Enabling Prediction for Optimal Fuel Economy Vehicle Control

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  – Thomas H. Bradley, PhD
Introduction

Autonomous vehicle technology improves driver and passenger safety

- Driver error is responsible for 90+% of crashes in the U.S.
- Primary reason for death of people between 15 and 24 years old
- Significant economic cost

Improving transportation safety is the #1 goal of transportation legislation

Improving vehicle fuel economy reduces economic costs, environmental degradation, and air pollution impacts

- 70% of all petroleum consumption
- 34% of all greenhouse gas emissions
- 23%-58% air pollution constituent emissions

Improving transportation fuel economy is the #2 goal of transportation legislation

We seek to use autonomous vehicle technology to improve fuel economy.

Implementation

Time (years)

Autonomous Vehicle Technology
Fuel Economy Technology
Our research goal

Paris Declaration on Electro-Mobility…U.N. Conv. 2015
We seek to use autonomous vehicle technology to improve fuel economy.

Predictive Energy Management

Sensors and Signals → Perception (Compute Worldview) → Vehicle Operation Prediction ➔ Planning (Compute Optimal Energy Control) ➔ Control_request ➔ Running Control (Component Limitations) → Vehicle Plant

Misprediction ➔ Energy Consumption

Autonomous Technologies
Mathematical Optimization

\[ \text{Cost} = \sum_{k=0}^{N-1} m_{fuel} \]

Minimum

Fuel Economy Results

<table>
<thead>
<tr>
<th>Drive Cycle</th>
<th>FE Improvement Over Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drive Cycle 1a</td>
<td>10.9%</td>
</tr>
<tr>
<td>Drive Cycle 1b</td>
<td>13.6%</td>
</tr>
<tr>
<td>Drive Cycle 2</td>
<td>12.9%</td>
</tr>
<tr>
<td>Drive Cycle 3a</td>
<td>10.2%</td>
</tr>
<tr>
<td>Drive Cycle 3b</td>
<td>22.6%</td>
</tr>
</tbody>
</table>
We use only currently available vehicle and infrastructure technology.
An artificial neural network makes 15 second velocity predictions

Predictive Energy Management

Driver Assistance Detection Data → Perception Neural Network → 15 sec Velocity Prediction → Planning Compute Optimal Energy Control → Running Control Component Limitations → Vehicle Plant Energy Consumption

Misprediction → Control Request → Control Actuation

GPS Location, Current Velocity (every 1 second)

Renewable Energy

Introduction

Methods

Results

Conclusions

Dynamic programming optimization and the Autonomie vehicle modeling software are used

Predictive Energy Management

Driver Assistance Detection Data

Perception Neural Network

Travel Time Data

GPS Location, Current Velocity (every 1 second)

15 sec Velocity Prediction

Planning Dynamic Programming

Control Request

Running Control Component Limitations

Control Actuation

Vehicle Plant Toyota Prius

Fuel Economy

Four real world city and four real world highway drive cycles are used.
Driver assistance detection data is recorded and used as an input

- Given new detection objectives
  - Traffic light detection, state
  - Vehicle in front speed change
  - Turn lane detection
  - Details in paper 2018-01-0593

Driver Assistance Detection Data

Perception Neural Network

GPS Location, Current Velocity (every 1 second)

Travel Time Data

15 sec Velocity Prediction

$\times = \text{Traffic Light Detected}$

- Velocity (mph)
- Distance (mi)

Conclusions
Travel time data is also recorded and used as an input

- Data gathered by cities
- Provides average vehicle velocities
- Informs signs, Google maps

![Diagram showing travel time data process]

Perception Neural Network

Driver Assistance Detection Data

GPS Location, Current Velocity (every 1 second)

15 sec Velocity Prediction

Results

Conclusion

Introduction
An artificial neural network is used to make 15 second predictions

- Features are learned automatically by the training algorithm
  - Adjusts **weights** and **biases**

```
Driver Assistance
Detection Data

Travel Time Data

Perception Neural Network

GPS Location, Current Velocity

Input

Output

Inputs

General Neuron

\[ a = f(wp+b) \]
```
Different drive cycle instances are used in set-up vs. application of the artificial neural network

