Exploring Cognitive Knowledge for Intelligent Vehicle Power Management in Military Mission Scenarios

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Summary

Growing environmental concerns coupled with the complex issue of global crude oil supplies drive automobile industry towards the development of fuel-efficient vehicles. Due to the possible multiple-power-source nature and the complex configuration and operation modes, the control strategy of a military vehicle is more complicated than that of a conventional vehicle. Furthermore, military vehicles often have heavier weights and are used to operate multiple functions such as engaging weapons, turning on sensors, silent watch, etc., which results in big load fluctuation. In this paper we present our research in optimizing power flow in a heavy vehicle for a given mission plan. A mission plan consists of a sequence of operations and speed profiles. The vehicle architecture will be modeled based on Stryker power system which consists of a diesel engine, a main battery pack, an auxiliary battery pack, and an APU. The APU can supply power to the auxiliary loads and auxiliary batteries only during silent watch mission. We will use PSAT (Powertrain System Analysis Toolkit) (http://www.transportation.anl.gov/software/PSAT/index.html) simulation program to construct the vehicle model along with the power system specified above. PSAT is a high fidelity simulation software developed by Argonne National Laboratory under the direction of and with contributions from Ford, General Motors, and Chrysler. PSAT is a "forward-looking" model that simulates vehicle fuel economy and performance in a realistic manner — taking into account transient behavior and control system characteristics. It can simulate a broad range of predefined vehicle configurations (conventional, electric, fuel cell, hybrid electric, light and heavy trucks). We developed

a dynamic programming algorithm to optimize the power flow during a given mission. The cognitive knowledge we explored including roadway type prediction and potential load requests associated with specific mission plan.

1. Introduction

Growing environmental concerns coupled with the complex issue of global crude oil supplies drive automobile industry towards the development of fuel-efficient vehicles. Vehicle power management has been an active research area in the past two decades, and more intensified by the emerging hybrid electric vehicle technologies. Most of these approaches were developed based on mathematical models or human expertise, or knowledge derived from simulation data. The application of optimal control theory to power distribution and management has been the most popular approach, which includes linear programming [1], optimal control [2,3,4], and especially dynamic programming (DP) have been widely studied and applied to a broad range of vehicle models [5, 6, 7, 8]. In general, these techniques do not offer an on-line solution, because they assume that the future driving cycle is entirely known. However these results have been widely used as a benchmark for the performance of power control strategies. In more recently years, various intelligent systems approaches such as neural networks, fuzzy logic, genetic algorithms, etc. have been applied to vehicle power management [9, 10, 11, 12, 13, 14, 15, 16]. Research has shown that driving style and environment has strong influence over fuel consumption and emissions[17, 18]. More information on vehicle power management can be found in [19].

Due to the possible multiple-power-source nature and the complex configuration and operation modes, the control strategy of a military vehicle is more complicated than that of a conventional vehicle. Furthermore, military vehicles often have heavy weights and are used to operate multiple functions such as engaging weapons, turning on sensors, silent watch, etc., which results in big load fluctuation. In this paper we present our research in optimizing power flow in a heavy vehicle for a given mission plan. We will formulate a general mission plan that is typical in military applications and develop an intelligent power controller (UMD-IPC) based cognitive knowledge extracted from the mission. We will

The vehicle architecture will be modeled based on Stryker power system which consists of a diesel engine, a main battery pack, an auxiliary battery pack, and an APU. The APU can supply power to the auxiliary loads and auxiliary batteries only during silent watch mission. We will use PSAT (Powertrain System Analysis Toolkit) (http://www.transportation.anl.gov/software/PSAT/index.html) simulation program to construct the vehicle model along with the power system specified above. Experiments show that our optimized power controller has the potential of giving significant reduction in fuel consumption.

2. Cognitive power management with application to military vehicles

Military vehicles have complicated power systems in order to support various missions. Although power systems in military vehicles are in conventional style, i.e. engine is used to provide power to drivetrain, military vehicles can have multiple batteries, and multiple loads. Figure 1 shows the architecture of the vehicle power system used by Stryker model.

