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Baseline Strategy for Remaining Range Estimation of Electric Motorcycle Applications

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***Abstract*—Accurate predicting the remaining range of electric motorcycles (EMs) is important to help optimizing the energy consumption and improving the utilization of remaining energy in the batteries and therefore extending their life. In this paper, a range estimation strategy is developed to estimate the elapsed travel distance of the motorbike application and hence, the remaining range can be predicted. Then, daily riding cycles of the EM are identified and classified through machine learning technique based on the training and testing dataset of various standard ride cycles, which are combined with the proposed range estimation strategy to estimate the remaining travel distance of the motorcycle as the baseline to underpin and support the energy management system of the electric vehicle applications. The developed complete model is finally evaluated on a mixed daily riding cycles showing the effectiveness of the approach.**

Keywords—Ride Cycle Classification, Remaining Range Estimation, Electric Motorcycles

I. INTRODUCTION

Throughout the last decades, electric and hybrid vehicles (EV/HEVs) have been significantly received attentions as a smart choice and friendly environment transportation due to their energy efficiency and low carbon emission. With the compact size, mobility, economical affordability and energy efficiency, electric motorcycles (EMs) have also gained boosting actions by vehicle manufacturers and policy makers to replace the conventional motorcycles in the market [1, 2].

In electric transportation systems, how far the vehicles can travel with their current remaining energy is directly related to the remained power and current battery state-of-charge (SoC) [3]. Literature shows that the manufacturers employ Environmental Protection Agency (EPA) standards and various deterministic approaches for range estimation based on the pre-calibrated or measured data from previous driving cycles. However, these methods do not always give accurate prediction because they ignore the effects of system dynamics and uncertainty loads. To improve the utilisation of the energy in the battery pack and maximise the performance of the optimal energy management system, development of the advanced control frameworks for EVs have become increasing research topic in recent years [4] besides the 2-wheelers EMs have not been yet investigated intensively due to their limited battery capacities and low travel ranges.

Advanced range estimation strategies for EVs including EMs are usually built based on one of the two approaches: i) historical knowledge-based approach and ii) model-based approach [3, 5]. The first category considers the past driving characteristics and the historical battery consumption rate. This approach is straightforward as it does not include the model while it uses the travel information for the estimation hence the accuracy is usually quite low and is sensitive to riding behaviours and operational conditions. In contrast, the model-based approach not only considers the past driving characteristics and the historical battery consumption rate, but also includes the mathematical models of vehicle subsystems to create a hybrid structure with historical parameters and physical system model.

In this study, a linear range estimation strategy is developed as the baseline approach for optimal remaining range estimation and is suitable for real-time applications. By integrating the proposed range estimation model with a simple but feasible ride cycle classification-based machine learning approach, the obtained complete EM model can accurately estimate the elapsed travel distance and predict the remaining range of a 2-wheelers motorcycle application. The developed classifier is based on a collection of features that are solely dependent on riding speed information. The outputs of the developed models can help to support the development of optimised energy management systems.

The remainder of the paper consists of the baseline range estimation strategy which is presented in Section II, the ride cycle classification strategy approach and the dataset for training and testing are explained and established in Section III, simulation results and discussion are depicted in Section IV while Section V finally remarks the conclusion.

II. BASELINE RANGE ESTIMATION STRATEGY

Accurate estimation of the energy consumption of the EMs is critical in order to predict the remaining range of such motorcycles. This task can help to develop the optimised energy management system for EMs. However, due to the transient dynamics of the driving profiles and operational conditions, it is difficult to estimate the remaining range accurately. In this study, a linear range estimation approach is employed to estimate the elapsed travel distance based on the calculated energy consumption rate in real-time and therefore the remaining range can be predicted. This approach can be used as the baseline for future remaining range estimation development. The approach consists of two estimation steps:

1. During the initial linear distance (*Lin.Range*), the remaining range is estimated based on the remaining battery SoC and the pre-calibrated consumption rate (*ConR0*). This is an open-loop interpolation process, therefore, within this period the remaining range is linearly interpolated disregarding the rider behaviours and operating conditions.
2. After the linear distance period, the consumption rate is recalculated based on the estimated distance error (*ErrF*)

between the actual elapsed distance and the estimated travel distance. The calculated consumption rate is defined as follows:

$$ConR.cal =$$
$$\max(k0, ConR - \max\left(k1, \min\left(\frac{ErrF}{k2}, k3\right)\right).\varphi.ConR) \quad (1)$$

where, *ConR.cal* is the calculated consumption rate, *ConR* is the pre-calibrated consumption rate, k_i $(i = 0 - 3)$ are the constants, φ is the consumption rate coefficient.

