2020-01-0748 Published 14 Apr 2020

Machine Learning Based Optimal Energy Storage Devices Selection Assistance for Vehicle Propulsion Systems

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Citation: Xu, B., Rizzo, D. and Onori, S., "Machine Learning Based Optimal Energy Storage Devices Selection Assistance for Vehicle Propulsion Systems," SAE Technical Paper 2020-01-0748, 2020, doi:10.4271/2020-01-0748.

Abstract

This study investigates the use of machine learning methods for the selection of energy storage devices in military electrified vehicles. Powertrain electrification relies on proper selection of energy storage devices, in terms of chemistry, size, energy density, and power density, etc. Military vehicles largely vary in terms of weight, acceleration requirements, operating road environment, mission, etc.

This study aims to assist the energy storage device selection for military vehicles using the data-drive approach. We use Machine Learning models to extract relationships between vehicle characteristics and requirements and the corresponding energy storage devices.

After the training, the machine learning models can predict the ideal energy storage devices given the target vehicles design parameters as inputs. The predicted ideal energy storage devices can be treated as the initial design and modifications to that are made based on the validation results. In the training phase, 80% of vehicle's data borrowed from the literature were used, and the remaining 20% was used for validation. Results obtained from the proposed design predict the battery size and peak power with mean errors of 3.14% and 8.17%, respectively.

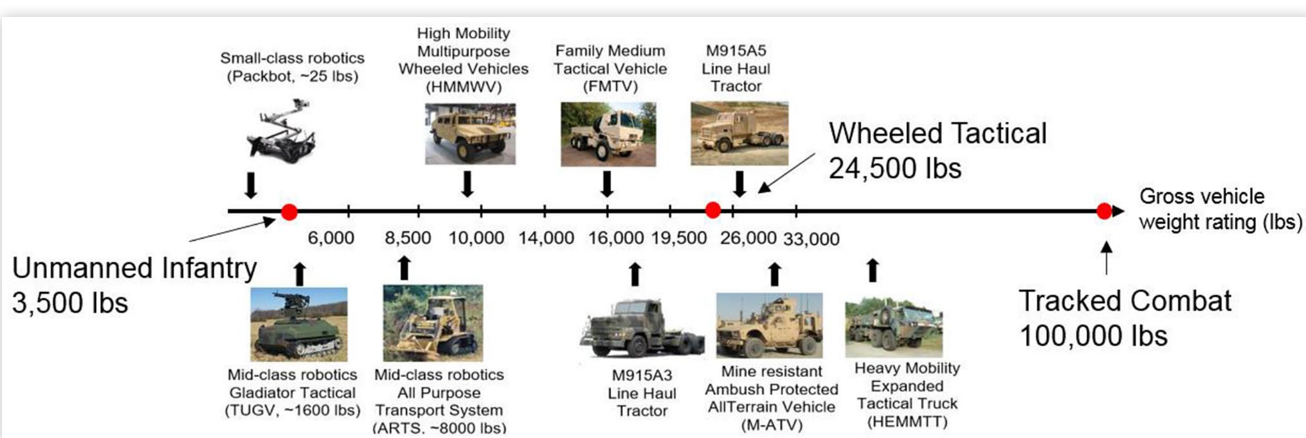
Introduction

Energy security and high fuel cost (up to $100/L [1]) have motivated the ongoing research on powertrain electrification of military vehicles. Low noise and low thermal signature are benefits that come with electrification which are highly desirable in military missions [1].

Numerous are the energy storage systems (ESS) available, which differ from chemistry, size, weight, peak power, cost, and safety features. At the same time, vehicle specifications can vary significantly based on the application, mission, usage (Fig. 1) resulting in different vehicle mass, acceleration time, range, top speed, and so forth. Selecting the most appropriate ESS for a specific class of vehicles is a challenging problem. This is addressed in this paper.

In literature, ESS selection and design were mostly conducted using physics-based powertrain models to satisfy

FIGURE 1 Military vehicle weight range.



vehicle power/ energy demands. The ESS selection problem was formulated as a multi-objective optimization problem by considering ESS weight, cost, and system health [2]. Genetic algorithm was utilized to solve the multi-objective problem and vehicle powertrain model was built based on physical constraints. ESS sizing of a fuel cell HEV was studied in [3]. Both power and energy requirement as well as aging were included in the design. Fuel cell, ultracapacitor, DC/DC converter, electric motor, inverter models and energy management strategies were built and used in the ESS sizing. The size of ultracapacitor was determined by fulfilling the transient peak power and the size of fuel cell was determined by fulfilling the slower load powers [4]. The size of ESS is calculated by matching the power and energy demand using iterative numerical method in [5]. ESS sizing of a fast charging station for Plug-in HEV was studied in [6].

In [7] high fidelity vehicle military model is used to optimally select the ESS as a standalone system or hybrid configuration (battery plus supercapacitors). Using simplified vehicle models with low accuracy may lead to not very accurate and misleading ESS selection results, on the other hand, using high fidelity vehicle models carries high development costs along with high computational requirements.

All the vehicle component models need experimental data to calibrate the parameters. Moreover, the model accuracy varies by component based on the complexity of the physics underlying the operation of the component. For example, transmission models have high accuracy [8] thanks to the simplicity of the gear shift physics, whereas the battery model accuracy could suffer [9] from the complex electrochemical reaction occurring during the charging and discharging [10].

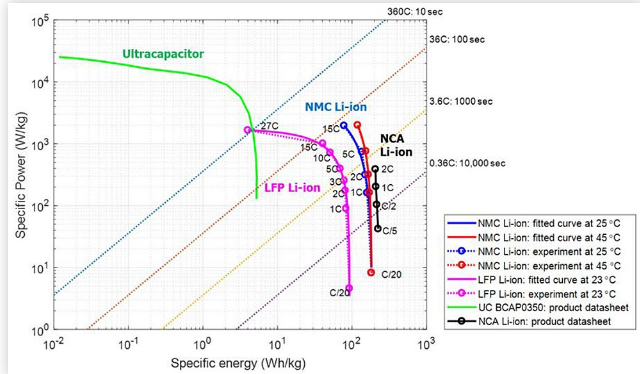
Even though commercial powertrain modeling software like Autonomie modularizes the component models [7], which can be integrated into different powertrain architectures, migrating component models from one vehicle to another is a challenging task. If the powertrain architecture is the same between two vehicles, the components will still require to be re-calibrated for the new vehicle. If the powertrain architecture is different, modification to the architecture is necessary prior the component models re-calibration.