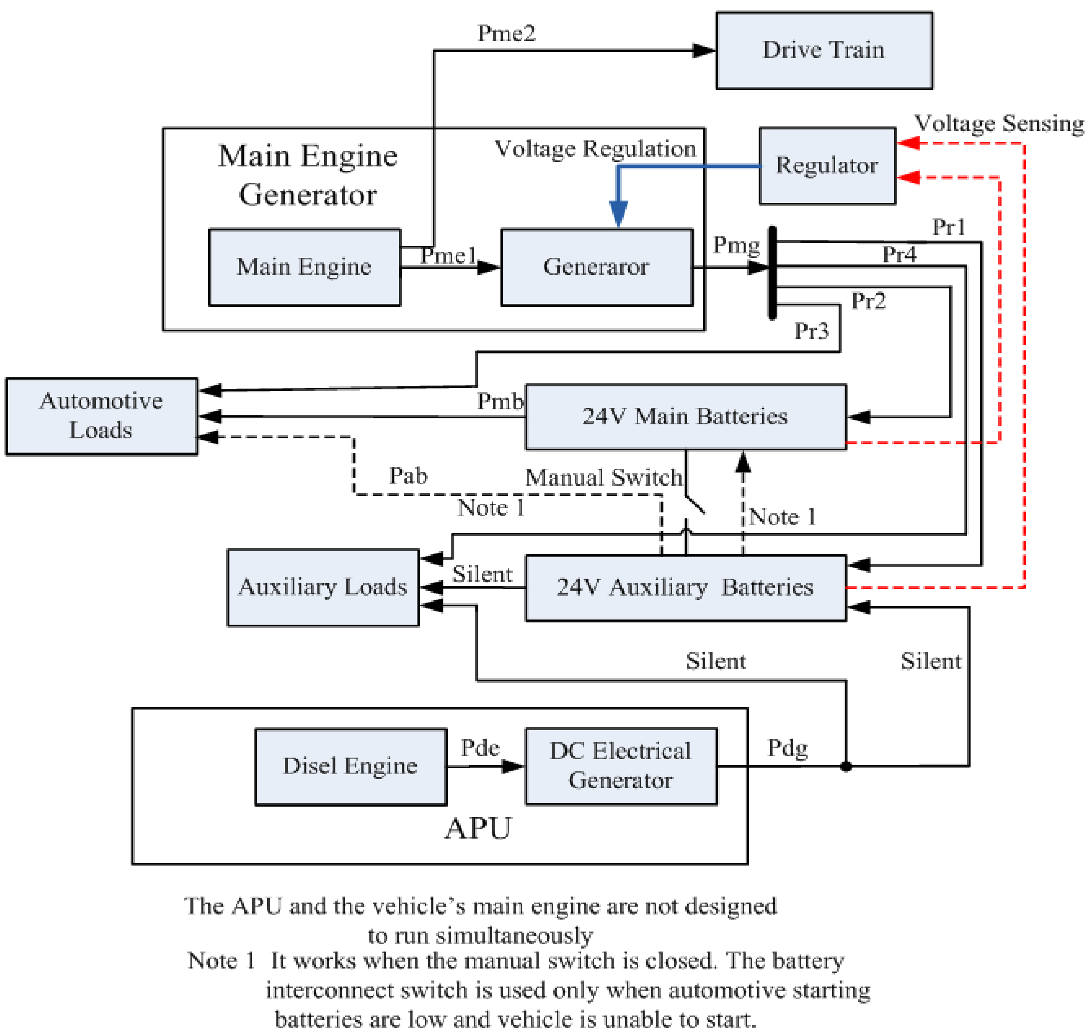
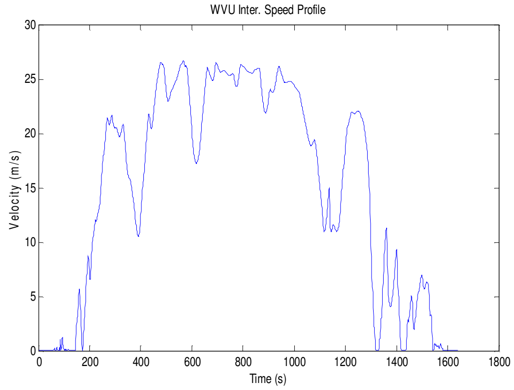


Figure 1. Vehicle power system in a Stryker vehicle.

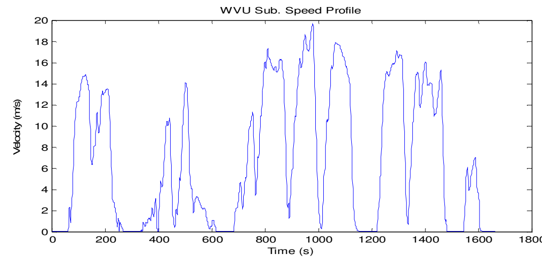
In this power system, there are two separate subsystems: the main engine system and the Auxiliary Power Unit (APU). The APU and the vehicle's main engine are not designed to run simultaneously. The connections marked as "note 1" will work only when the manual switch is closed. The switch between the two batteries is turned on only when main battery is too low to start the vehicle.

This research attempts to extract the cognitive knowledge from mission plan that is useful in training an intelligent power controller (UMD-IPC). From power management point of view, a mission plan consists of a sequence of events and roadway types the vehicle travels on during the mission. From events we are able to extract operation modes of devices that require operation power, and from these operation modes, we are able to define the load requests throughout the mission, For the Stryker power system model, a mission plan can be described as follows. M_Plan = $\{(rd(t), Auto\_ld(t), Aux\_ld(t)), silence\ (t) \mid t = 0, ..., t_{end}\}$, where rd(t) is the roadway type the vehicle is traveling on at time t, Auto_ld(t) and Aux_ld(t) are the automotive load and auxiliary load, respectively, at time t, silence (t) = 1 means the vehicle is not moving otherwise it is moving. Rich knowledge can be extracted based on the roadway types such as typical speed profiles of military vehicles when travel on these roads, such as the optimal power settings for each of these roadway types.

