Intelligent Traction Control in Electric Vehicles Using an Acoustic Approach for Online Estimation of Road-Tire Friction

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Abstract—Torque control of electric motor via current gives the advantage of simplicity and fast response over the complicated torque control of an internal combustion engine which may depend on several parameters ranging from fuel valve angle to gas pedal position and several delay factors. Although traction control system (TCS) for in-wheel-motor (IWM) configuration electric vehicles (EV) has advantages, the performance of the control system, as in most traction control cases, still depends on (1) accurate estimation of road-tire friction characteristics and (2) measurement of slip ratio requiring expensive sensors for obtaining wheel and chassis velocity. The main contribution of this work is design and integration of an acoustic road-type estimation system (ARTE), which significantly increases the robustness and reduces the cost of TCS in IWM configuration EVs. Unlike complicated and expensive sensor units, the system uses a simple data collection set-up including a low-cost cardiod microphone directed to vicinity of road-tire interface. The acoustic data is then reduced to features such as linear predictive, cepstrum and power spectrum coefficients. For robust estimation, only some of these coefficients are selected based on minimum intra-class variance and maximum inter-class distance criteria to train an artificial neural network (ANN) for classification. The road types can be grouped into: Asphalt, gravel, stone and snow with a correct classification rate of 91% for the test data. The predicted road-type is used to select the correct friction characteristic curve (μ-λ) which helps calculating the appropriate torque command for the particular road-tire condition. The system has been evaluated in extensive simulations and the results show that extreme torque values are suppressed stabilising the vehicle for several driving scenarios in a more energy-efficient and robust manner compared to previous systems.

I. INTRODUCTION

When TCS structures are examined, the simplest application is model following controller (MFC) studied in [1]. In the MFC, a model representing the longitudinal dynamic behaviour of the vehicle body produces the reference angular velocity of the wheel which is later compared with the actual value of the angular velocity of the wheel to produce an error signal. This error signal is then conditioned by a high-pass filter, amplified and fed back to current controller in order to control the electric motor torque value in turn. The MFC is very simple and straightforward with an accurate electric motor model; therefore, it could help reaching the desired traction forces. However, it has a major disadvantage as it does not measure the real dynamics between the tire and the road in terms of friction coefficient or slip ratio at all. The slip ratio used for the control of motor torque is a pre-set value which does not dynamically change according to the current road condition.

Another important TCS structure proposed by the same research group is based on slip ratio control (SRC) [2-5]. In the SRC system, actual slip ratio is measured using the difference between the velocities of vehicle chassis and the wheel. As a reference value to be compared with the measured slip ratio, optimal slip ratio is estimated using a either a fuzzy inference system or gradient descent algorithm using mu-lambda curves. The cues from a driving force observer are also included in the SRC with fuzzy system, yielding indirect but important indications reflecting the road and tire interaction. In the SRC, actual road-tire dynamics are taken into account. The performance of the SRC is mainly dependent on how well the force observer can track the actual driving force between the road and tire. A second drawback may come from the pre-loaded μ-λ characteristics of one or several road conditions (i.e. curves obtained by Magic Formula [6]) to be used in fuzzy inference to estimate the real road surface characteristics for the correct λopt, i.e. optimum value of the slip ratio for the particular road. It is clear from the operational perspective that SRC uses a double estimation process to derive the optimum slip ratio to be tracked by adjusting the motor torque based on a questionable pre-loaded initial condition for the μ-λ characteristics. In brief, SRC could perform better than a MFC system because of the dynamic information is included; however, still the impediment of the estimation process may hinder the performance.

Finally, as the third TCS under examination ‘maximum transmissible torque estimation’, MTTE, is considered [7,8]. The method in MTTE structure is fundamentally different from SRC structure because it needs neither chassis velocity nor the estimation of tire-road condition. In MTTE, the uncertain dynamics between the road and tire together with its effect on the chassis-wheel velocity difference is accounted in the relaxation term alpha (α) and an observer-based strategy is followed.