In this paper, we want to use the existing vehicle - ESS pairs already used/implemented in production vehicles as a database for our machine learning (ML) models. Such a database will serve as a platform from which the ML techniques can learn the relationship between the vehicle and ESS. ML has been successfully implemented in relationship modeling between products manufacturing process and products failure [20], between heat source condition and dynamic programming optimized actuator position [21], between malware features and type of malware [22].

The existing ESS selections used for HEVs and EVs are used in the ML algorithm. We use an approach similar to the one used in [11] for the new drug design, where the ML learn from old drug database and design new drug for given requirements [11].

Moreover, the data used in this work are from in production vehicles, which consider not only the power/energy demand, but also all kinds of realistic problems in production, such as cost, safety, durability, weight, aging, geometry. These factors are hardly considered in the aforementioned ESS selection literature.

FIGURE 2 Enhanced Ragone plot [12].

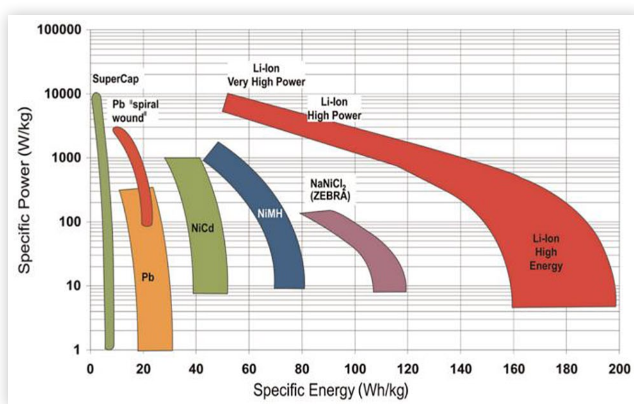


In this paper, we use the enhanced Ragone plot (eRP) shown in Fig. 2 to assist the ESS selection algorithm. Compared with the traditional Ragone plot in Fig. 3, the eRP carries information about chemistry, temperature and C-rate of different energy storage which can provide valuable insights for the ESS selection.

The approach used in this study is summarized as follows:

1. A database is built based on the existing EV-ESS pairs available on in production vehicles.
2. To address the problem of limited available EV-ESS pairs data, a simulation tool built in [12] is used to generate "synthetic data" for two classes of military vehicles, namely the tracked combat vehicle (weight: 100 klb) and unmanned infantry vehicle (weight: 3500 lb).
3. Four ML models are implemented to explore the relationship between the vehicle characteristics and ESS characteristics.
4. Feature importance is determined by ML models to assist the understanding of the relation between vehicle design requirements (e.g., acceleration time, weight, top speed, and range) and ESS characteristics (e.g., peak power and battery size).
5. The trained ML models are then used in the ESS selection to predict the ESS for a given vehicle characteristic.

FIGURE 3 Ragone plot [13]. SuperCap: supercapacitor; Pb: lead; Li-ion: lithium-ion; NiCd: nickel-cadmium; NiMH: nickel-metal hydride; NaNiCl2: sodium-nickel chloride; ZEBRA: Zero Emission Battery Research Activities.



The rest of paper is organized as follows: The dataset exploration section explains the dataset. Basic preprocess is conducted to uncover some of characteristics in the dataset. After that, the problem formulation is presented to standardize the integration of machine learning models and ESS selection. The results of the model training and prediction process are presented in results section, where different machine learning models are compared. Finally, the study ends with conclusion.

Machine Learning Models

Machine Learning shines in the complex system modeling tools where conventional modeling methods are time-consuming or have low accuracy (e.g., image processing [14], language translation [15], voice recognition [16], robotics [17]). However, ML models lack physical insights and have poor performance on unseen scenarios, such as extrapolation. In this study, four ML algorithms are explored. Those are:

Linear Regression: this is a linear approach to model the relationship between one dependent variable and one or more independent variables. The relationships are often fitted using the least squares approach.

Random Forest Regression: this is an ensemble learning method for regression that operates by constructing a multitude of decision trees at training time and outputting the mean prediction of the individual trees. By outputting the mean prediction, it reduces the overfitting probability of the decision trees.

Bagging Regression: this is a machine learning ensemble meta-algorithm designed to improve the stability and accuracy of machine learning algorithms used in regression. It also reduces variance and overfitting.

Neural Network Regression: It is based on a collection of connected units (artificial neurons), which is inspired by the brain biological structure. It has different layers of neurons and neurons are inter-connected layer by layer. The information is transported through the neurons by different weights, bias and activation functions.

Dataset Exploration

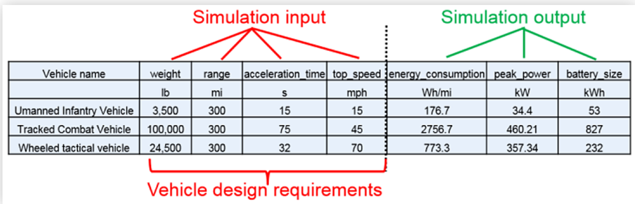
Dataset plays a vital role in the machine leaning methods. In this work, the history data from ESS and EVs is collected and combined into a dataset. Most of the vehicles studied are commercial vehicles that are available on the market and a few military vehicles are included for the methodology concept proof.

The dataset is described in Table 1. The vehicle characteristic parameters include weight, electric range, acceleration time, top speed and energy consumption per mile. The battery characteristic parameters include peak power and battery size (chemistry may be added later here).

TABLE 1 Dataset of EV vehicle and ESS characteristics.

Vehicle name	Weight lb	Range mi	Acceleration time s	Top speed mph	Energy consumption Wh/mi	Peak power kW	Battery size kWh
e-tron	5490	204	5.5	124	455	300	95
i3	2965	153	7.2	93	298	125	42.2
i3s	3034	153	6.8	100	298	135	42.2
Bolt EV	3580	238	6.5	90	283	150	60
500e	2980	84	8.9	85	301	83	24
Clarity Electric	4024	89	12	95	296	120	25.5
IONIQ Electric	3164	124	9.9	102	248	88	28
Kona Electric	3715	258	7.6	104	281	150	64
I-PACE	4784	234	4.5	124	443	294	90
Niro EV	3854	239	7.8	104	301	150	64
Soul EV	4806	243	7.6	90	296	150	64
LEAF	3433	150	7.4	104	301	110	40
LEAF e+S	3780	226	6.5	100	312	160	62
LEAF e+SV/SL	3811	215	6.5	100	324	160	62
EQ fortwo Coupe	2363	58	11.4	81	312	60	17.6
EQ fortwo Cabrio	2383	57	11.7	81	330	60	17.6
Model 3 Standard Range	3627	220	5.6	130	257	211	59.5
Model 3 Standard Range Plus	3627	240	5.3	140	253	211	59.5
Model 3 Long Range AWD	4072	310	4.5	145	291	307	80.5
Model 3 Performance LR AWD	4072	310	3.2	162	291	353	80.5
Model S Long Range	4883	370	3.7	155	304	311	100
Model S Performance LM	4941	345	2.4	163	324	451	100
Model X Long Range	5421	325	4.4	155	351	386	100
Model X Performance LM	5531	305	2.7	163	351	568	100
e-Golf	3455	125	9.6	93	283	100	35.8

FIGURE 4 The inputs and outputs to the vehicle simulation tool from [1] to select ESS for the two military vehicles. This action expands the dataset to the military vehicle.