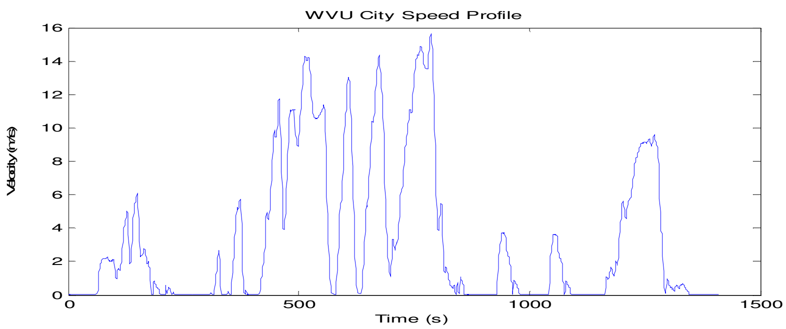
In this study, we divided roadway types into three categories, interstate, suburban and city. Since a Stryker is a heavy vehicle, we use three truck speed profiles provided by PSAT(see Figure 2) to characterize these roadway types.



(a)



(b)



(c)

Figure 2: Three speed profiles used as the benchmark of roadway types, (a) interstate, (b) suburban, (c) city.

For each roadway type, we generate optimal power settings using a dynamic programming algorithm. With the optimal power settings we train the UMD_IPC, the online intelligent power controller. Figure 3 illustrates the power control scheme. The driver or operator turns the main engine on or off. When it is off, the vehicle is in the silent mode. Only at this mode, it is possible to run the APU. The APU can be switched on manually by the driver or automatically turned on by the UMD_IPC to charge the auxiliary battery. When the engine is on, UMD_IPC calculates the optimal power to be charged to and discharged from the main battery, P_b, and the auxiliary battery, P_{ab}, which are used in turn to calculate optimal engine generator power and optimal engine power. When the vehicle is the silent mode, the UMD_IPC calculates the optimal P_{ab}, and, if the switch between the two batteries are closed, the optimal P_b. The P_{ab} along with the auxiliary load, P_{al} are used to calculate the optimal auxiliary engine power.

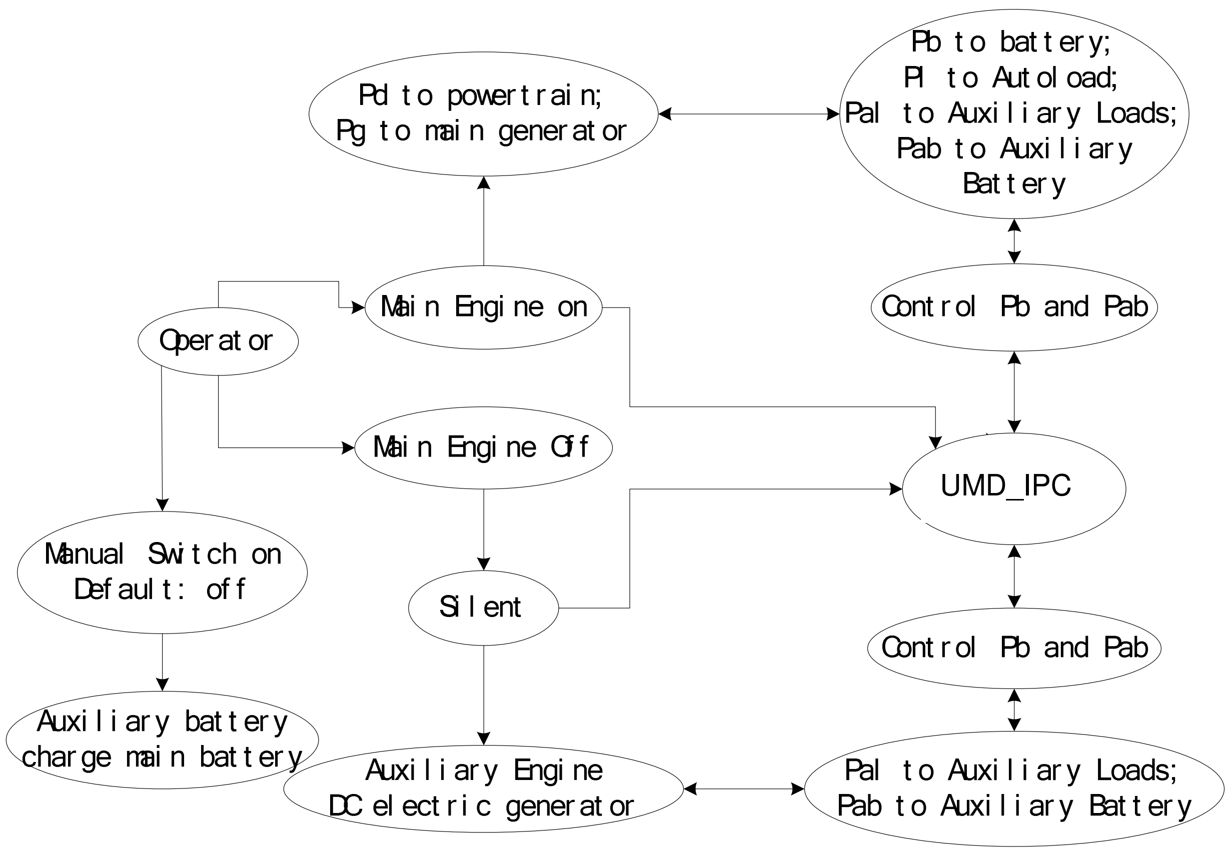


Figure 3. Intelligent power control scheme in a Stryker vehicle.

