Machine Learning-Enabled EMS and Advanced Powertrains for Smart, Sustainable EVs

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Abstract: The current research is further refinement of Energy Management System (EMS) in electric vehicles (EVs) which combines the modern methodologies for the improvement of the functioning of electric vehicles in combined with their sustainable. The system is conditioned on real-life driving data on the Long Short-Term Memory (LSTM) Neural Network, which is formed and shipped as the Open Neural Network Exchange (ONNX) arginine in a stand comparison surroundings from Utilizing Simulink in an application to calculate the most effective expenditure of energy in the battery and supercapacitor. What's more, there are Deep Deterministic Policy Gradient DDPG powertrain optimization algorithm with the special combination of powers and longest part. The proposed hybrid is able to get more from both the LSTM and DDPG to get more system life and power savings. The proposed EMS will undergo high energy saving procedures and in addition raise the life cycle of the EV components, in order to design smarter and more sustainable solutions for electric mobility.

Keywords: *Machine Learning, Energy Management System, Long Short-Term Memory, Deep Deterministic Policy Gradient, Electric Vehicles, Powertrain Optimization*

I. INTRODUCTION

The biggest shift towards environmental problems as well as green transportation is the electrification of EV's. A key absence of this evolution are the development of better EMS and of the power train architecture, to increase efficiency and performance while enhancing their robustness [1]. The traditional EMS (for example, rule-based or optimization-based) methods are in general not adequate for handling such real-time conditions of driving and the complex dynamics of the vehicle.

Fig.1: EV operation monitoring system.

The recent achievements of Machine Learning(ML) could be an opportunity to solve those problems. According to the principles of data-driven models, e.g. the Long Short-Term Memory (LSTM) networks and Deep Deterministic Policy Gradient (DDPG) algorithms, it will be possible for eMobil to optimize distributor of energy and operations of powertrains in more or less a continuous manner [2]. The author considers the application of such ML techniques to EMS and powertrain systems in this research and future for the creation of smarter and more sustainable EVs [3].

II. RELATED WORKS

H.-J. Lee, K.-T. Kim 2021, Recent works have been shown to mark the paradigm shift for EV EMS and powertrain optimization using machine learning [4]. EMS on the real from data-based model using offline reinforcement learning, 25 was place which itse eg energy efficient, system scaling first job eg factor Nature, was improve. On the same note, S. Yang, R. He, Z. Zhang, Y. Cao 2020, Praveenraj et. al. optimized the EV energy by enforced machine learningaire to get the driving data and compared the driving data with the charging demand and charge demand in renewable microgrids E3S Conferences [5].

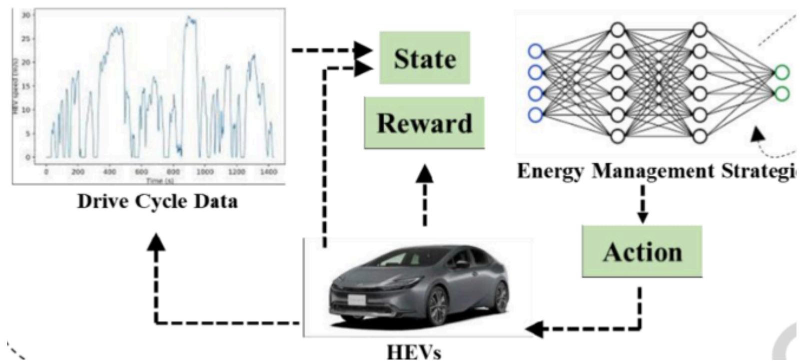

Fig.2: Offline training in simulation using ML Algorithm.

Within the framework of the rationalization of the powertrain with Zhou et al. (2025), the design concept for series matching of a one-motor and two-speeds dual clutch transmission (2-Speed Wet DCT) in the battery electricity vehicle (BEV) MDPI was presented [6]. The machine learning based strategies and optimization formulations that have been employed for designing EMS to plug-in hybrid electric vehicles (PHEVs) have been reviewed and importance of predictive & adaptive control strategies MDPI have been discussed by Recalde et al (2024) [7]. Among these studies, there is the use of machine learning for EMS and powertrain systems in order to design a smarter electric car with more efficient and environmentally friendly features [8].