Vehicle name	weight	range	acceleration_time	top_speed	energy_consumption	peak_power	battery_size
	lb	mi	s	mph	Wh/mi	kW	kWh
Umanned Infantry Vehicle	3,500	300	15	15	176.7	34.4	53
Tracked Combat Vehicle	100,000	300	75	45	2756.7	460.21	827
Wheeled tactical vehicle	24,500	300	32	70	773.3	357.34	232

To expand the dataset to include military vehicles, a vehicle simulation tool in is used [7]. The simulation tool designs the peak power and battery size for the military vehicle given the vehicle characteristics. The input and output of the simulation tool are shown in Fig. 4.

The vehicle requirements are the simulation inputs and the battery related parameters (energy consumption, peak power and battery size) are the simulation output.

PCA Analysis

Principle component analysis is a method to analyze the variation of a dataset to avoid feature repetition and reduce data dimension [18]. In this study, weight, range, acceleration time, top speed and energy consumption data are fed into the PCA algorithm. The PCA results are shown in Fig. 5. The first three principle components dominate and have the largest data variation (99.57%). As the dataset capacity increases to the level of Gigabytes (or larger), the PCA will reduce the data dimension and save significant amount of computation time and computation memory. However, in this study, the dataset is less than one Megabyte and thus, all the features are kept in the machine learning model training for the accuracy improvement.

Feature Importance

The contribution of each feature to the prediction accuracy is indicated by feature importance. In other words, the feature importance indicates the connection between the target and the features. Higher feature importance values indicate closer connection and vice versa. Feature importance is calculated by comparing the error increase of different cases that the

FIGURE 5 PCA results of vehicle characteristics.

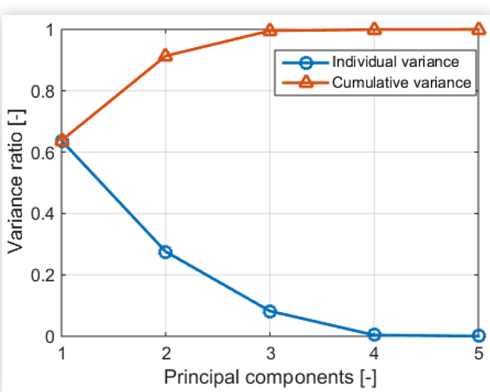
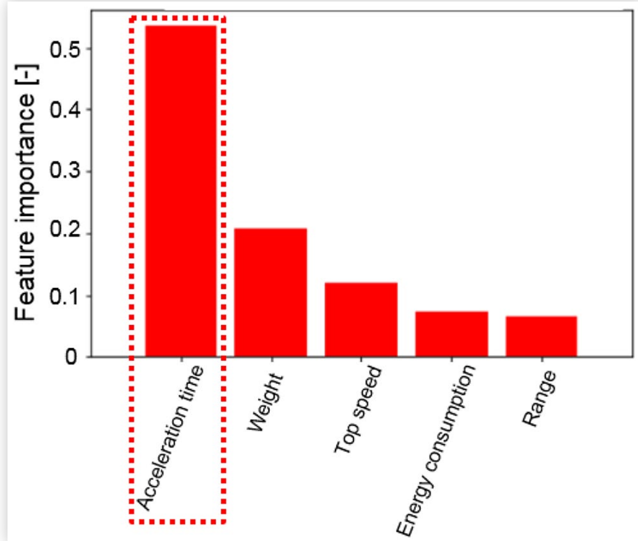


FIGURE 6 Feature importance ranking in the battery peak power prediction.



corresponding feature sample values are randomly permuted among all the samples [19]. The random forest method is used here to conduct the feature importance analysis. The results of battery peak power feature importance are shown in Fig. 6 that shows that the acceleration time design requirement largely impacts the peak power selection. During the acceleration test, vehicles generally operate in full throttle and electric motor peak power at the later phase of acceleration. The results of an acceleration test example are shown in Fig. 7. At the later phase of acceleration test, the vehicle hits the maximum speed as the

FIGURE 7 Electric motor torque and vehicle speed during an EV acceleration.

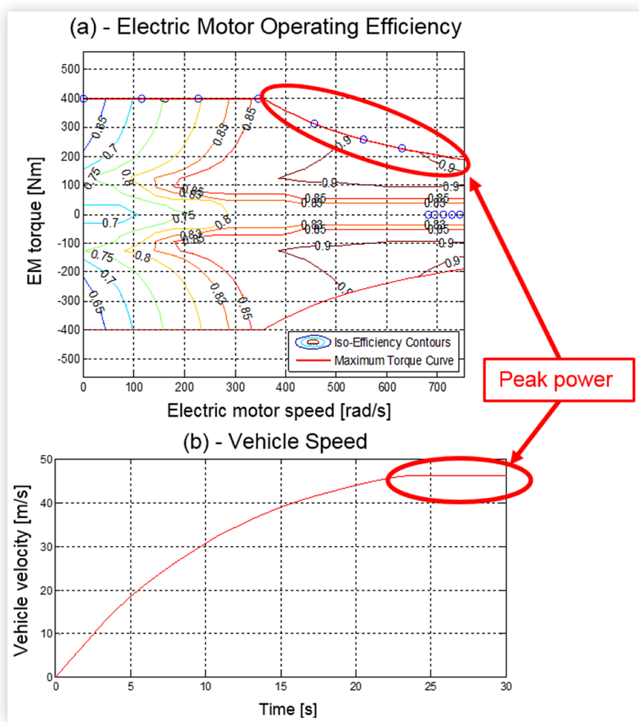
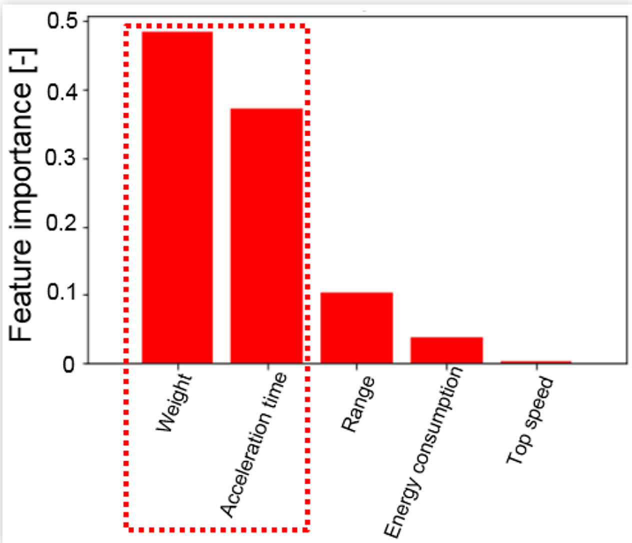