3. Experiments

We will use PSAT (Powertrain System Analysis Toolkit) (http://www.transportation.anl.gov/software/PSAT/index.html) simulation program to construct a Stryker vehicle model with the power system specified above. PSAT is a high fidelity simulation software developed by Argonne National Laboratory under the direction of and with contributions from Ford, General Motors, and Chrysler. PSAT is a "forward-looking" model that simulates vehicle fuel economy and performance in a realistic manner — taking into account transient behavior and control system characteristics. It can simulate a broad range of predefined vehicle configurations (conventional, electric, fuel cell, hybrid electric, light and heavy trucks).

Figure 4 shows the Stryker model built using PSAT. It is a conventional Vehicle Configuration that has a Detroit diesel engine with 7.3L, Initial power 171 kW and scaled to 261 kW, a generator scaled to 16.8 kW, two Hawker Genesis Batteries with 13 Cells, 27 Volts Nominal and 120 Ah Capacity, and 2 passive axles used to incorporate any drag coefficients. Its transmission is an AlissonB500 model with gear ratios modified to what shown in Table I, and the final drive has the ratio 7.85:1. The wheels/tires have 0.533 m radius and 0.0115 rolling coefficient.

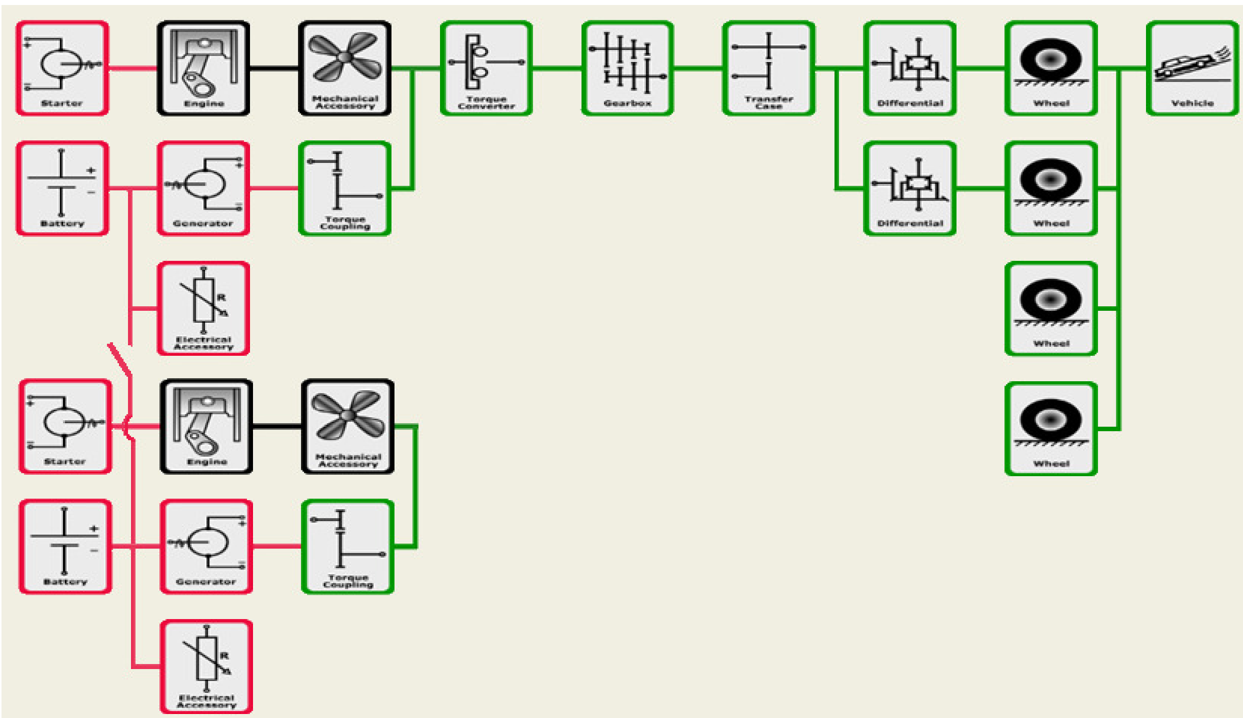


Figure 4. A Stryker vehicle model built using PSAT simulation software.

Table 1. Gear ratio used in simulated Stryker vehicle model

Gear	1st	2nd	3rd	4th	5th	6th
Ratio	3.49:1	1.86:1	1.41:1	1.00:1	0.75:1	0.65:1

The Auxiliary Power Unit (APU) is a liquid cooled, diesel engine powered, DC electrical generator, designed to provide auxiliary electrical power during silent watch missions. The APU generates 123 usable amps at 28.5 volts. The APU and the vehicle's main engine are not designed to run simultaneously. The APU will shut down within 60 seconds if simultaneous operation is attempted.

