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Power Management of Plug-in Hybrid Electric Vehicles Using Neural Network Based Trip Modeling

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***Abstract*—The plug-in hybrid electric vehicles (PHEV), utilizing more battery power, has become a next-generation HEV with great promise of higher fuel economy. Global optimization charge-depletion power management would be desirable. This has so far been hampered due to the a priori nature of the trip information and the almost prohibitive computational cost of global optimization techniques such as dynamic programming (DP). Combined with the Intelligent Transportation Systems (ITS), our previous work developed a two-scale dynamic programming approach as a nearly globally optimized charge-depletion strategy for PHEV power management. Trip model is obtained via GPS, GIS, real-time and historical traffic flow data and advanced traffic flow modeling. The Gas-kinetic based model was used for the trip modeling in our previous study. The complicated partial deferential equation based model with several parameters needs to be calibrated had for implementation. In this paper, a neural network based trip model was developed for the highway portion, using the given data from WisTransPortal. The real test data was used for the training and validation of the network. The simulation results show that the obtained trip model using neural network can greatly improve the trip modeling accuracy, and thus improve the fuel economy. The potential of the advantages were indicated by the fuel economy comparison.**

I. Introduction

The hybrid electric vehicle (HEV) has provided a promising alternative means for sustainable mobility [1-4]. The benefits of HEV include the improvement of fuel economy and the reduction of emissions. The propulsion power of HEV comes from two or more kinds of energy sources, e.g., the gasoline internal combustion engine (ICE) and battery, diesel engine and battery, battery and fuel cell (FC), battery and ultra-capacitor, and battery and flywheel [4-6].

The plug-in hybrid electric vehicle (PHEV) is a new generation of HEV with higher battery capacity and the ability to be recharged from an external electrical outlet. Unlike the conventional HEV which can sustain little purely electric range, the PHEV can sustain a longer all-electric range (AER). More fuel can be replaced by the four times cheaper grid electricity in the US [7]. The great potential of PHEV in fuel economy enhancement indicates a tremendous saving of fuel consumption for the nation and a possibly shorter payback time for the customer with regard to the modified powertrain and battery pack. Such encouraging promise has attracted significant attention to PHEV technology from both government and private sectors, e.g. the President's Advanced Energy Initiatives announced in early 2006 [8] and the Department of Energy (DOE)'s FreedomCar program [9].

Similar to conventional HEV, power management is an important operational factor for PHEV to enhance fuel economy and reduce emissions. Limited by the current battery technology, the PHEV with 10 ~ 20 miles AER is considered, according to the DOE authority [9], to be more commercially feasible within the near future, although much higher AER can be obtained from showroom vehicles by using more battery packs. For PHEV-10 or PHEV-20, the electric vehicle (EV) mode cannot sustain the whole trip for most commuters. Therefore, it is necessary to optimize the power management strategies for PHEV. While most conventional HEV's are operated to maintain the battery state-of-charge (SOC) at a constant level (known as "charge-sustaining" mode), PHEV presents a somewhat different scenario: it is desirable to use as much battery power as possible when the vehicle reaches the destination, i.e., the SOC is expected to drop to the lowest possible level. Such an operation is known as the "charge-depleting" mode. A key issue is how to achieve the optimal charge-depleting mode or what kind of depleting profile is the best. A simple strategy is to run the PHEV in the charge-depleting mode (i.e., the EV mode) first until a low threshold of SOC, e.g., 0.3, is reached. Then the vehicle is operated in the charge-sustaining mode, maintaining the SOC constant until the end of the trip. But this naive approach is far from optimal in terms of fuel efficiency.

In the past decade, HEV power management has been studied from control and optimization perspectives. The rule-based control strategies, such as fuzzy logic control techniques, divided the actual driving conditions into different scenarios [5] [11]. Rule-based controllers are easier to implement, while the resultant operation may be quite far from optimal due to the omission of the detailed dynamic models. Driving mode classification was studied in pattern recognition methods [12] based on the current and previous driving condition. A blend of pattern learning and fuzzy classification was presented in [13] [14]. Dynamic feedback control approaches solve for the control strategies based on the current and previous operation, which are easier for the