FIGURE 8 Feature importance ranking in the battery size prediction.



EM power reaches its maximum value. When EM speed is under 350 rad/s, the EM torque is fixed at 400Nm and the EM output power keeps rising. However, when the EM speed hits 350 rad/s, the EM reaches its maximum power and as the EM speed increases further, the maximum torque is compromised, which leads to the curve between the 350 rad/s and 750 rad/s in Fig. 7(a).

The larger the EM maximum power, the faster the vehicle accelerates, thus the shorter the acceleration time of the vehicle.

Therefore, the acceleration plays a vital role in the battery peak power prediction as shown in Fig. 6.

The results of battery size feature importance are shown in Fig. 8. It can be observed that the vehicle weight and acceleration time requirements dominate the impact on the battery size selection. The reason is that the vehicle rolling resistance is proportional to the vehicle weight. The heavier the vehicle, the higher the energy consumed. For a given battery chemistry, the power density is generally constant. The larger/heavier the battery is, the more power the battery can output.

As discussed in the previous paragraph, the acceleration time is an indicator of peak power. Thus, acceleration time largely impacts the battery size. Even though the range, the energy consumption and top speed are not as important as weight and acceleration time, they are not negligible. The combined feature importance of range, energy consumption and top speed accounts for 14%, thus they still make noticeable contribution to the battery size prediction.

Problem Formulation

The machine learning model is built from an optimization problem. The variables are the model parameters and the optimization goal is the model error minimization. The vehicle and ESS data are the input to the models and the models optimize their parameters to build a relation between the vehicle characteristics and ESS characteristics, such that for given vehicle characteristics, the models can accurately predict the ESS characteristics. The cost functions of the model are as follows:

$$e_{P_{bat}} = \sum_{i=1}^{N} \left(P_{bat,data,i} - P_{bat,ML,i} \right)^2 \tag{1}$$

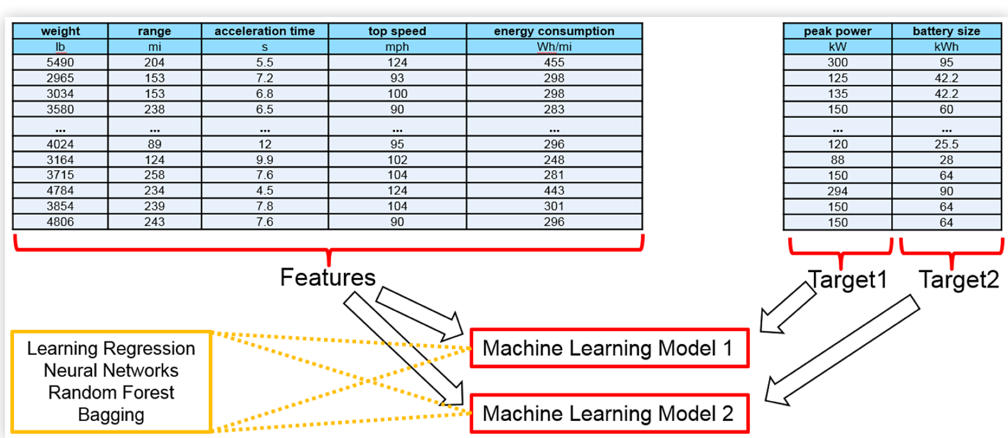
$$e_{C_{bat}} = \sum_{i=1}^{N} \left(C_{bat,data,i} - C_{bat,ML,i} \right)^2 \tag{2}$$

where e is error, P_{bat} is battery peak power in the unit of [kW], C_{bat} is battery size in the unit of [kWh], N is the number of training data points. Battery peak power and battery size predictions are modeled separately. As shown in Fig. 9, the relationship between peak power and features is modelled by machine learning model 1. The relationship between battery size and features is modelled by machine learning model 2.

Results

In this section, results from the application of four machine learning algorithms are fully explored by first modifying the

FIGURE 9 Inputs and output (target) of the machine learning models.



weight	range	acceleration time	top speed	energy consumption
lb	mi	s	mph	Wh/mi
5490	204	5.5	124	455
2965	153	7.2	93	298
3034	153	6.8	100	298
3580	238	6.5	90	283
...	...	...	...	...
4024	89	12	95	296
3164	124	9.9	102	248
3715	258	7.6	104	281
4784	234	4.5	124	443
3854	239	7.8	104	301
4806	243	7.6	90	296

peak power	battery size
kW	kWh
300	95
125	42.2
135	42.2
150	60
...	...
120	25.5
88	28
150	64
294	90
150	64
150	64

parameter setups. Then, the four algorithms are compared based on the training performance and the algorithm selection is conducted. The selected algorithms are used in the prediction process.

Training Performance

The parameter settings in the four machine learning algorithms are searched using a grid search algorithm. The machine learning modeling process is implemented in Python and the models are from the sk-learn machine learning library. The type of parameters and the variation range are listed below:

1. Linear Regression: parameter setup no necessary.
2. Random Forest: The number of estimators varies (1, 2, 3, 5, 7, 10, 15, 20, 30). Max depth varies (1, 2, 3, 5, 7, 10, 15, 20, 30).
3. Bagging: Number of estimators varies (1,2,3,5,10,20,30,50,100,200).
4. Neural Networks: The number of neurons in each layer varies (1, 2, 3, 5, 7, 10, 15, 20, 30, 50, 100, 200, 500, 1000, 2000) and the number of hidden layer varies (1, 2).