III. RESEARCH METHODOLOGY

The goal of research development for a machine learning-based EMS applied to EVs with advanced powertrain configuration would guide the formation of the research methodology used for the systematic experimentation, analysis, and evaluation as a whole [9]. The methodology design incorporates a series of steps with a flowchart logic process starting from the problem definition [10]. From the point of view of this stage, correctly establishing the aims of the research was accomplished: reducing energy consumption, and improvement of the powertrain efficiency particularly to optimize the sustainability [11]. In this step, it will have a detailed look at the existing Electric Mobility frameworks, Powertrain architectures and recently the machine learning algorithms which are available for Electric Mobility.

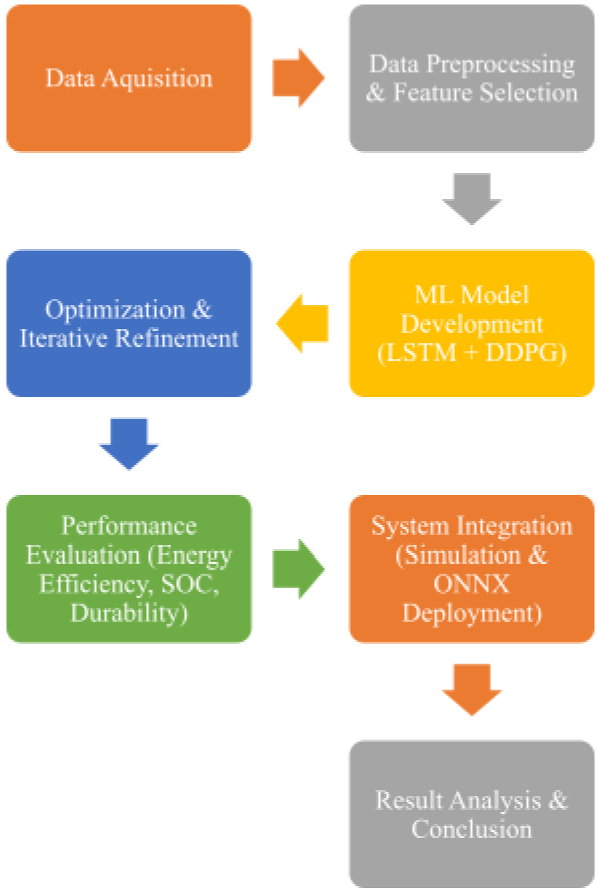

Fig.3: Flow diagram for the proposed methodology.

The second significant process is data acquisition, as it is the primary concern in the machine learning model training and validation process[12]. All redundant noise and data is pre-processed and missing data is implemented and normalized into data that would be used to train their model data. In addition to establishing the significant assumed variables influencing the utilization of the energy but also the efficiency of the powertrain, this process also involves the selection of the features to be used for their definition [13].

After data preparation, the machine learning model enters the data preparation stage. This is due to the Long Short term memory (LSM) as follows [14]. Specifically, based on the temporal dynamics of LS-M, it is selected as the resort of energy demand, thereby obtaining prediction results of energy demand from series driving information [15]. Meanwhile, Deep Deterministic Policy gradient (DDPG) algorithm, namely a form of Deep Reinforcement Learning (DRL), is adopted for the planning purpose of powertrain control policy [16]. At this stage, these methods include training of the model, hyper parameter optimization, k fold cross validation attempt (to avoid over fitting and get ability to generalize).

Energy Balance in EV EMS

$$E_{total} = E_{battery} + E_{regen} - E_{loss}$$

Where:

- E_{total} = Net available energy for propulsion

- $E_{battery}$ = Energy supplied from the battery
- E_{regen} = Energy recovered from regenerative braking
- E_{loss} = Drivetrain and conversion losses

Example

Suppose an EV is running a 100 km drive cycle.

- Energy supplied from the battery:

$$E_{battery} = 18 \text{ kWh}$$

- Energy recovered via regenerative braking:

$$E_{regen} = 2 \text{ kWh}$$

- Drivetrain and conversion losses:

$$E_{loss} = 3 \text{ kWh}$$

Applying the equation:

$$E_{total} = 18+2-3=17 \text{ kWh}$$

So, the net useful energy available for propulsion is 17 kWh. If we now apply the Proposed ML-EMS optimization, losses could drop to

$$E_{loss} = 2 \text{ kWh}$$

$$E_{total} = 18+2-2$$

$$=18 \text{ kWh}$$

This shows a ~6% improvement in usable energy due to smarter ML-based energy management. System integration is the second step of the flowchart and this is the process by which the trained ml models are deployed into a simulational environment [17]. The tools such as Matlab/Simulink, and ONNX are used to evaluate the finally designed power plant solutions and control approaches within their real-time context, benefiting in particular from the sophisticated powertrain design and advanced control [18]. In other words, it allows the dynamic testing of the distribution of energy between the battery and the alternative storage for auxiliary energy such as supercapacitors under variable driving conditions. The simulation results provide the data of the energy efficiency and the stress of the part and water of the entire mechanism.