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real-time implementation purpose. An optimal control design approach was studied [15] [16]. For the power management problem, a major drawback of rule-based, driving-mode based, and the dynamic feedback control based approaches is the absence of global optimality, i.e. the power distribution is not optimized for the whole trip. In order to obtain the globally optimal solutions, dynamic programming (DP) techniques have been investigated [18-22] for the power management of various types of HEV. The application of a DP algorithm have relied on certain driving cycles, e.g., the standard driving cycles provided by the U. S. Department of Transportation (DOT). The DP based work has all been considered not applicable for real-time implementation because the trip model (driving cycle) is future information for vehicle operation. Therefore, it was claimed that global optimization result can only used as reference for power management design. More research has been done to seek other alternative methods to optimize the power control. In addition to DP, quadratic programming and model predictive control frameworks were also explored [22]. An adaptive algorithm based on the equivalent consumption minimization strategy (ECMS) was developed based on the on-line adaptive estimation of an equivalence factor based on the current driving conditions [23]. Good parameter tuning was required in order to achieve similar performance as the DP methods. Dependency on the current driving conditions makes this method more suitable for charge-sustaining strategy, but quite difficult for PHEV where charge-depleting control is desired.

For conventional HEV, the battery energy is very limited. The charge and recharge of the battery occurs within short time periods. Thus the overall fuel economy is more affected by the transient behavior. In comparison, PHEV has much larger on-board battery energy; i.e., it takes much longer time to use up this energy. The fuel economy of PHEV is more dependent on the optimal balance for different segments of the trip. A global optimization method, e.g., DP, is more desirable. Recent work on global optimization based PHEV power management obtained by Argonne National Laboratory [10] shows the significant improvement in fuel economy when the global optimization is applied compared to the depleting-sustaining strategy.

In order to achieve the global optimality for a trip, the trip model for an individual trip is required in advance. Another difficulty is the computational load for global optimization algorithms in the microprocessor inside the vehicle. A two-scale dynamic programming algorithm has been developed for improving the computation efficiency while maintaining the optimality of the power management [24]. This approach was based on trip prediction and modeling facilitated by the Intelligent Transportation Systems (ITS), Geographical Information Systems (GIS) and Global Positioning Systems (GPS) [25-27]. Our simulation study showed that the computation time can be dramatically shortened, indicating its great potential for practical implementation. Later on, the trip modeling was improved by applying the advanced traffic flow theory. The gas-kinetic model, a representative mesoscopic model, was applied to the highway segments with on/off ramp traffic [28]. The Gipps car following model, a microscopic model, is applied to local road trip modeling with assumption of the availability of vehicle position/speed on a road segment via GPS transmitting devices [28]. Also, the traffic signal sequence is used to synchronize the local road trip modeling.

Gas-kinetic based traffic model has quite a few parameters to be calibrated for the implementation. A simplified way to find the driving pattern for the highway portion is using neural network. Neural network is an effective approach for pattern recognition and function fitting. The driving pattern on highways near on/off ramps usually has the typical shape of uneven triangle. It is caused by the ramp flow traffic merging into the main road traffic, so braking and acceleration patterns occur. The function fitting tool of neural network was used for the study. Simulation results will show the improvement of the trip modeling using the approach.

II. PHEV Power Management With Two-scale Dynamic Programming

A. Dynamic Optimization of HEV Power Management

The control strategy of the HEV power management can be computed through the dynamic optimization approach used on the dynamic models of the vehicle. Given the driving cycle, the strategy which minimizes the fuel consumption, or combined fuel consumption and emissions can be obtained. A numerical dynamic programming approach is adopted to solve this finite horizon dynamic optimization problem in [20].

In our study, fuel economy is the only term to be optimized. During the optimization process, it is necessary to satisfy the inequality and equality constraints to satisfy the speed and torque demands and meanwhile to ensure safe/smooth operation of the engine/battery/motor [20].A simplified but sufficiently complex vehicle model has been adopted in our previous study. In this study, we have kept the adoption of this model [20] [30].

B. Dynamic Programming

Dynamic programming is a general dynamic optimization approach which can provide globally optimal solution to the constrained nonlinear programming problems [31]. Based on Bellman's Principle of Optimality, the optimal policy can be obtained by solving the sub-problems of optimization backward from the terminal condition. The subproblem for the ($N-1$)-th step is to minimize

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

For step k ($0 < k < N-1$), the sub-problem is to minimize:

$$J^*_k[x(k)]=\min_{u(k)}\{L[x(k),u(k)]+J^*_{k+1}[x(k+1)]\} \tag{2}$$

where $J_k^*[x(k)]$ is the optimal cost-to-go function at state $x(k)$ starting from time stage k. The above recursive equation is solved backward to find the control policy. The minimizations are performed subject to the inequality constraints and the equality constraints imposed by the driving cycle.