For the purpose of experiments we constructed the following drive cycle based on the cognitive knowledge discussed in the last section, Mission_EX = {(rd(t), Auto_ld(t), Aux_ld(t)), silence (t) | t = 0, ..., t_{end}}, where rd(t)=city for t = 0 ~ 2460, rd(t) = interstate for t = 2450 ~ 4500, Auto_ld(t) = 4KW during non-silent period and 0 during the silent period. The Aux_ld(t) = 4KW during the non-silent mode and 2KW during the silent mode. silence (t) = 1 when t = 1350 ~ 2460, otherwise, silence (t) = 0. The vehicle speed profile for this drive cycle is shown in Figure 5. Automotive loads and auxiliary loads are shown in Figure 6.

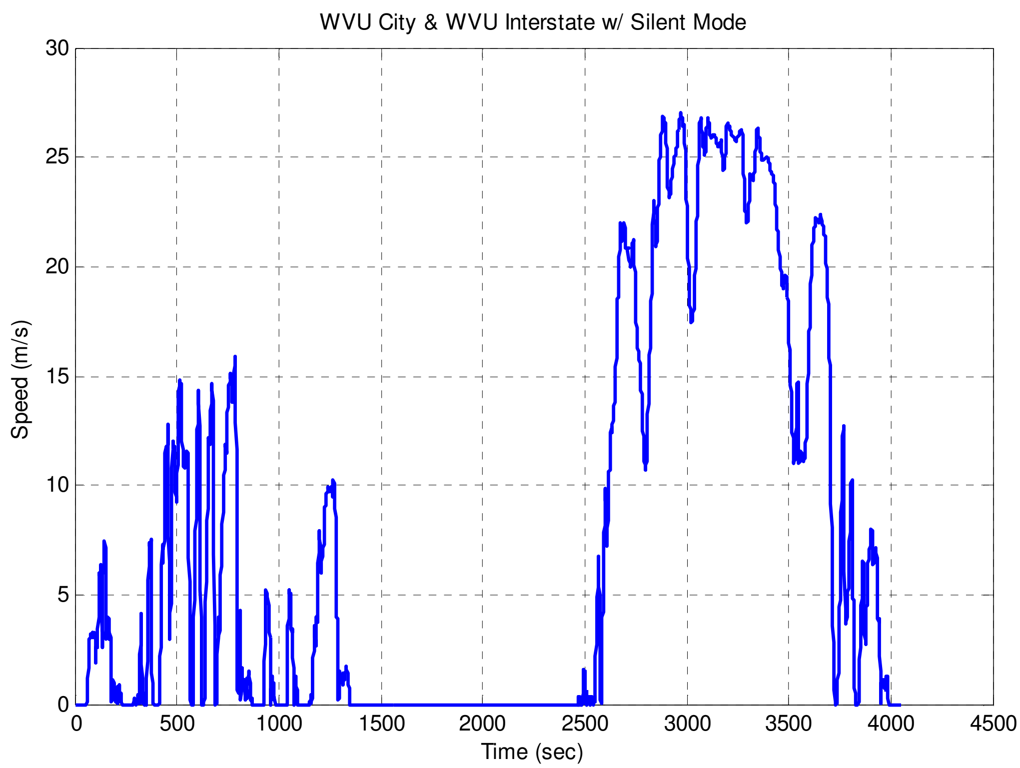
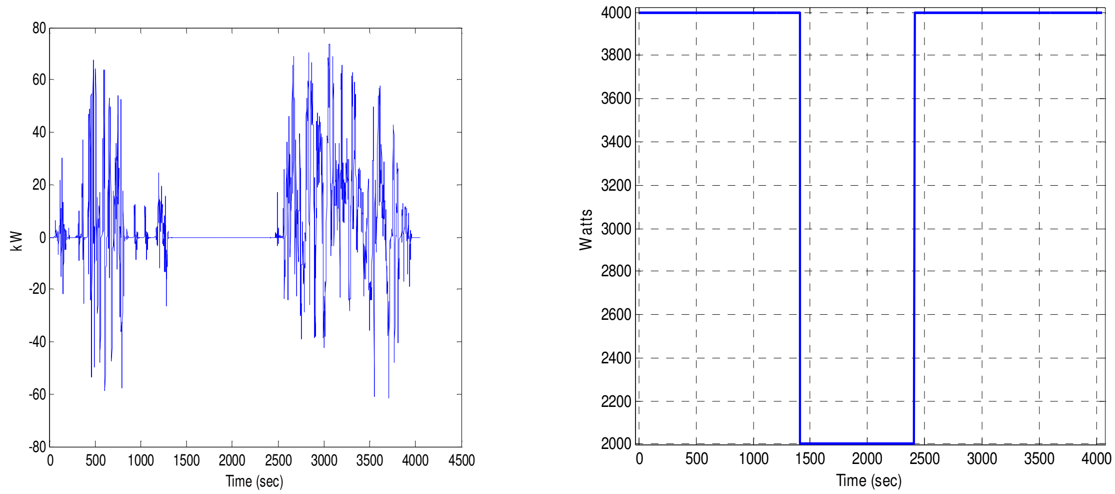


Figure 5. Speed profile of the drive cycle used in experiments



(a) (b)

Figure 6. Automotive loads and auxiliary loads used in experiments.