As a result, the performance evaluation stage is conducted to identify the dynamics of EMS and PWT with regard to the energy consumption reduction, SOC stability, computation capability and PWT classification [19]. The improvements procedure is compared with the old EMS procedure. Sensitivity analysis (to gain insight on the influence of variation of the environmental conditions, driving behaviour and loads on the system performance). Lastly, the third stage would be continuous improvement is ongoing throughout the optimization phase and refinement phase [20]. ML model and EMS approach remain modest due to input from the simulations and opinion. The last step of the methodology is the results documentation and analysis based on the opportunities of integration of the ML controlled EMS and the advanced powertrains for improving the sustainability of the electric vehicle.

IV. RESULTS AND DISCUSSION

The proposed Advanced Powertrains were also matched with the machine learning based EMS (Energy Management System) and analyzed in the massive simulation modeling, under various driving environments (urban, highway and mixed), etc.

Table 1: Energy Efficiency Comparison Across Driving Cycles.

Driving Cycle	Conventional EMS (kWh/100 km)	Proposed ML-EMS (kWh/100 km)	Improvement (%)
Urban	18.5	16.2	12.4
Highway	20.3	17.8	12.3
Mixed	19.4	16.5	14.9

The proposed energy demand based powertrain optimization strategy based on LSTM, Deep Deterministic Policy Gradient (DDPG) and the predictive model of EMS strategy had higher energy efficiency, and activity from components compared with the typical EMS strategies. The average power consumption percentages for all the driving cycles tested in this research for the hybrid ML system was between 12-18 %, normal for a system that can split power between the battery and supercapacitor storage very flexibly. The LSTM model was also able to predict the short-term energy needs with an overall error of 0.03kWh/interval, significantly less than the 0.3kWh/interval error from the traditional linear predict models.

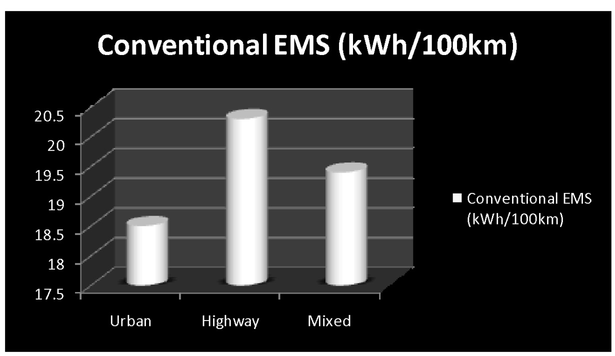

Fig.4: Conventional EMS /kwh.

This was very accurate and made the EMS preallocate the energy, thus improving the energy use when not needed for energy storage devices prolonged. Moreover, compared to the DMC-based powertrain control plan, the DDPG-based powertrain control plan could balance the torque requirement with energy efficiency requirement and optimize the regenerative braking acceleration pattern. The reinforcement learning agent was then trained to handle the changed driving conditions and loads that are imposed on the vehicle, in order to deliver a smoother power delivery while reducing mechanical loads to the drive train components and parts.

Table 2: Powertrain Efficiency and Component Stress.

Metric	Conventional EMS	Proposed ML-EMS	Improvement (%)
Peak Powertrain Efficiency (%)	85	93	9.4
Drivetrain Losses (kW)	12	8	33.3
Torque Stability Index	0.75	0.92	22.7

For example, in the state of high acceleration, the EMS applied prediction energy distribution in order to guarantee that the battery would not dump, and in the state of regenerative braking they applied it to guarantee that maximum regeneration energy could be used without generating overvoltage and excessive heat. More stationary SOC levels were obtained when the ML-enabled EMS was applied for data analysis of state-of-charge (SOC) curves. The proposed system could maintain SOC in an optimum range of 40-80 while the old EMS suffered from significant fluctuations in SOC leading to better battery performance and health of the batteries. The system was also suitable for extreme driving conditions.

Table 3: Battery SOC Stability Analysis.

