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Energy Management in Electric Vehicles with Batteries and Supercapacitors based on Machine Learning Techniques

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Abstract

The Electric Vehicle (EV) success will be achieved if the Energy Storage System (ESS) offers a long lifetime, reduced costs, reduced charging time, and higher powers and energy densities [Wh/kg]. Unfortunately, the actual technology does not fully provide all these characteristics in a single source. Motivated by this issue, in recent years, there has been an increased interest in developing storage systems with multiple energy storage technologies [1].
One important question that emerges when designing a hybrid ESS is to decide how to split the demanded power between the multiple sources of the EV [2]. Current real-time strategies are mainly based on heuristic control approaches, as rule based algorithms. However, difficultly they will provide the global optimal solution. The alternative is to implement optimal control methods as linear programming, optimal control theory or dynamic programming. Nevertheless, these methods are difficult or even impossible to implement and thus to obtain the optimal solution in real-time. Furthermore, many energy management approaches in electric vehicles do not incorporate the information about the road type and driving conditions. Machine Learning techniques can been implemented in order to identify the road type and traffic conditions, the driving trends, and based on the state of the vehicle a proper power allocation can be obtained [3]. Therefore, neural networks (NN) ability to integrate fundamental and technical analysis for electric power split of batteries and SCs will be investigated. In addition, to have a better estimation of the driver's behavior a dynamic network will also be applied, due their ability to be trained to learn with sequential data. Figure 1 presents the results for different NN architectures in comparison to the optimal solution.

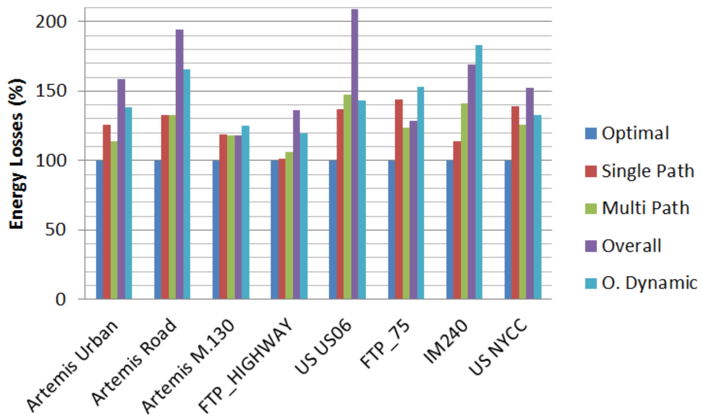

Figure 1: Energy losses for IPOPT solution, for classification and regression NN (single and multiple optimal paths) and for overall regression NNs.

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