An effective way to solve the above cost function numerically is to do the quantization and interpolation [32] [33]. For continuous state space and control space, the state and control values are first discredited into finite grids. At each step of the optimization search, the function $J_k[x(k)]$ is evaluated only at the grid points of the state variables. If the next state $x(k+1)$ does not fall exactly on a quantized value, then the value of $J_k^*[x(k+1)]$ as well as $G[x(N)]$ are determined through linear interpolation. At each step, the backward DP with interpolation method was used [31] [34]. For most cases, the vehicle can be assumed fully charged to the highest healthy level, typically SOC of 0.8, while the healthy low level of SOC is 0.3. Therefore, for the DP problem to be solved, the initial and terminal values of SOC are 0.8 and 0.3, respectively.

C. Two-Scale Dynamic Programming Based Charge-Depletion Power Management

After the driving cycles are obtained by trip models for individual trip, the DP technique can be used to find the trip based optimal power management strategy. The major issue remained is that the computation of global optimization is too complex to be implemented on board and also the actual driving cycle may be different from that produced by the trip model because of the variation of actual traffic situation. A two-scale DP procedure was proposed in [24]

III. Trip Modeling Enhancement

The purpose of the trip modeling is to find the driving cycle (e.g., travel speed, time, acceleration and deceleration) for each trip with specified origin and destination. For each trip, we can use path-finding algorithms inside the geographic information system (GIS) to search for the driving path and the relevant road information such as segment length, slope, speed limit and intersection/traffic light distribution. For arterial and express roads, historical and real-time traffic data can be obtained from roadside sensors. Traffic speed and flow information can be modeled based on such data [25-27].

Trip modeling includes two scenarios: local road and freeway. For the local road, traffic flow sensing is currently not common yet. So the traffic flow measurement is assumed not available for this stage of work. A simplified trip modeling approach with using of the traffic lights signals which can be obtained from the traffic management center was discussed [30] [35]. The case for study that was taken from *Mapquest* [36] was also discussed in detail in those two papers. On most freeways in the metropolitan areas, traffic flow sensors have been widely deployed and thus both historical and real-time traffic data are available for trip modeling. There are large databases of the archived ITS data. For example, the Wisconsin Department of Transportation has archived the traffic flow data in its WisTransPortal that is maintained by the Wisconsin Traffic Operations and Safety (TOPS) Laboratory[37]. This WisTransPortal allows the users to access the traffic data on the web. The procedures for traffic data based model were discussed [30]. Gas-kinetic based traffic model was used for the trip modeling of freeway portion considering the on/off ramp traffic flows, and Gipps car-following model used for the trip modeling of local road [28].

The case of our research is the trip model on the freeway considering the effect of the on- or off-ramp. The diagram is shown in Figure 1. The blue dots are the detectors fixed along the main road and ramps, which can obtain the traffic flow, speed information. At current step, we consider only the one lane situation, which means lane changing is not considered right now.

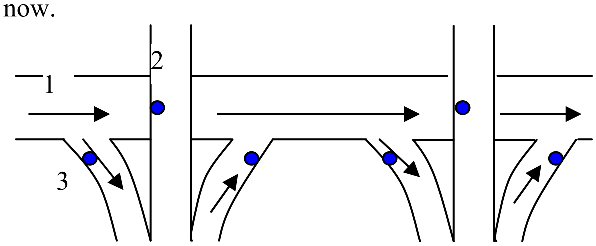


Fig. 1. Traffic Flow of Highway with On/Off Ramps

IV. Neural Network Used in On/Off Ramp

A. Flow Affected Driving Pattern on Highway

Gas-kinetic based traffic model has quite a few parameters to be calibrated for the implementation, such as A_0, ΔA, τ, γ, T etc [28]. which requires study on field recorded traffic data. Such calibration would be tedious and inconvenient from the vehicle development perspective. In this section, a data-driven approach is proposed to model the trip model around on/off ramps based on field recorded traffic data using Multi-layer Perceptron (MLP) type of neural networks. Such method is easier for practical implementation because the vehicle can acquire the on/off ramp traffic data for the target route from transportation agencies