Note that the variation ranges are modified based on the trend of the results. Necessary range extensions are made to ensure the best parameter setup is covered in the range.

Linear Regression Results: The mean training error percentage from linear regression is 3.9% for the battery size and 20.7% for the battery peak power. The battery size error is much less than the battery peak power error. The training results of battery size and battery peak power are shown in Fig. 10 and Fig. 11, respectively. As shown in the upper left corner of Fig. 10, the maximum battery size error is only 5.96 kWh and the training results match the dataset extremely well, especially for vehicle #21, i.e., the Tracked Combat Vehicle. The battery size of this vehicle is nearly ten times of the battery size from the rest of the vehicles. This indicates that the battery size is strongly linearly correlated with the vehicle characteristics. However, the Linear Regression algorithm does not perform very well in the battery peak power

FIGURE 10 Battery size training results and dataset comparison. Linear Regression algorithm is used in the training.

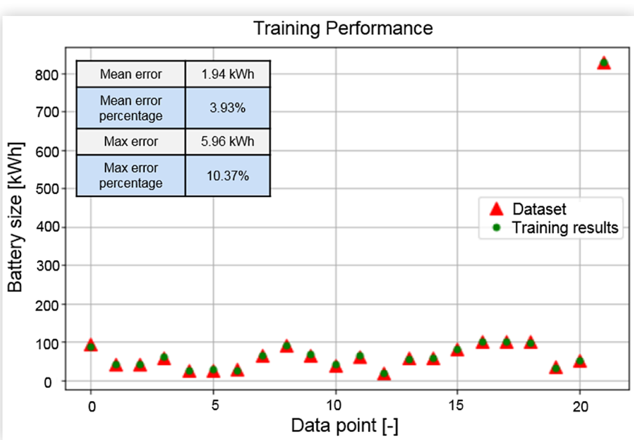
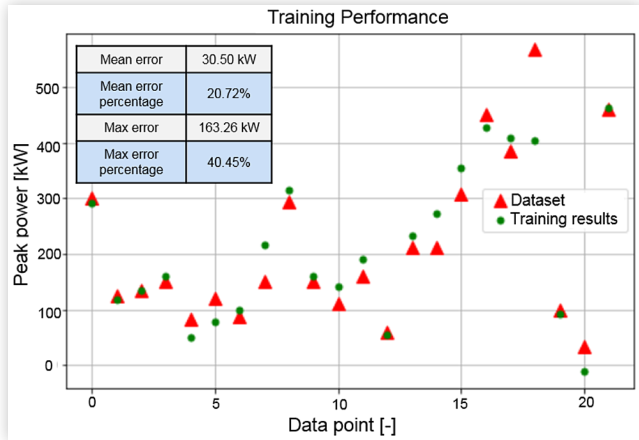


FIGURE 11 Battery peak power training results and dataset comparison. Linear Regression algorithm is used in the training.



training, as the mean error is 20.7%. The details of the error can be observed in Fig. 11. Even though the training peak power is around the dataset for the majority of vehicles, the gaps are obvious. Some vehicles exhibit significant training error, such as vehicle #18. Digging into the training dataset of vehicle #18, it is found out that this is Tesla Model X Performance LM (last second row of Table 1) and it has similar vehicle characteristic with Tesla Model S Performance LM (last fourth row of Table 1). Both Vehicles have similar weight and acceleration time. Tesla Model S Performance LM is vehicle #16 in Fig. 11. The model does a good job in the vehicle #16, whereas it substantially underestimates the peak power of vehicle #18. According to the importance ranking of battery peak power prediction in Fig. 6, vehicle acceleration time dominates and its importance is more than twice of the vehicle weight. Even though the weight of vehicle #18 is larger than the weight of vehicle #16 (5531 lb. vs 4941 lb.), the acceleration time is longer than vehicle #16 (2.7 s vs 2.4s). Due to acceleration time is much more important in the peak power prediction, the model predicts lower peak power for vehicle #18 than vehicle #16 (402 kW vs 423 kW) as shown in Fig. 11.

Random Forest Results: There are two varying parameters in the random forest algorithm parameter setup: number of estimators and max depth of the estimators. Fig. 12 and Fig. 13 show the mean training error percentage results by varying these two setups in the operating range. Both the battery size and battery peak power training error have similar trend with respect to the variation of number of estimators and max tree depth, as the error are more sensitive to the max tree depth than the number of estimators. When the max tree depth is greater than 5, the error reaches its minimum level and does not show obvious drop as the max tree depth further increases. The minimum mean error percentage in the battery size training is 9.34%, which is produced with 5 estimators and max tree depth at 7. For the battery peak power, the minimum mean error is 16.09%, which occurs at 3 estimators and max tree depth at 7.

Bagging Results: The optimization results from the bagging algorithm are shown in Fig. 14 and Fig. 15. For the battery size in Fig. 14, the minimum training error occurs at 3 estimators with 8.58% mean error percentage. When the

FIGURE 12 Battery size mean training error percentage with different parameter setups of Random Forest algorithm.

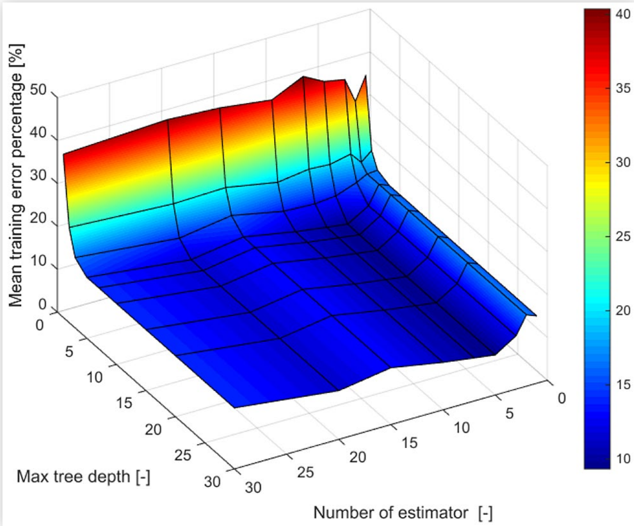


FIGURE 13 Battery peak power mean training error percentage with different parameter setups of Random Forest algorithm.