- **Set-up** *(determining weights and biases)*
  - 3 of 4 drive cycles used
Different drive cycle instances are used in set-up vs. application of the artificial neural network

- **Application** *(fixed weights and biases)*
  - 1 of 4 drive cycles used

![Diagram](image.png)
Different drive cycle instances are used in set-up vs. application of the artificial neural network

- Reported result is an average of all permutations

<table>
<thead>
<tr>
<th>Test 1</th>
<th>Test 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Set-up: cycles 1, 2, 3</td>
<td>- Set-up: cycles 1, 3, 4</td>
</tr>
<tr>
<td>- Application: cycle 4</td>
<td>- Application: cycle 2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Test 2</th>
<th>Test 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Set-up: cycles 1, 2, 4</td>
<td>- Set-up: cycles 2, 3, 4</td>
</tr>
<tr>
<td>- Application: cycle 3</td>
<td>- Application: cycle 1</td>
</tr>
</tbody>
</table>

- City fuel economy result = average(Test 1, 2, 3, 4)
- Note: This is also done for the highway drive cycles
**Dynamic programming is used to determine the optimal control**

**Mathematical form**

\[ S(k + 1) = S(k) + f(S, u, w, k) \Delta t \]

\[ J = \sum_{k=0}^{N-1} f(S, u, w, k, \Delta t) \]

\[ S_{\text{min}}(k) \leq S(k) \leq S_{\text{max}}(k) \quad (k = 0, \ldots N) \]

\[ u_{\text{min}}(k) \leq u(k) \leq u_{\text{max}}(k) \quad (k = 0, \ldots N - 1) \]

\[ S = \text{State variable} \quad k = \text{Timestep number} \]
\[ u = \text{Control variable} \quad N = \text{Final timestep} \]
\[ w = \text{Input variable} \quad \Delta t = \text{Timestep size} \]
Dynamic programming is used to determine the optimal control

**Hybrid vehicle applied form**

\[
SOC(k+1) = SOC(k) + f(SOC, P_{ICE}, v, k) \Delta t
\]

\[
J = \text{Cost} = \sum_{k=0}^{N-1} m_{fuel} \Delta t
\]

\[
SOC_{\text{min}} \leq SOC(k) \leq SOC_{\text{max}} \quad (k = 0, \ldots, N)
\]

\[
P_{ICE,\text{min}} \leq P_{ICE}(k) \leq P_{ICE,\text{max}} \quad (k = 0, \ldots, N - 1)
\]

**SOC** = State of charge  \( m_{fuel} \) = Mass of fuel  
**\( P_{ICE} \)** = Engine power  
**\( v \)** = Vehicle velocity
Dynamic programming is used to determine the optimal control

Gen. 3 (2010-2016) Toyota Prius applied form

\[
SOC(k + 1) = SOC(k) - A_1 + A_2 \sqrt{A_3 - A_4 v(k) + A_5 v(k)^3 + A_6 \dot{v}(k) v(k) - A_7 P_{ICE}}
\]

\[
\text{Cost} = \sum_{k=0}^{N-1} f(P_{ICE}) + W \left( \text{SOC}_f - \text{SOC}(N) \right)^2
\]

40 % \leq \text{SOC}(k) \leq 80 % \quad (k = 0, \ldots, N)

0 \text{ kW} \leq P_{ICE}(k) \leq 73 \text{ kW} \quad (k = 0, \ldots, N - 1)

\[C_1 [f(P_{ICE})] + C_2 v(k) \leq C_3\]

\(SOC = \text{State of charge}\)

\(m_{fuel} = \text{Mass of fuel}\)

\(P_{ICE} = \text{Engine power}\)

\(v = \text{Vehicle velocity}\)

\(A_{1-7} = \text{Constants}\)