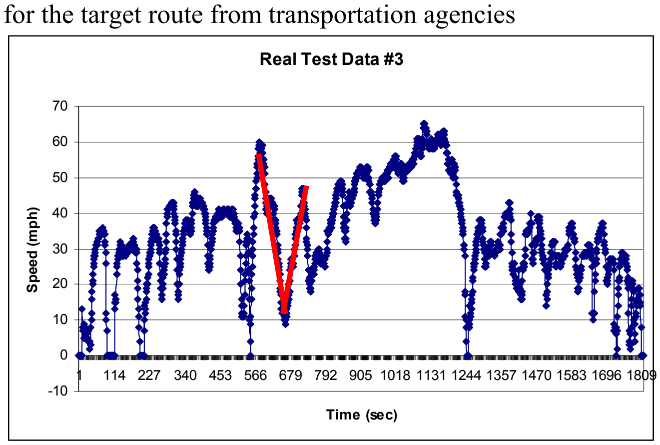


Fig. 2. A Case of Real Test Data Showing the Ramp Flow Effect

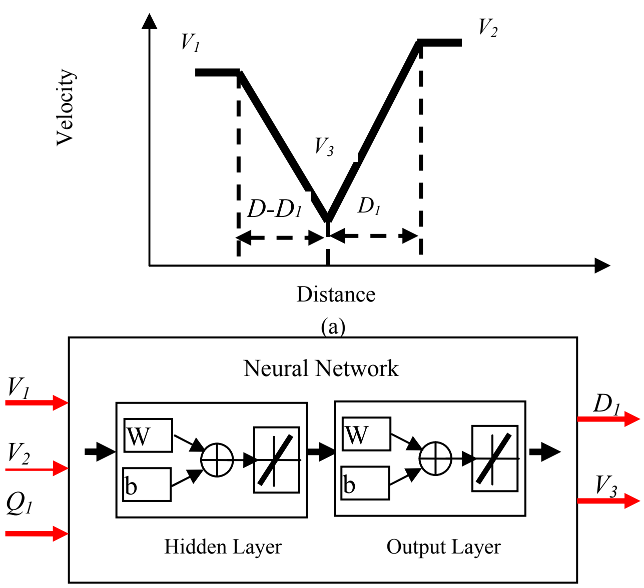
The driving pattern on highways near on/off ramps usually has the typical shape of uneven triangle shown in Figure 2 which is a case of real test data from the GPS receiver. A typical ramp flow affected driving pattern is pointed out as the red lines in the figure. The traffic flow is first slowed down as approaching to the on/ramp due to the mixing of inflow. After passing the mixing segment, the vehicle can accelerate gradually

Given a set of the training data, the back propagation based neural network can train the weights of the neurons. Least mean square (LMS) is used for the neural network. The function fitting tool of neural network was used for the study. The neural network model can be set as 3 inputs, 2 outputs model. The schematic diagram of the neural network is shown in Figure 3. V_1 is the upstream speed, V_2 is the downstream speed, V_3 is the valley speed, Q_1 is the ramp flow, D is the distance between two main road detectors, and D_1 is the distance between the valley speed location and the downstream main road detector. V_1, V_2 and Q_1 are inputs, while D_1 and V_3 are outputs. The detailed procedures for the neural network based highway trip modeling are as follows.

1) Obtain the driving pattern data sets x =[V_1, V_2, Q_1], y =[D_1, V_3], from the real test data of the highway portion. These data sets will be used for the training data sets for the neural network.

2) One case of the data sets obtained from WisTransportal will be used as the validation data sets.

3) The output data set results of the validation case will be picked out and combined with the data of the main road detectors of highway. A newly developed speed profile of highway portion using neural network fitting will be obtained.



(b)

Fig. 3. Schematic Diagram of The Neural Network

B. Study Case

Ten days real driving tests were carried out in May 2008. The real driving data were obtained from the GPS receiver (Garmin Forerunner 301) and stored to PC using the software nRoute. The speed, location and grade data can be obtained from GPS receiver. Since 2 of the 10 days don`t have data available in WisTransPortal, so the rest 8 days` data were used for the study, and test day #1`s data will be used as the validation case. The data sets of $V_1$, $V_2$, $V_3$, $D_1$ can be obtained from the cases picked out from the real test data. $Q_1$ can be obtained from WisTransPortal database, i.e. the first days` ramp flow data were collected as shown in TABLE 1. NA means data not available for that detector at that time.