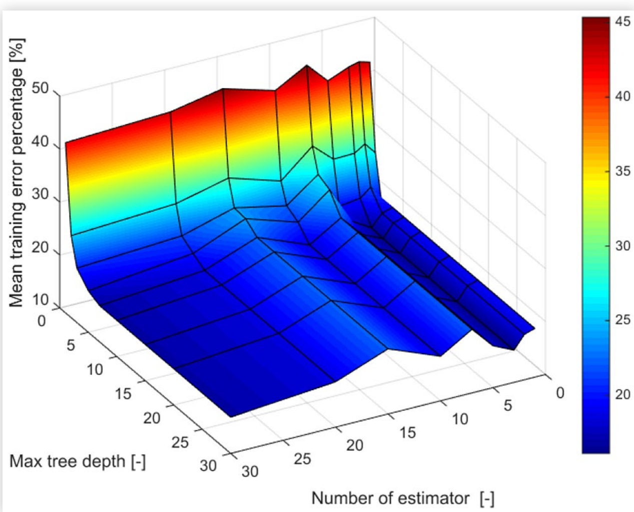


FIGURE 14 Battery size mean training error percentage with different number of estimators of bagging algorithm.

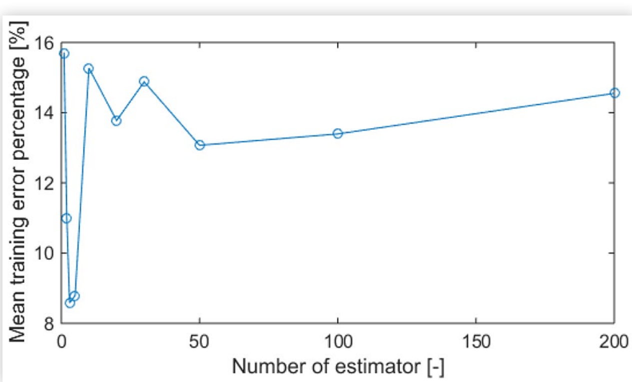
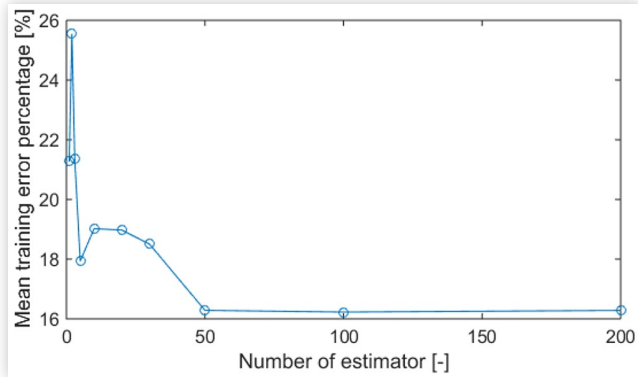


FIGURE 15 Battery peak power mean training error percentage with different number of estimators of bagging algorithm.



number of estimators increases to 10, the mean training error percentages rises sharply and crosses 12%. For the battery peak power in Fig. 15, the minimum training error occurs at 100 estimators with 16.96% mean error percentage. The minimum error occurs at large number of estimators.

Neural Networks: The battery size training results from the Neural Networks with single hidden layer and two hidden layers are shown in Fig. 16 and Fig. 17, respectively. When the

FIGURE 16 Battery size mean training error percentage with different number of neurons of Neural Network. Only single hidden layer is considered in the neural network.

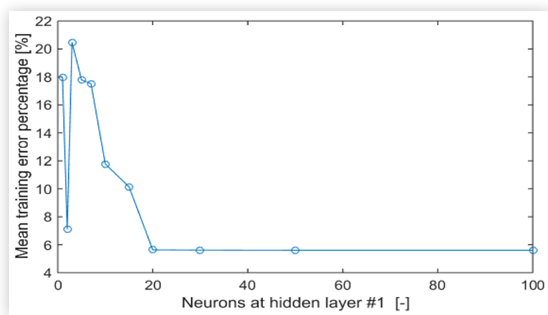
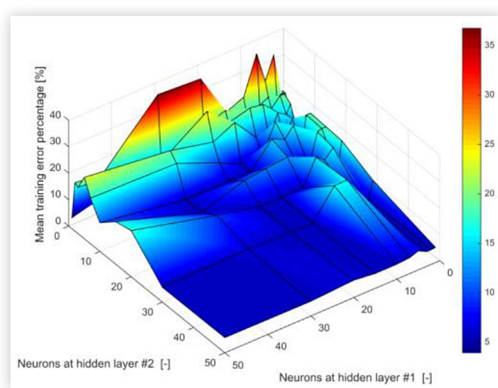


FIGURE 17 Battery size mean training error percentage with different number of neurons of Neural Network. Two hidden layers are considered in the neural network.



number of layers is fixed, the number of neurons in each layer are swept. In all four cases, the error change significantly at small number of neurons range (<20) and turns to stable at large number of neurons range (>20). This is because the simple structure of Neural Networks at small number of neurons is not able to fit the data. As the number of neurons increases, the model complexity rises and the curve fitting capability increases at the same time. Thus, the error fluctuation is reduced. The peak power training results with single hidden layer and two hidden layers are shown in Fig. 18 and Fig. 19, respectively. As the hidden layer increases from one to two, the best battery size mean training error percentage slightly reduces from 5.6% (twenty neurons) to 5.5% (thirty neurons at hidden layer #1 and fifteen neurons at hidden layer #2) and the best battery peak power mean training error percentage slightly reduces from 24.6% (one neuron) to 24.1% (thirty neurons at hidden layer #1 and twenty neurons at hidden layer #2). These two error reductions are almost negligible, thus one hidden layer is enough in this application.

The best training results from all four algorithms are summarized in Table 2. Among the four algorithms, the Linear Regression algorithm has the minimum error in the battery size training (3.93%) and Random Forest algorithm has the minimum error in the battery peak power training (16.09%). Thus, these two algorithms are selected for the next prediction section. The details of Linear Regression training results on battery size and Random Forest training results on battery power are shown in Fig. 20 and Fig. 21, respectively. In the training data, the first 20 vehicles (#0-#19) are passenger vehicles and the last two vehicles (#20 and #21) are military vehicles. Battery size training accuracy is high for both passenger vehicles and military vehicles as shown in Fig. 20, whereas the battery peak power training accuracy is relatively low for the two military vehicles as shown in Fig. 21. The peak power prediction model overestimates the peak power of vehicle #20 and underestimates the peak power of vehicle #21. This undesirable accuracy could result from the acceleration time difference of military vehicles and passenger vehicles. The feature importance analysis results show that the

TABLE 2 Best results in the algorithms parameter setups grid searches.