Two types of cognitive power management are explored. First type is to construct the UMD_IPC to follow the target SOCs during drive cycles based on the mission plan. Since we know from the mission plan that there is a silence period between t = 1350 and t = 2460 and we are given that we can use the APU power to charge both batteries during the silence mode, we make the target SOC = 30% during the non-silent time, and target SOC = 70% at the silence time. Note during the silence mode, the APU also supplies power to the auxiliary loads. The target SOCs for the drive cycle is shown in Figure 7.

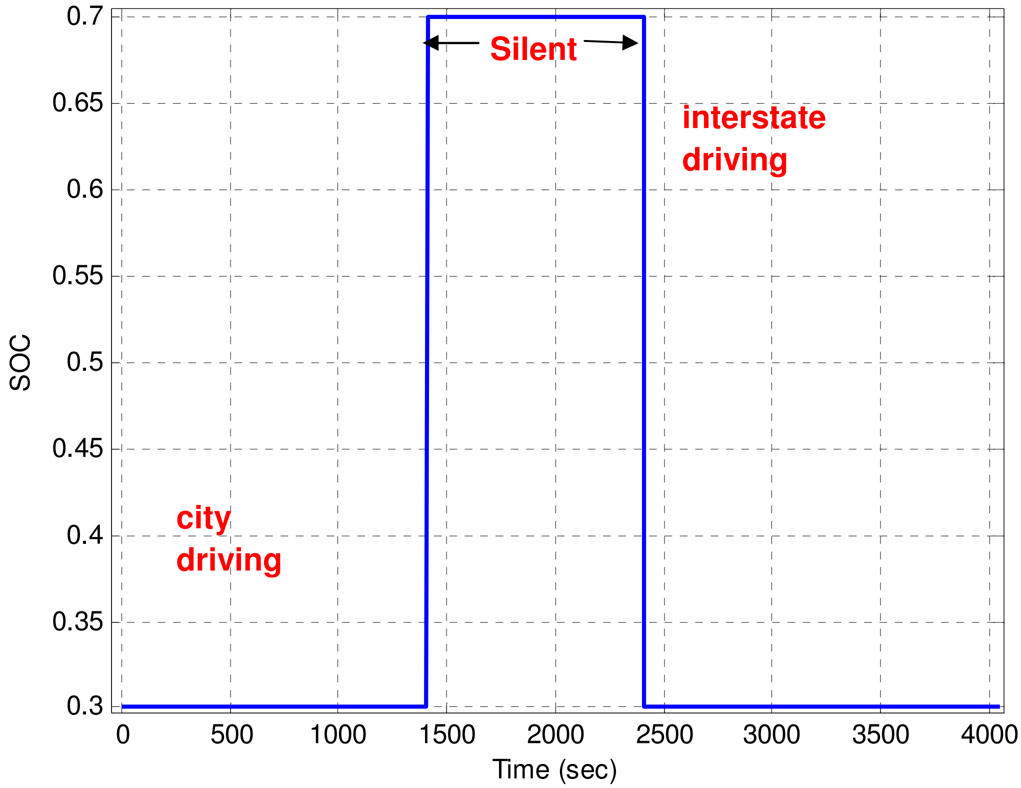


Figure 7. A target SOCs used in experiments.

The second type of cognitive power management is to train the UMD_IPC on the optimal power settings generated by Dynamic Programming on the drive cycle meet the specification of the given mission plan. The experiments are ongoing and will be included in the final paper.

4. Conclusion

We have presented our research in cognitive power management in military vehicle applications. We presented an abstract representation of drive cycles for military vehicles based on a given mission plan. The representation can be extended to incorporate more complicated mission plans that involve more events and knowledge that can be used to manage the vehicle power system for not only fuel economy but also more reliable power system. We presented two power management strategies, one uses target SOCs during driving and silence mode to achieve better fuel economy, one is to use Dynamic Programming to achieve optimal power settings.

References

[1] E. D. Tate and S. P. Boyd, “Finding ultimate limits of performance for hybrid electric vehicles,”, SAE Paper-01-3099, 2000.

[2] M. Back, M. Simons, F. Kirschaum, and V. Krebs, “Predictive control of drivetrains,” in *Proc. IFAC 15th Triennial World Congress*, Barcelona, Spain, 2002.

[3] J. Bumby and I. Forster, “Optimization and control of a hybrid electric car,” *Inst. Elect. Eng. Proc.*, pt. Part D, vol. 134, no. 6, pp. 373–387, Nov. 1987.

[4] S. Delprat, J. Lauber, T.M. Guerra, and J. Rimaux, “Control of a parallel hybrid powertrain: optimal control,” *IEEE Trans. Veh. Technol.*, vol. 53, no. 3, pp. 872–881, May 2004.

[5] C.-C. Lin, H. Peng, J.W. Grizzle, and J.-M. Kang, “Power management strategy for a parallel hybrid electric truck,” IEEE Trans. Contr. Syst. Technol., vol. 11, no. 6, pp. 839–849, Nov. 2003.

[6] T. Hofman and R. van Druten, “Energy analysis of hybrid vehicle powertrains,” in *Proc. IEEE Int. Symp. Veh. Power Propulsion*, Paris, France, Oct. 2004.