TABLE I

RAMP FLOW OF DAY #1 FROM WISTRANSPORTAL

Ramp Locations.	Q_1 (vehicles/h)
STH 167/Mequon Rd.	700
County Line Rd.	480
Brown Deer Rd.1	250
Brown Deer Rd.2	450
Good Hope	530
Silver Spring Rd.	580
Hampton	530
Capitol Dr.	220
9th and Abert PI	410
Keefe	NA

For the neural network model, one hidden layer with 20 nodes is used, and 12 epochs were taken to converge. Totally 43 cases of from the real test data sets (10 real test data were collected from the GPS receiver) were chosen as the trained data, and 9 out of them were chosen as the validation cases..

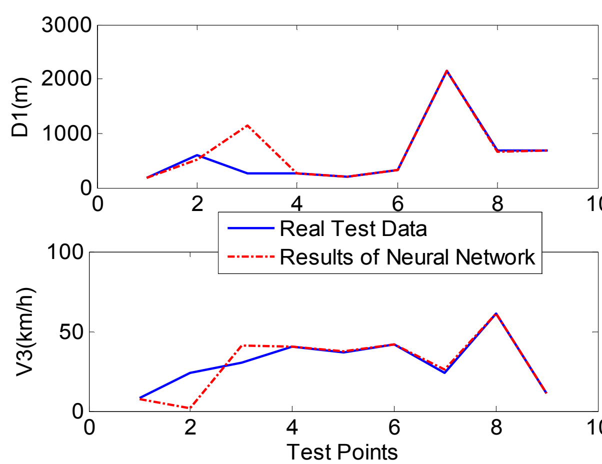


Fig. 4. Comparison of Output From Neural Network and Real Test Data

The outputs of the neural network of validation case are compared with the real test driving data in Figure 4. The test points are defined as the valley points between two traffic detector points. Most of the points were well fitted except very few. Combing the outputs from neural network (NN) and the main road detector data, the interpolation model with NN can be obtained. The speed profiles of interpolation model using WisTransPortal data, interpolation model using WisTransPortal data with NN, and the real test data of highway portion are compared in Figure 5. The portion is only the highway portion starting from zero just for simplicity. The three SOC profiles are DP results SOC profiles for the three cases correspondingly. Detailed fuel economy results will be studied in next section.

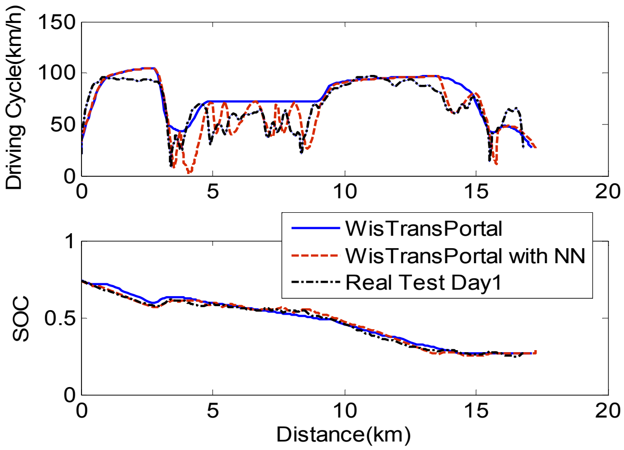


Fig. 5. Comparison of the Three Trips and the Corresponding SOC from DP

The solid line is the trip model using interpolation method using the data of day #1 from WisTransPortal. Compared to the real test data of the same day, this approach obviously missed some dynamics of the traffic on the highway portion. By adding the neural network results to the available data, the new approach WisTransportal with NN can be used to predict some ramp flow affected traffic dynamics on highway, which is more close to the real test data.

V. Simulation Results

The study used the same SUV model from the ADVISOR program as in our previous studies [29][30]. Its parameter and characteristic data were obtained by averaging the data of 1998 models of Ford Explorer, Jeep Grand Cherokee, and Chevy Blazer with the conventional powertrains. The resultant SUV has the ICE power of 102 kW. The vehicle was hybridized by downsizing the engine and adding an electric motor. The ICE was downsized to 75 kW, and a 50 kW AC electric motor was selected from the database in ADVISOR. The energy storage unit is a 10 A-h lithium battery. The ICE and motor are connected through a typical parallel configuration.

To see the potential and advantages of using the neural network based trip model for highway, the following simulations were carried out for comparison.

1) DP was applied to the three trips data (2 trip models and 1 real test data).