	Linear Regression	Random Forest	Bagging	Neural Networks
Battery size mean error percentage	3.93%	9.34%	5.58%	5.50%
Battery peak power mean error percentage	20.72%	16.28%	16.96%	24.10%

FIGURE 18 Battery peak power mean training error percentage with different number of neurons of Neural Network. Only single hidden layer is considered in the neural network.

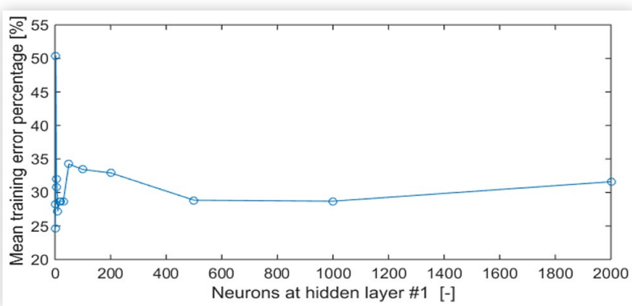


FIGURE 19 Battery peak power mean training error percentage with different number of neurons of Neural Network. Two hidden layers are considered in the neural network.

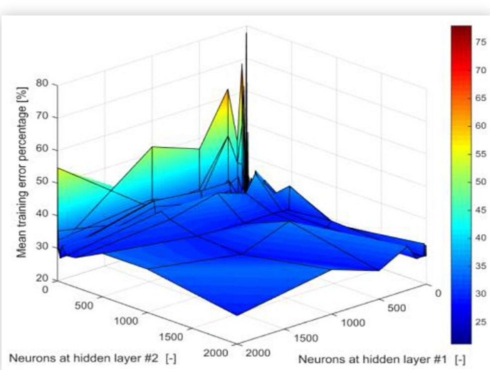


FIGURE 20 Battery size training performance using Linear Regression algorithm.

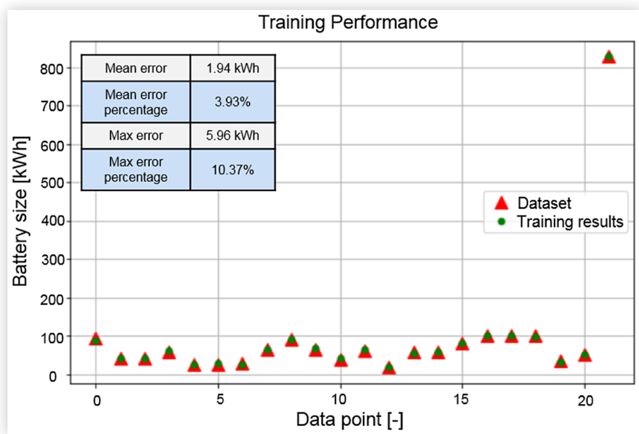
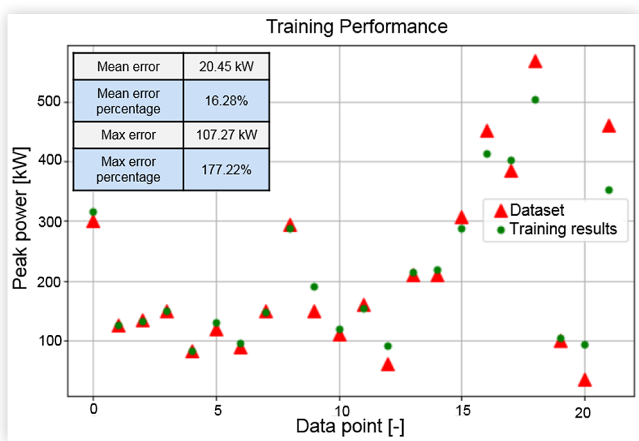


FIGURE 21 Battery peak power training performance using Random Forest algorithm.



acceleration time dominates in the peak power prediction as shown in Fig. 6. According to

Table 1, the acceleration time range of all the passenger vehicles is 2.4s-12s, whereas the acceleration time of three military vehicles are all above 12s. Different from the feature importance ranking of peak power, the vehicle weight takes the lead in the feature importance ranking of battery size as shown in Fig. 8.

Prediction Performance

Different from the training process, which treats both vehicle characteristics and ESS characteristics as inputs, the prediction process only takes the vehicle characteristics as the inputs. ESS characteristics are the outputs of the prediction process. The outputs are compared with the value from the dataset. The prediction results of battery peak power by Random Forest algorithm and battery size by Linear Regression algorithm are shown in Fig. 22. The mean prediction error percentage for both battery size and peak power is in the range of 3.14% - 8.17%, which is satisfactory and leaves some room for improvement. Maximum error percentage are large (25.73%) in both peak power and battery size prediction due to the small absolute values of data point #0. The absolute error in prediction vehicle #0 is 15.4kW, which is only one third of the max error (53.11kW vehicle #4) among the six vehicles. Similar to the peak power prediction, the maximum error and maximum error percentage of battery size prediction occur at different vehicles. The large errors should be reduced if more data points are added in the respective vehicle classes. Among the six vehicles, vehicle #5 is Wheeled Tactical military vehicle and the rest five vehicles are passenger vehicles. The peak power and battery size prediction errors of vehicle #5 are 2.1% and 4.9%, respectively. The battery peak power prediction error 4.9% is less than the training errors of the military vehicles #20 and #21 in Fig. 21. The small error in the Wheeled Tactical military vehicle ESS peak power prediction could be the result of good interpolation performance. Interpolation occurs when the target value is between the higher and lower boundaries of the table values in the table lookup process. In the ESS selection process, the lookup table contains the information of Unmanned Infantry Vehicle and Tracked Combat military vehicle. Due to the large difference of the vehicle weight between these two military vehicles shown in Fig. 4, they create a large gap for other military vehicles to interpolate in the table. The parameters of the Wheel Tactical military vehicle are between the parameters of Unmanned Infantry Vehicle and Tracked Combat military vehicle as shown in Fig. 4. Therefore, the small error in the Wheeled Tactical military vehicle ESS prediction could be the results of interpolation. This observation indicates that in order to achieve excellent prediction accuracy, training dataset should cover the data range in the prediction data. In other words, the prediction should be by interpolation rather than extrapolation.