Similarly, the remaining range is estimated based on the remaining battery SoC and the re-calculated consumption rate. Figure 1 depicts the flow diagram of the developed range estimation approach.

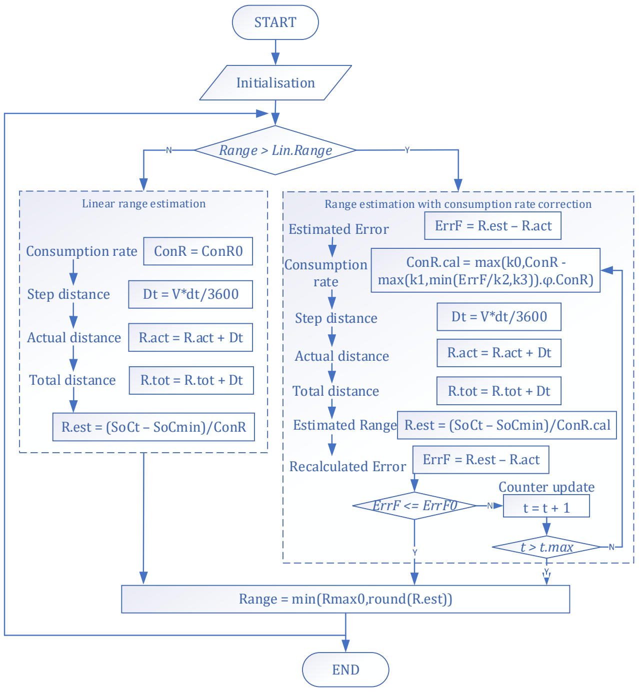

Figure 1: Linear range estimation approach.

III. Ride Cylce Classification Strategy

Identifying the riding cycles of EMs is not straightforward due to their highly transient dynamics, which are dependent on driver behaviours and operating conditions. To the best of the authors' knowledge, there is very limited research on riding cycles classification for EMs, especially for the range estimation related purposes. As an attempt to fill the missing gap, this section focuses on the development and evaluation of a simple but feasible and effective ride cycle classification strategy for high performance EMs. In this study, support vector machine (SVM) is employed as the classification algorithm with linear polynomial kernel function to maximise the accuracy of the classifier. The major advantage of this approach is that the definition of model features is solely based the speed profiles information of the riding cycles.

A. Support Vector Machine

To build the riding cycle classification model, SVM is selected and deployed. SVM is one of the most robustness and powerful classification black-box technique. This algorithm proposes a set of hyperplanes to separate the selected set of data in a high dimensional space. The defined hyperplanes have the largest distance to the nearest training data points of various classes. This approach minimises the classification error and reduces the misclassification probabilities [6, 7].

The SVM algorithms maps the n-dimensional input vector $X \in \mathbb{R}^n$ into the richer (high dimensional) feature space $\mathcal{H}$ by Φ and constructs an optimal separating hyperplane in this space.

$$f(x) = W^T\Phi(X) + b \quad (2)$$

where, f is the decision surface (classifier) in space $\mathcal{H}$, Φ is the $\mathbb{R}^n \rightarrow \mathcal{H}$ projection, W is the normal vector to hyperplane and b is the bias term.

The classifier in (2) can be rewritten as follows:

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i k(x_i, X) + b \quad (3)$$

where, the coefficients α_i are obtained by maximising the following functional:

$$W(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i,i=1}^{N} \alpha_i \alpha_j y_i y_j k(x_i, X) \quad (4)$$

w.r.t the constraints:

$$\sum_{i=1}^{N} \alpha_i y_i = 0 \;\; and \;\; 0 \le \alpha_i \le C \;\; , \;\; i = 1, \dots, N \quad (5)$$

Coefficient α_i defines maximal margin hyperplane in high dimensional feature space where the data mapped through a non-linear function Φ such that $\Phi(x_i).\Phi(x_j)=k(x_i,x_j)$. C is the penalising constant where the data points cross the boundary. Details of the SVM model derivation can be found in [8].