2) Obtain the power splitting ratio (PSR) of the two trip model of DP. PSR is defined as the P_{em}/P_{req}, where P_{em} is the power request from electric motor, and P_{req} is the total power request.

3) Directly apply the PSR obtained from the above step to the real test data. The fuel economy results and SOC trajectories can be obtained and compared.

The fuel economy results of DP for the three cases are 3.72, 3.94, 4.49 L/100km respectively. Apply the PSR obtained from the DP results of the interpolation model of WisTransPortal without NN to the real test data, the fuel economy is 4.34 L/100 km, which is about 16.7% degradation compared to the DP result of the real test data. When applying the PSR obtained from the DP results of the interpolation model of WisTransPortal with NN to the real test data, the fuel economy is 3.58 L/100 km, which is about 17.5% improvement compared to the case without NN (4.34), However, the little even better result of direct apply of the PSR of the interpolation model of WisTransPortal with NN compared to the DP result of real test data may be caused by numerical error of the DP algorithm.

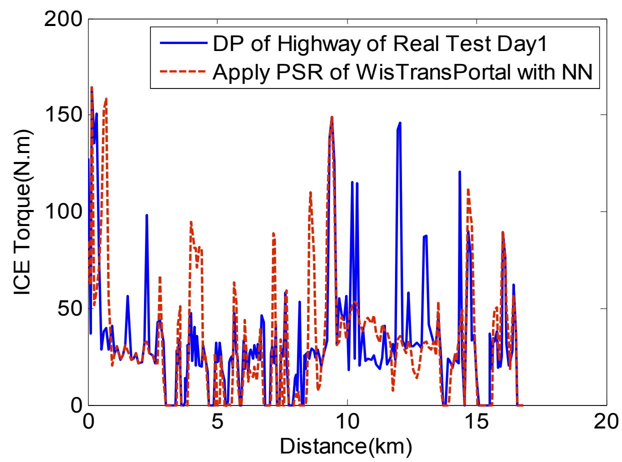


Fig. 6. Comparison of the ICE Torques of DP and Direct Apply of PSR

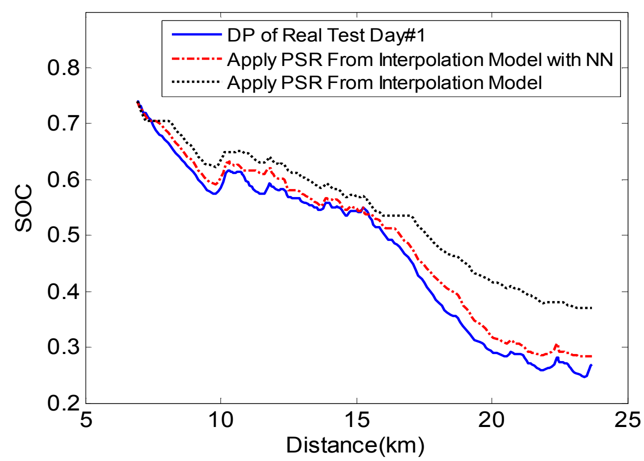


Fig. 7. Comparison of the Obtained SOC Profiles

The ICE torque comparison of the DP result of real test data and the direct use of PSR of interpolation model with NN are shown in Figure 6.

Applying the PSR from the two models to the feed forward battery model, the obtained real SOC trajectories for the cases are compared with the DP based results in the Figure 7. The final SOC value for the direct application of PSR from interpolation model with NN is 0.28, and the final SOC value for the direct application of PSR from interpolation model without NN is 0.37. The final SOC values difference demonstrate the difference in fuel economy results.

The interpolation model with NN has very close results both in final SOC values and fuel economy with the DP case. However, a little even worse result in fuel economy of DP may caused by the numerical error of DP algorithm.

VI. Conclusion

In this paper, a neural network based trip model for highway portion was studied. A 3 inputs, 2 outputs network was developed for the fitting of the driving pattern on highway near on/off ramps. The trained neural network can obtain a good fitting of the driving pattern. The simplified approach makes the trip model on highway much easier.

Potential of using the approach are illustrated by the fuel economy results comparison. The interpolation model without using NN has big degradation of fuel economy when applying the PSR obtained from the model to the real driving data. By using the interpolation model with NN, the fuel economy is greatly improved. The NN model presents a simplified and effective way for this detailed model of trip model considering the on/off ramp flows.

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