steps, 50, the last 50 time steps and 50 in between for hwy-UDDS
Figure 5-17 represents the error in the first 50-time-step (dash line), the ones from 201 second to 250 second (diamond line), and the last 50-time-step (circled line). It seems that the error oscillates at the beginning and then converges quickly. There is also some repeat but not very much.

Figure 5-18 Weight adaptation for a certain neuron for hwy-UDDS

Figure 5-18 is how a certain weight varies during the entire driving cycle.

iv. UTDS Test

The UTDS is a driving cycle built up by the researchers in the hydraulic hybrid vehicle group at the University of Toledo. The driving cycle is built up for testing as a non-standard driving schedule. And this is a urban schedule rather than a highway cycle.
There are many stop-and-start processes. Figure 5-19 shows the speed profile of the UTDS.

Figure 5-19 Speed profile of the UTDS

Figure 5-20 shows the comparison of the desired speed (blue line) and the predicted speed (red line). It is obvious that the forecasted speed matches the desired one, just like the results for those three standard driving schedules.
Figure 5-20 Speed comparison between the predicted and the desired

Figure 5-21 gives a better view of the variation of the error. The green line represents how the error varies at the first 50 seconds which is still the learning mode of the neural network; while the red line shows how the error changes for the last 50 seconds which is the forecasting mode of the neural network. From the figure, it is clear that there is much fluctuation at the beginning. And the error converges and almost diminishes at the end.
Figure 5-21 Error at the first 50 seconds and the last 50 seconds

Figure 5-22 shows the error along the entire driving cycle. The error for the UTDS seems a little bit larger than the error for other driving cycles. This is because for the UTDS cycle, there are more stop-and-start processes and the acceleration and deceleration are much sharper than any of the other cycle.
5.2. Fuel Consumption Results

The fuel consumption results are tested in the vehicle propulsional system evaluation tool (VPSET) developed by Southwest Research Institute.

i. Operation Trajectory

As the 20 steps forecasting values are found as well as the dynamic programming optimization algorithm, we could track how the intelligent controller split the power flow between the two sources. Figure 5-23 is the simulation results of the series hydraulic hybrid vehicle under the DP policy with a 20 seconds prediction window size over the
FUDS and FHDS cycles with engine shut-down technology [10]. From the top to bottom are the vehicle speed, state of charge, engine power and accumulator power respectively.

From Figure 5-23, we can find that the DP algorithm supposes to launch the hybrid vehicle by using the hydraulic power since the SOC drops very quickly at each launching process. And then the IC engine is activated to charge the accumulator and maintain the SOC in a certain range. During the deceleration process, the accumulator could be charged using the braking energy and the SOC increases to a certain range to restore energy. And the engine only shut down in several times rather than keeping it off whenever it is not accelerating the vehicle, which is used by the rule-based control strategy. For the highway driving cycle, there are not as many stop-start processes as the urban driving cycle. Once the accumulator depletes, it could not be charged to high SOC even in deceleration process. In this case, the IC engine is kept on all through the cycle.
Figure 5-23 Simulation results with 20 seconds prediction window size: (a) FUDS; (b) FHDS [10]
Figure 5-24 shows the other optimal control variables trajectories over the FUDS and FHDS cycles with 20 seconds prediction window size. The variables are normalized engine P/M displacement factor which is defined as the ratio of the current operation displacement to the maximum displacement, driving P/M displacement factor and gear ratio. The engine P/M could only operate in pump mode for the simplification consideration of the DP calculation. On the other hand, the engine P/M could also operate as a motor to start the engine which enables getting rid of the electric starter used in the conventional vehicles.
Figure 5-24 Some optimal control variables trajectories with 20 seconds prediction window size: (a) FUDS; (b) FHDS [10]
ii. Summary

With downsizing the IC engine and replacing the mechanical drivetrain with the hydraulic one, there is 205 kg increase in the mass of the vehicle.

Table 4-1 shows the fuel economy of the hydraulic hybrid vehicle with different type of power split controller compared with the baseline conventional truck. And in addition, Table 4-2 shows the percentage fuel economy improvement over the baseline [10].