[7] I. Arsie, M. Graziosi, C. Pianese, G. Rizzo, and M. Sorrentino, “Optimization of supervisory control strategy for parallel hybrid vehicle with provisional load estimate,” in *Proc. 7th Int. Symp. Adv. Vehicle Control (AVEC)*, Arnhem, The Netherlands, Aug. 2004.

[8] Koot, M.; Kessels, J.T.B.A.; de Jager, B.; Heemels, W.P.M.H.; van den Bosch, P.P.J.; Steinbuch, M., Energy management strategies for vehicular electric power systems, IEEE Transactions on Vehicular Technology, Volume 54, Issue 3, Page(s):771 – 782, May 2005

[9] V. H. Johnson, K. B.Wipke, and D. J. Rausen, “HEV control strategy for real-time optimization of fuel economy and emissions,”, SAE Paper-01-1543, 2000.

[10] J.-S. Won, R. Langari, and M. Ehsani, “Energy management strategy for a parallel hybrid vehicle,” in *Proc. Int. Mechan. Eng. Congress and Exposition (IMECE ’02)*, New Orleans, LA, Nov. 2002, pp. IMECE2002–33 460.

[11] G. Paganelli, G. Ercole, A. Brahma, Y. Guezennec, and G. Rizzoni, “General supervisory control policy for the energy optimization of charge-sustaining hybrid electric vehicles,” *JSAE Rev.*, vol. 22, no. 4, pp. 511–518, Apr. 2001.

[12] Jungme Park, ZhiHang Chen, Leonard Kiliaris, Ming Kuang, Abul Masrur, Anthony Phillips, Yi L. Murphey, “Intelligent Vehicle Power Control based on Prediction of Road Type and Traffic Congestions,” 2008 IEEE 68th Vehicular Technology Conference, 22–25 September 200 8 Calgary, Canada.

[13] ZhiHang Chen, M. Abul Masrur, and Yi L. Murphey, “Intelligent Vehicle Power Management using Machine Learning and Fuzzy Logic,” Proceedings of FUZZ-IEEE, June 2008

[14] Yi L. Murphey, ZhiHang Chen, Leo Kiliaris, Jungme Park, Ming Kuang, Abul Masrur, Anthony Phillips, “Neural Learning of Predicting Driving Environment,” IJCNN, 2008

[15] Fazal U. Syed, Dimitar Filev, Hao Ying, “Fuzzy Rule-Based Driver Advisory System for Fuel Economy Improvement in a Hybrid Electric Vehicle,” Annual Meeting of the NAFIPS, 24-27 June 2007 Page(s):178 - 183
[16] A. Sciarretta, L. Guzzella, and M. Back, “A real-time optimal control strategy for parallel hybrid vehicles with on-board estimation of the control parameters,” in *Proc. IFAC Symp. Adv. Automotive Contr.*, Salerno, Italy, Apr. 19–23, 2004.
[17] E. Ericsson, “Variability in urban driving patterns,” *Transportation Res. Part D*, vol. 5, pp. 337–354, 2000.
[18] E. Ericsson, “Independent driving pattern factors and their influence on fuel-use and exhaust emission factors,” *Transportation Res. Part D*, vol. 6, pp. 325–341, 2001.
[19] Yi L. Murphey, “Intelligent Vehicle Power Management: an overview” Studies in Computational Intelligence (SCI) 132, 169-190, www.springerlink.com. Springer-Verlag Berlin Heidelberg 2008

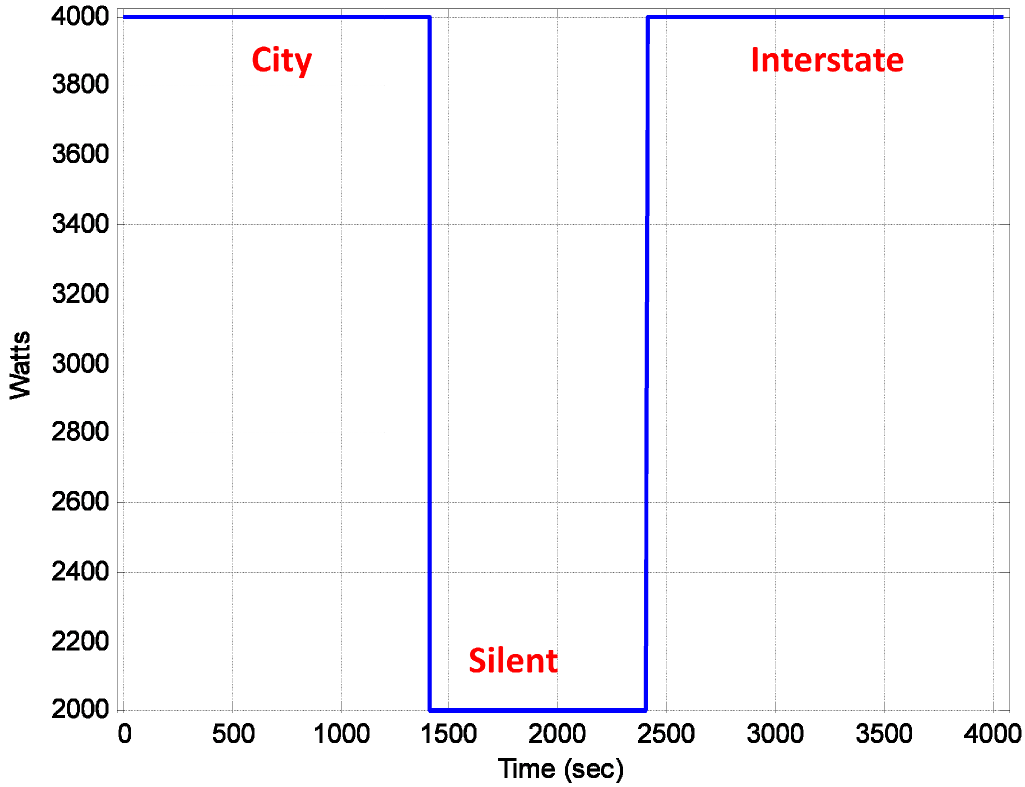
Drive cycle	Power controller	Total Fuel (g)	Ending SOC (%)	Total Fuel After SOC Correction (g)	Savings (%)
WVU Interstate	PSAT	7401.6	64.14	7425.7	
	DP	7008	70	7008	5.62
WVU sub.	PSAT	4876.1	63.78	4902.6	
	DP	4220.6	70	4220.6	13.9
WVU City	PSat	2648.7	63.73	2675.4	
	DP	2066.5	70	2066.5	22.76