B. Development of Ride Cycle Classification

This section presents the details of ride cycle classification strategy. Riding cycles are constructed by number of data points over time, to support the classifier, it is necessary to reduce their dimension. In this case, characteristics of the ride cycles must be extracted, and the obtained characteristics are called features from now on. As mentioned in the previous section, only speed profile information is utilised to define the ride cycle features as depicted in Table I.

Table I: Feature extraction for cycle classification

No.	Feature	Description	Unit
1	MeanV	Average velocity over time interval	m/s
2	MaxV	Maximum velocity over time interval	m/s
3	MinV	Minimum velocity over time interval	m/s
4	StartV	Start velocity of such time interval	m/s
5	EndV	End velocity of such time interval	m/s
6	MeanA	Average acceleration over time interval	m/s^2
7	MaxA	Maximum acceleration over time interval	m/s^2
8	MinA	Minimum acceleration over time interval	m/s^2
9	StartA	Start acceleration of such time interval	m/s^2
10	EndA	End acceleration of such time interval	m/s^2

Then, the SVM technique is applied to construct the classification model taken the following steps:

1. Select ride cycles for training and extract the features of each ride cycles based on pre-defined time interval.
2. For each C, split the whole feature dataset randomly into train and test data
3. Train the SVM model and store the success rate
4. For cross-validation, the selected training data will be splitted randomly into 5 folds. Four of them are in turn to be the training data set while the remaining one is the validation set. Then, average the success rates
5. Update C value and restart step 2 for optimisation.

In this study, a linear polynomial kernel function is chosen and used due to the complexity of the selected cycling profiles and the ability of deploying the model in real-time applications. The time interval of 20 sample lengths is used, which shows the trade-off between the calculation complexity and the amount of cycle information. The time interval for feature extraction and SVM model training/testing diagrams are depicted in Figure 2 and 3, respectively, while Figure 4 shows the selected riding cycles for the study.