Table 5-1 Fuel economy for rule-based and intelligent controller compared with the baseline

<table>
<thead>
<tr>
<th>Fuel Economy (mpg)</th>
<th>Baseline</th>
<th>Rule-based</th>
<th>DP</th>
</tr>
</thead>
<tbody>
<tr>
<td>FUDS</td>
<td>9.46</td>
<td>20.70</td>
<td>28.06</td>
</tr>
<tr>
<td>City-UDDS</td>
<td>6.53</td>
<td>20.42</td>
<td>28.64</td>
</tr>
<tr>
<td>Hwy-UDDS</td>
<td>12.20</td>
<td>13.66</td>
<td>17.71</td>
</tr>
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</table>

Table 5-2 Fuel economy improvement for rule-based and intelligent controller compared with the baseline

<table>
<thead>
<tr>
<th>Fuel Economy Improvement(%)</th>
<th>Baseline</th>
<th>Rule-based</th>
<th>DP</th>
</tr>
</thead>
<tbody>
<tr>
<td>FUDS</td>
<td>-</td>
<td>118.8</td>
<td>196.7</td>
</tr>
<tr>
<td>City-UDDS</td>
<td>-</td>
<td>212.7</td>
<td>338.6</td>
</tr>
<tr>
<td>Hwy-UDDS</td>
<td>-</td>
<td>12.0</td>
<td>45.2</td>
</tr>
</tbody>
</table>

It is easy to see that the fuel economy improvements over the FUDS and UDDS driving cycles are significant since there are more stop-start processes than any of the
highway driving cycles. The hydraulic hybrid can restore the energy in the hydraulic accumulator when braking which is always wasted as heat for the conventional counterparts. When launching the vehicle next time, the hydraulic energy is released to accelerate the truck. In addition, the intelligent control based on ANNs and DP seems to farther overshadow their rule-based counterpart since it is based on large amount of calculation rather than engineers’ intuition. And the fuel economy over the city driving schedules are much higher than that of the highway driving schedules. The two primary reasons for this effect are fundamental to the hybrid vehicle configuration and the driving cycles. First, the regenerative braking system is more effective with frequent stop-start processes. Second, the aerodynamic drag coefficient of the hybrid truck is 0.5, which is very high. The aerodynamic drag force for the highway driving cycles is larger than that of the city driving cycles. The drag is proportional to the square of the vehicle speed.
Chapter 6 SUMMARY AND CONCLUSION

This chapter summarizes the presented analytical work and simulation model of the optimal controller for a series hydraulic hybrid vehicle, including a neural network speed predictor and a dynamic programming optimiser. In addition, it also presents the conclusions and recommendations for future research.

6.1. Summary

The objective of this thesis is to build an optimal controller to split the power flow from the two power sources for a SHHV, the IC engine and the hydraulic accumulator. The artificial neural network predictor is used to forecast the vehicle speed with a 20 second prediction window size. The predicted speed value is used by the dynamic programming to search the optimal control trajectory concerning the fuel economy.

This study derives a mathematical model of the optimal controller with two subsystems: the artificial feed forward neural network and the deterministic dynamic programming algorithm. The network has three layers, input layer, hidden layer and output layer. The time series forecasting method is used by the network for prediction. The predicted speed values are used by the dynamic programming algorithm to search the global (global for this 20 second window size) minimum of the fuel consumption.
Three different driving cycles were used to test the performance of the network. They are federal urban driving schedule, city urban dynamometer driving schedule and highway urban dynamometer driving schedule respectively. The predicted speeds are compared with the actual ones.

The theoretical model is created in MATLAB/SIMULINK.

The fuel consumption test is carried out in the VPSET environment.

6.2. Conclusions

The model is able to learn and train the weights after five times repeat for different driving cycles.

The model is able to forecast vehicle speed values 20 seconds ahead with an error less than 7%.

The intelligent controller combining ANN and DP has the capability to improve the fuel economy significantly with different driving cycle tests for the SHHV.