Connection to the Enhanced Ragone Plot

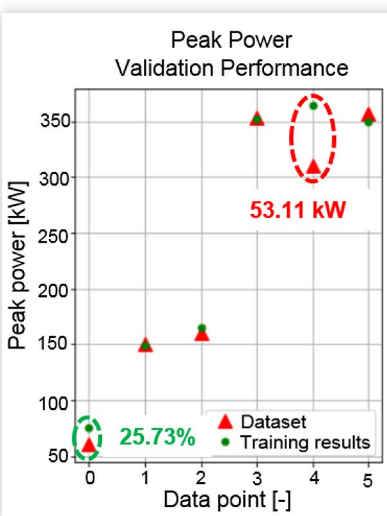
In order to connect the vehicle characteristics and requirements to the ESS capabilities, the predicted vehicle PE-ratio is plotted as a straight line on the enhanced Ragone plot. The PE-ratio calculation using the machine learning predicted peak power and battery capacity is presented in the following equation:

$$PE_{pred} = \frac{P_{pred,max}\left(kW\right)}{E_{pred}\left(kWh\right)} = \frac{P_{\rho,pred}\left(W/kg\right)}{E_{\rho,pred}\left(Wh/kg\right)} \tag{3}$$

where PE_{pred} is the predicted Power to Energy Ratio of vehicle, $P_{pred,max}$ is the maximum predicted power, E_{pred} is the predicted vehicle energy to get the designed range, $P_{\rho,req}$ is the predicted specific power, $E_{\rho,req}$ is the predicted specific energy.

Three vehicles (Tesla model 3 performance version, Nissan Leaf and Wheeled Tactical Military vehicle) are plotted in the enhanced Ragone plot based on their predicted PE-ratios. Feasible solutions can be found in the enhanced

FIGURE 22 Peak power and battery size prediction performance.



Mean error	13.82 kW
Mean error percentage	8.17%
Max error	53.11 kW
Max error percentage	25.73%

Mean error	2.78 kWh
Mean error percentage	3.14%
Max error	8.63 kWh
Max error percentage	6.57%

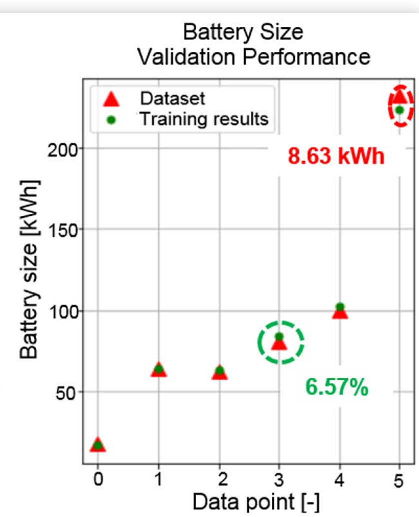
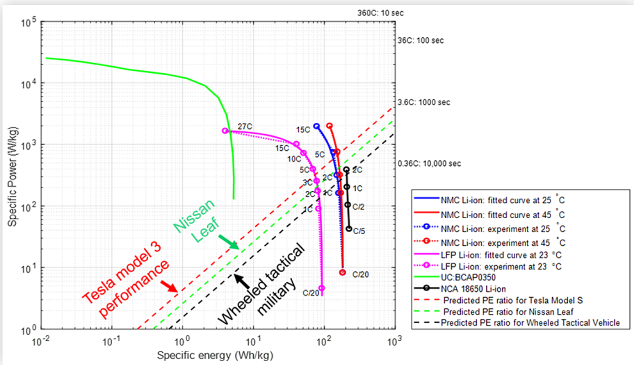


FIGURE 23 The predicted PE ratio is plotted on the enhanced Ragone plot to connect the vehicle design requirement and the ESS characteristics.



Ragone plot for both vehicles and different ESS chemistry can be selected.

In the ESS design process, the vehicle design requirements are converted to the predicted peak power and battery size via trained Machine Learning models. The peak power and battery size are then converted to PE ratio and integrated in the enhanced Ragone plot for ESS selection. The Machine Learning models developed in this study only find the predicted PE ratio and assist the ESS selection rather than conduct the entire ESS selection. The results of Machine Learning can be regarded as the optimized initial design of the ESS rather than the final design. In the future, as more information about the vehicle characteristics and ESS characteristics are added in the dataset, more functionality the Machine Learning will have, such as ESS chemistry selection, hybrid ESS design.

Limitation

Even though the preliminary results show moderate model accuracy, there are two limitations that needs to be considered in the ML-based ESS selection method development: (i) the difference between military vehicles and commercial vehicles, and (ii) the database size. Military vehicles and commercial vehicles have different objectives. For military vehicles, functionality is more important over fuel economy and cost. Military vehicles are heavier and have poor fuel economy. For commercial vehicles, fuel economy, cost, and even appearance are important features. They do no need to run in extreme environments (e.g., high temperature and extreme bumpy road). These different characteristics between military vehicles and commercial vehicles result in different design targets. Therefore, in the database collection phase, these differences need to be considered. The database size is also important for a ML model. In general, the more data, the better accuracy the ML model can achieve. However, this does not mean the ML model cannot be used in case a small data set is available. As long as data set is representative, the ML model can still achieve acceptable accuracy. If possible, the designer should collect as much data as possible in the database construction phase.

Conclusion

This study conducts the ESS selection with the help of Machine Learning methods. It takes the advantage of existing dataset collected from the electric vehicle on the market and significantly reduces the total amount of effort in the ESS selection compared with traditional physics-based ESS selection. The results are also encouraging. Here are the conclusions drawn from the analysis of this study:

1. Machine Learning models can extract the relationship between vehicle characteristics and ESS characteristics and make acceptable predictions (mean accuracy 3.14-8.17%) on the battery size/ peak power given the vehicle characteristics.
2. Vehicle acceleration time requirements show the largest impact on the peak power selection of the ESS.
3. Both vehicle weight and acceleration time dominate the impact on the battery size selection.
4. In the ESS design process, the vehicle design requirements are converted to the predicted peak power and battery size via trained Machine Learning models. The peak power and battery size are then converted to PE ratio and integrated in the enhanced Ragone plot for ESS selection.

Even though the ESS characteristics prediction accuracy is moderate, the results are still preliminary and there is room to improve ESS selection methodology in the future: (i) the maximum battery peak power prediction error is as large as 25.73%, thus the robustness of the machine learning method needs improvement; (ii) the dataset are based on the data related to available on the market EVs and their corresponding ESSs. Thus, the fast-changing vehicle and battery technology advancement should be considered in the dataset to increase the representativeness of the data; (iii) the model performance based on different size of dataset will also be considered in future study.

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ISSN 0148-7191