The SOC correction is calculated as follows. We applied DP optimization program to the WVU interstate drive cycle twice. The first run had the initial SOC at 50% and ending at 70%, and the second run had the same initial SOC but the ending was at 64.5%. The SOC correction factor λ is calculated as follows.

λ=(Cummulative_Fuel_1 – Cummulative_Fuel_2)/(SOC_DP_1 – SOC_DP_2)

Fuel consumption based on SOC Correction is calculated as follows

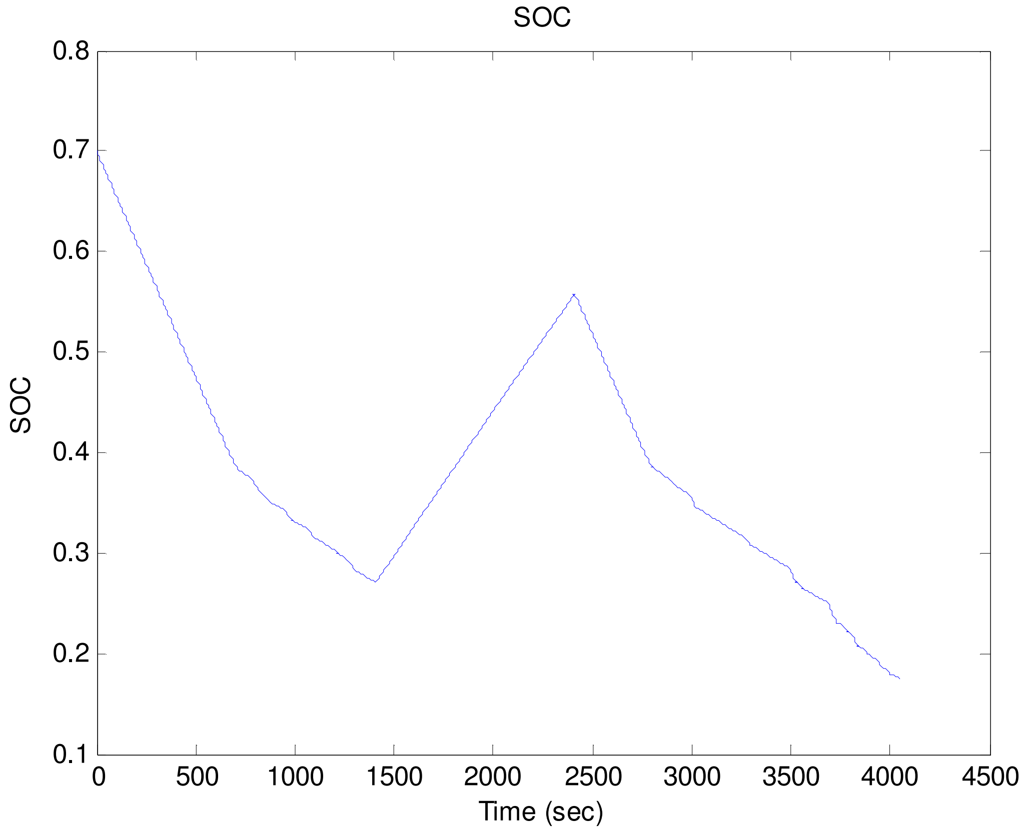
Corrected_Cumulative_Fuel = PSat_Cummulative_Fuel + (70 – Ending_Psat_SOC)* λ



Charging Control Rules

- During city and interstate cycle, soc drops to target, 0.3.
  - No charging is done during these times
- During silent mode, a constant current is used to charge until soc reaches 0.7

Sample Simulation - SOC


SOC
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
SOC
0
500
1000
1500
2000
2500
3000
3500
4000
4500
Time (sec)