6.3. Recommendations and Future Work

The study presented in this thesis represents an infrastructure for future work that is related to the artificial neural network for a series hydraulic hybrid vehicle. Some recommendations and future works include:
Based on the static feed forward neural network model, a dynamic or feedback neural network model could be built up and tested using the same driving cycles.

A comparable neural network which forecasts just one-step-ahead and feedback as an input for next forecast could be built to compare the results with the current model.
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## Appendix A: Vehicle specification used in the simulation

<table>
<thead>
<tr>
<th></th>
<th>Conventional (V8 6L)</th>
<th>Series (V6 4.5L)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum power @ 3300 rpm [kW]</td>
<td>237</td>
<td>178</td>
</tr>
<tr>
<td>Maximum torque @ 2100 rpm [N-m]</td>
<td>773</td>
<td>580</td>
</tr>
<tr>
<td>Maximum speed [rpm]</td>
<td>4500</td>
<td>4500</td>
</tr>
<tr>
<td>Engine inertia [kg-m²]</td>
<td>0.22</td>
<td>0.17</td>
</tr>
<tr>
<td>Torque converter inertia [kg-m²]</td>
<td>0.068</td>
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</tr>
<tr>
<td>Engine P/M inertia [kg-m²]</td>
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</tr>
<tr>
<td>Effective drive P/Ms inertia [kg-m²]</td>
<td>-</td>
<td>0.11</td>
</tr>
<tr>
<td>Transmission 1st gear ratio</td>
<td>3.45</td>
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</tr>
<tr>
<td>Transmission 2nd gear ratio</td>
<td>2.24</td>
<td>1</td>
</tr>
<tr>
<td>Transmission 3rd gear ratio</td>
<td>1.41</td>
<td>-</td>
</tr>
<tr>
<td>Transmission 4th gear ratio</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>Transmission 1st gear ratio inertia [kg-m²]</td>
<td>0.226</td>
<td>0.13</td>
</tr>
<tr>
<td>Transmission 2nd gear ratio inertia [kg-m²]</td>
<td>0.133</td>
<td>0.03</td>
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<tr>
<td>Transmission 3rd gear ratio inertia [kg-m²]</td>
<td>0.083</td>
<td>-</td>
</tr>
<tr>
<td>Transmission 4th gear ratio inertia [kg-m²]</td>
<td>0.061</td>
<td>-</td>
</tr>
<tr>
<td>Transmission 1st gear ratio efficiency</td>
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</tr>
<tr>
<td>Transmission 2nd gear ratio efficiency</td>
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<td>0.993</td>
</tr>
<tr>
<td>Transmission 3rd gear ratio efficiency</td>
<td>0.9957</td>
<td>-</td>
</tr>
<tr>
<td>Transmission 4th gear ratio efficiency</td>
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<td>-</td>
</tr>
<tr>
<td>Differential gear ratio</td>
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<td>3.21</td>
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<tr>
<td>Differential inertia [kg-m²]</td>
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<td>0.09</td>
</tr>
<tr>
<td>Differential efficiency</td>
<td>0.96</td>
<td>0.96</td>
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<tr>
<td>Accumulator efficiency</td>
<td>-</td>
<td>0.97</td>
</tr>
<tr>
<td>Vehicle mass [kg]</td>
<td>7340</td>
<td>7545*</td>
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<tr>
<td>Frontal area [m²]</td>
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<td>6.767</td>
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<tr>
<td>Aerodynamic drag coefficient</td>
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<tr>
<td>Rolling resistance coefficient</td>
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<td>0.005</td>
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<tr>
<td>Wheel radius [m]</td>
<td>0.4131</td>
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<tr>
<td>Wheel inertia [kg-m²] (each one)</td>
<td>4.68</td>
<td>4.68</td>
</tr>
<tr>
<td>Number wheels on rear axle</td>
<td>4</td>
<td>4</td>
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</table>

Note: An estimated vehicle mass increase of 205 kg is accounted for in this simulation.