\(C_{1-3} = \text{Constants}\)

\(W = \text{Penalty Weight}\)
Dynamic programming is used to determine the optimal control

**Gen. 3 (2010-2016) Toyota Prius applied form**

\[
SOC (k + 1) = SOC (k) - A_1 + A_2 \sqrt{A_3 - A_4 v(k) + A_5 v(k)^3 + A_6 v(k)^2} - A_7 P_{ICE}
\]

\[
\text{Cost} = \sum_{k=0}^{N-1} f (P_{ICE}) + W (\text{SOC}_f - \text{SOC}(N))^2
\]

- 40 % ≤ SOC(k) ≤ 80 %  \ (k = 0, ...N)
- 0 kW ≤ P_{ICE}(k) ≤ 73 kW  \ (k = 0, ...N - 1)
- \[C_1 [f (P_{ICE})] + C_2 v(k) ≤ C_3\]
Autonomie is used to simulate the generation 3 (2010-2016) Toyota Prius

- Developed by Argonne National Labs
- Physics-based and highly accurate
- We validated the model against real world operation

<table>
<thead>
<tr>
<th>EPA Drive Cycle</th>
<th>Simulated Fuel Economy</th>
<th>Measured Fuel Economy</th>
<th>Percentage Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>UDDS</td>
<td>76.9 mpg</td>
<td>75.6 mpg</td>
<td>1.7%</td>
</tr>
<tr>
<td>HWFET</td>
<td>68.8 mpg</td>
<td>69.9 mpg</td>
<td>-1.7%</td>
</tr>
<tr>
<td>US06</td>
<td>45.9 mpg</td>
<td>45.3 mpg</td>
<td>1.3%</td>
</tr>
</tbody>
</table>

Kim et. al. “Autonomie model validation … for 2010 Toyota Prius.”
2012 SAE Technical Paper
Different groupings of technology are used in the system and compared to other relevant data points

- Perfect full drive cycle prediction
- Perfect 15 second prediction
- Prediction using only GPS data
- Prediction using GPS, detection data
- Prediction using GPS, detection, traffic data

Max. FE improvement (ceiling)
Max. FE from any 15 sec. prediction
Actual prediction from these perception models
Different groupings of technology are used in the system and compared to other relevant data points

- Perfect full drive cycle prediction: 19.6%
- Perfect 15 second prediction: 11.9%
- Prediction using only GPS data: 5.3%
- Prediction using GPS, detection data: 6.2%
- Prediction using GPS, detection, traffic data: 4.8%

For city driving, just GPS and detection data works best
Different groupings of technology are used in the system and compared to other relevant data points

- Perfect full drive cycle prediction: 11.0%
- Perfect 15 second prediction: 8.4%
- Prediction using only GPS data: 1.6%
- Prediction using GPS, detection data: 1.9%
- Prediction using GPS, detection, traffic data: 2.3%

For highway driving, GPS, detection, and travel time data works best
Travel time data hinders city driving fuel economy improvements

• Velocity prediction accuracy doesn’t always correlate with fuel economy improvements

• More research is neccessary
Significant improvements in fuel economy are possible using only currently available technology

**Predictive Energy Management**

- **Perception Neural Network**
  - GPS Location, Current Velocity (every 1 second)
  - Travel Time Data

- **Planning Dynamic Programming**
  - 15 sec Velocity Prediction
  - Control Request

- **Autonomie Software**
  - Running Control Component Limitations
  - Control Actuation

- **Vehicle Plant Toyota Prius**

- **Fuel Economy**

**Introduction**

**Methods**

**Results**

**Conclusions**
Future work is focused on understanding the advantages that future autonomous vehicle technology provides

- Add vehicle to infrastructure communication (V2I)
  - Traffic light status and changing times
- Add vehicle to vehicle communication (V2V)
  - Other vehicle locations and states
Future work is focused on understanding the advantages that future autonomous vehicle technology provides.
Thank you

Zachary D. Asher, PhD