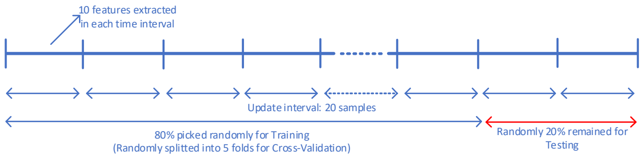

Figure 2: Time interval definition for feature extraction

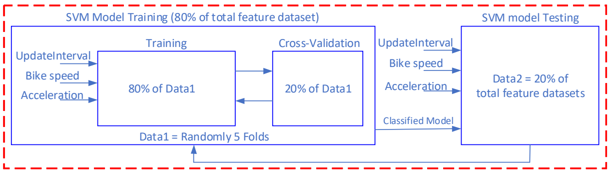

Figure 3: SVM model training and testing

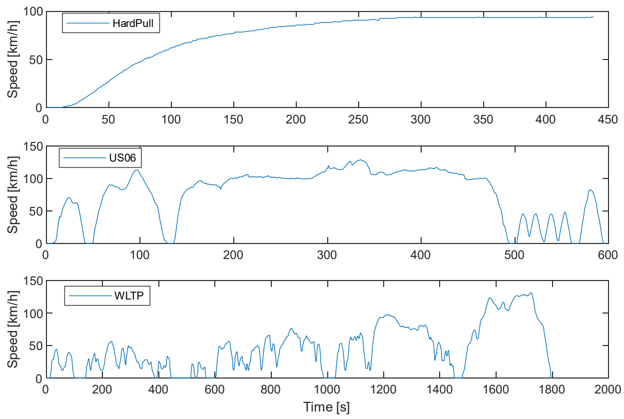

Figure 4: Selected ride cycles of EMs

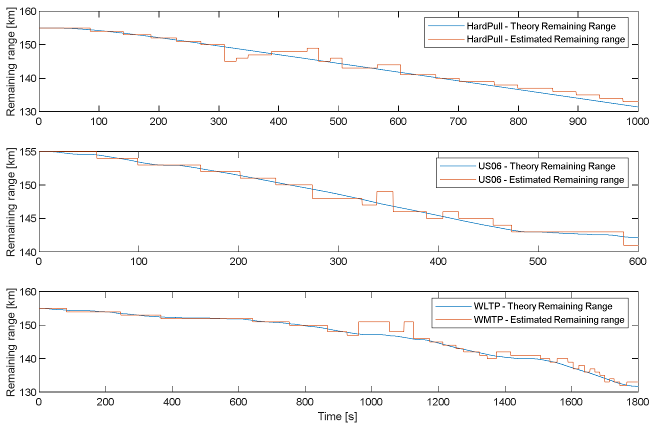

Figure 5: Remaining distance profiles of the selected ride cycles

IV. Results and Discussion

The implementation of the developed range estimation strategy is deployed using the selected ride cycles in order to pre-estimate the total remaining range of the EM. The tests are carried out when the battery is fully charged. The results of this process can be used as the baseline for the future remaining range estimation. Figure 5 represents the estimated remaining distance when running the with such riding cycles. The results show that the proposed range estimation strategy can estimate the elapsed distance quite well. There is still a large error at the beginning of self-calculated consumption rate period, however, the process is quite smooth after that.

The SVM classification model is trained, cross-validation and finally testing using the defined features dataset. Figure 6 presents the confusion matrix which shows the testing results of the model. It can be seen that the average accuracy of the developed model can reach to 94.7% over 188 observations where the WLTP profile can be identified with 100% of accuracy, which is significant and can be employed for remaining range estimation.

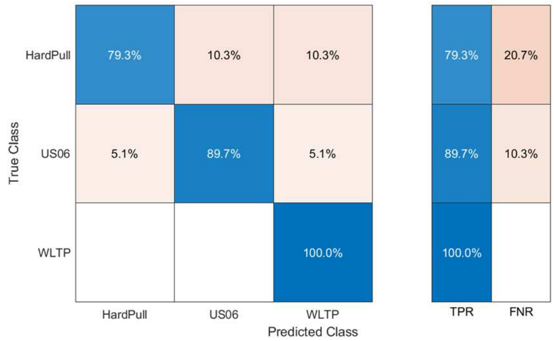

Figure 6: SVM model training result

The optimised model of the developed SVM classification strategy is finally integrated into the EM 1D model in order to evaluate the performance and implementation ability to operate in real-time simulation environment. Figure 7 depicts the implementation of the optimised SVM model. A mixed ride cycle representing a daily operational profile is finally designed and utilised for testing the integrated complete model. Simulation results show that the proposed SVM model can classify the ride cycle correctly. The predicted profile label matches well with the actual profile. Figure 8 shows the simulation results of the integrated complete model.

By employing the optimised SVM model and the developed remaining range estimation algorithm, the complete model can firstly classify and identify correct riding cycle label and is capable to predict the elapsed travel distance and therefore potential predict remaining range of any daily operational profiles. Nevertheless, it is essential to develop an optimal strategy to effectively utilise the outputs of the developed classification model for developing energy management systems for the EM applications.

V. Conclusions

This paper presents a SVM machine learning approach for the ride cycles classification of EMs for remaining range estimation strategy purposes. The validation and simulation results of the integrated classification-based linear range estimation strategy underpin the implementation of the developed model in real-time environment. Although the proposed linear range estimation strategy can perform well in most of the cases, it might cause heavy load for the control hardware, especially when the algorithm working during the correction portion due to the integration loop. However, it can be considered as the baseline for further development and comparison and is the premier to build optimised energy and battery management systems for EMs to maximise the travel distance and improve the battery life, which will be under investigation by the authors.