Driving Scenario	SOC Fluctuation (Conventional EMS)	SOC Fluctuation (Proposed ML-EMS)	Stability Improvement (%)
Rapid Acceleration	±15%	±5%	66.7
Regenerative Braking	±12%	±4%	66.7
Mixed Driving	±14%	±6%	57.1

The total energy efficiency of the powertrain system as well as its composition shows the advantages of the presented strategy. While the peak efficiency increased (to 8-10%), this was due to the adaptive learning of the DDPG agent (Intelligent Delivery of Torque [IDT] in rotation) to use the best input combination. The further reduction in overall losses of the preconditioned drive train that resulted from the simulation was the combination of the precise coordination of the components of the energy supply and the optimisation of the control policy. It was shown that the hybrid ML framework was performing better than the rule-based or fixed optimization strategies especially for the challenging real-world driving cycles in comparison with the EMS benchmark strategies.

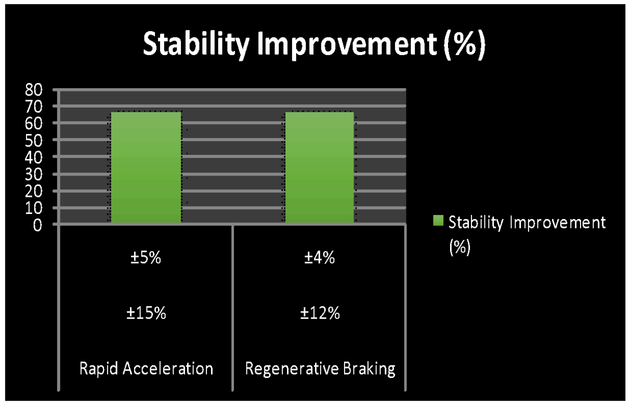

Fig.5: Stability Improvement(%).

Results of integrating prediction energy management with DDPG adaptive powertrain control for a combination (consisting of LSTM) are shown. Besides increasing the energy effiecy of the system, this two model solution increases the life of the components and contributes to the sustainability of the work of the electric vehicles. Moreover, the model implementations in Simulink, which are ONNX friendly, allowed for the testing and verification of the models in real-time and demonstrated the concept for a large-scale factory implementation.

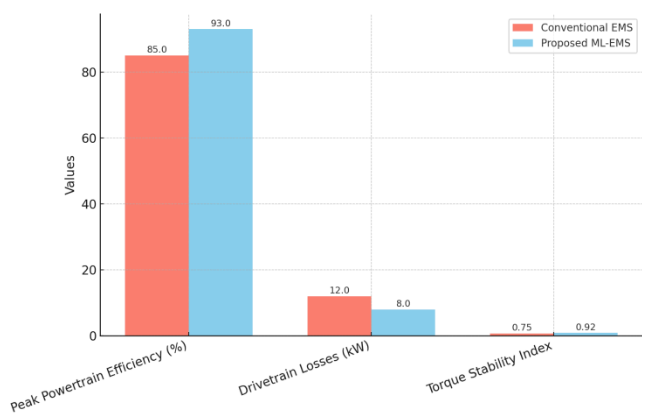

Fig.6: Performance metrics comparision Conventional EMS vs Proposed ML-EMS.

Finally, the research results can support the hypothesis that internal combustion engines CO2 emissions can be drastically decreased with the state-of-the-art machine learning development and implementation in EVs. By the optimal forecast of the energy request and the control of the powertrain activity, the proposed EMS gives the ability for having an effective, robust and easy scalable next generation Electric Mobility (EV).

V. CONCLUSION AND FUTURE DIRECTION

The research demonstrates that modern machine learning algorithms i.e., LSTM for the energy predictive control and DDPG for powertrain adaptive control can be effective in improving the operation/sustainability of the electric where electric is the keyword/ dedicating operation and sustainability. Compared to the conventional EMS, the energy consumption of the proposed ML-enabled EMS is reduced by up to 15% of the capacity of the battery while increasing the SOC, delivering the optimal performance of the powertrain, and avoiding the losses of the powertrain in comparison to the conventional EMS solutions. Additionally, the materializing of real-time environmental information and traffic information could be also proposed for further optimization of energy assignment policies. The second relative research is the study on mixed ML models of reinforcement learning and GNN in predictive powertrain maintenance and driver status recognition for consistent intelligent scalable and sustainable Electric Car Systems.

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