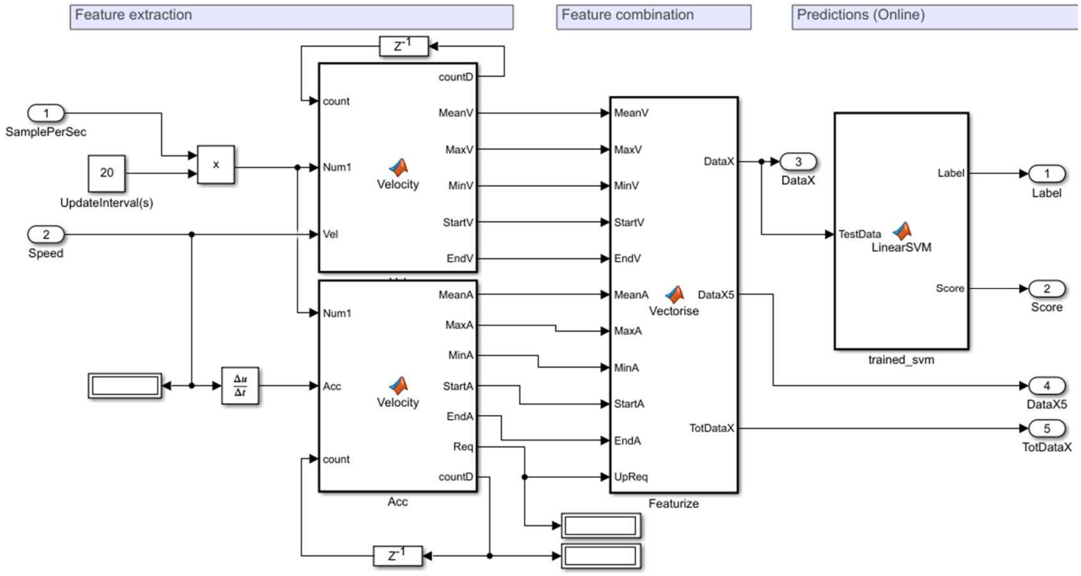

Figure 7: Implementation of proposed SVM model

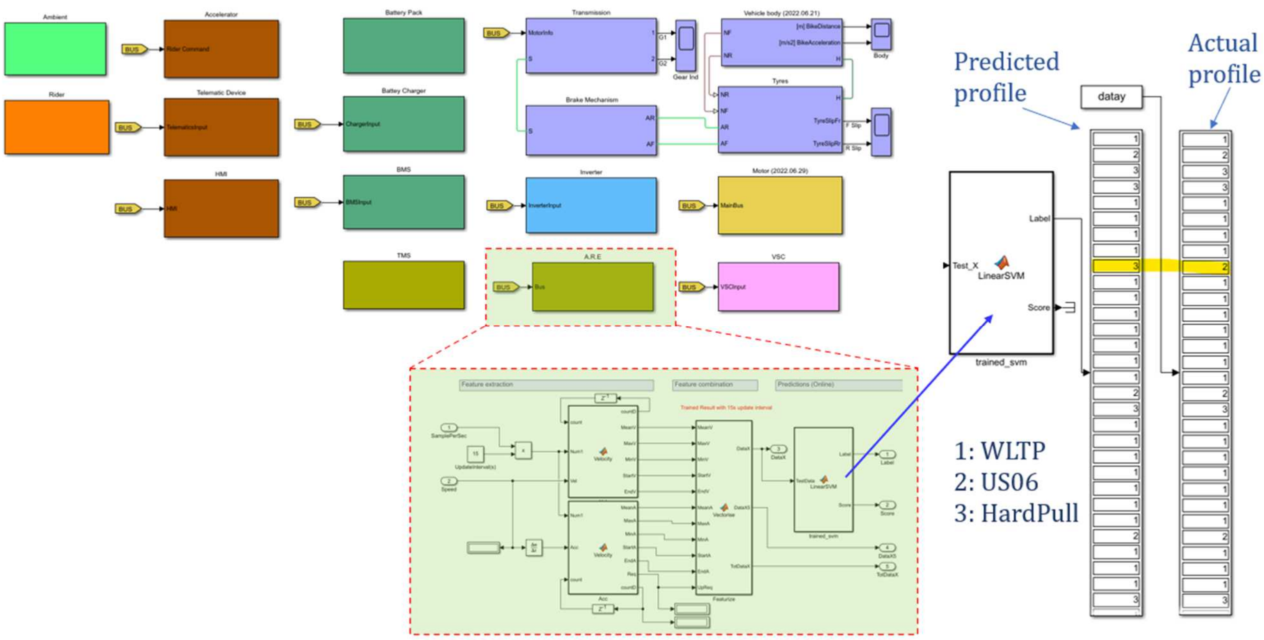

Figure 8: Simulation results of the complete model

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