In addition to these three TCS structures, it is worth mentioning several recent studies on control sub-systems or sensor development to be used in traction control. In [9], tire-road coefficient was estimated using a novel wireless piezoelectric tire sensor for measuring the deflections on the tire sidewalls and employing the conventional brush model of tire. This work again indicates the necessity of using a plausible model for obtaining the tire-road friction coefficients although a specialized sensor is developed. Being relatively new in the area, acoustic methods are also employed in road condition estimation in a limited capability distinguishing between the dry and wet asphalts in [10]. In [11], an adaptive vehicle speed control is applied using a
frictional condition estimation which is independent from the longitudinal motion. In order to achieve friction estimation without affecting the longitudinal motion control of the vehicle, they employed the actuation redundancy of an IWM configured EV. While applying brakes to rear wheels, the front wheels are actuated in a way to counteract this effect; therefore, producing enough richness in the excitation signals to identify the friction coefficient. Using this method, it was possible to identify the friction characteristics of the particular road without disturbing the longitudinal motion of the vehicle.

In this work, we propose an intelligent road condition estimator which is capable of distinguishing between asphalt, gravel, snow and ice using an acoustic-based estimation. The system is called ‘Acoustic Road Type Estimation’ system or ARTE in short. It uses several signal processing methods for feature extraction from the acoustic signal and a pattern classifier using artificial neural networks. In addition to this, detailed analysis and comparison of traction control systems in the perspective of robustness, stability and energy consumption is given. After comparing the previously proposed systems, we integrate ARTE to these TCS systems. Observations from simulations are indicating significant improvements in the response of the systems in terms of reduced slip ratios and less torque effort. It proves that integration of ARTE leads to a more robust TCS with more convenient power consumption strategy in torque control of the electric motor.

The remaining parts of the paper are organized as follows: In Section II, an overview and comparative analysis of several TCS proposed for light-weight electric vehicles is given emphasizing on robustness, stability and power consumption issues. Section III, ARTE structure is detailed including acoustic system design, signal processing, and feature selection process. In Section IV, the pattern classification is performed by ANN to distinguish road types dynamically and performance of the ARTE system in estimation accuracy is tested. Last, in Section V, the ARTE system is integrated in several TCS structures proving that it helps both improving the robustness and stability of TCS and the power consumption of the system. Thus ARTE has proved to help controlling the vehicle with less effort/power or load on the actuator. The conclusions are drawn in Section VI together with the future improvement and expansion ideas on ARTE system.

II. OVERVIEW AND ANALYSIS ON TRACTION CONTROL IN ELECTRIC VEHICLES

Traction control systems we analyse in this work are, in order, model following controller (MFC), slip ratio controller (SRC) with Fuzzy Inference of the optimal slip ratio, and finally maximum transmissible torque estimation (MTTE) structure which is based on an observation of the actual driving force. The essence of a traction control system is in the estimation and control of the friction forces between the tire and the road. The difficulty lies in the fact that those forces can be neither estimated nor controlled in a direct manner. Therefore, each TCS structure includes a method to estimate the friction either using an observer or an indirect inference system. Some of these methods allow a better stability and robustness of the final system (i.e. SRC and MTTE); the others may have quite straightforward and rough operation (i.e. MFC). A general physical model of the interaction between the road and tire is given in Figure 1 explaining the traction force that is mainly responsible for the longitudinal motion of the vehicle as well as affecting the lateral dynamics. Since the friction cannot be directly measured several models (i.e. Pacejka and LuGre. [12]) are suggested for estimating the friction force between the tire and the road using more available parameters.

Before assessing the performance of all TCS structures under different torque demand conditions, as a first step in the analysis we briefly mention MFC, SRC and MTTE structures. First, the basic operation principles of these TCS structures are examined, then using their block-diagrams descriptive transfer functions including the torque or the current as input and velocity of the wheel, chassis or the slip ratio as the output (i.e. \( \frac{\lambda(s)}{I_{\text{ref}}(s)} \)) are derived. Additional stability conditions are also derived to compare the systems in terms of their dependency on the controller and/or vehicle dynamics parameters. This also helps seeing the potential or the limits of the particular TCS structure under examination. It should be also noted that all TCS approaches here ignores the effects of external disturbances such as air-drag force and rolling resistance.

A. Model Following Controller (MFC)

MFC structure has an ideal model and the aim is to make the real vehicle dynamics (i.e. the angular velocity of the wheel) follow the model output which is defined as ideal. However, when the model result and reality are far away from each other, the actuators might be overloaded and even saturated. In Figure 2, opened up version of the original MFC system block diagram is shown for the analysis. From the block-diagram in Fig 2, it can be understood that the real value of the moment of inertia reflected in the wheels deviate from the ideal value in the model because of the multiplication of the \( M_r^2 \) term with \((1-\lambda)\). This means that the real vehicle is felt lighter on the wheels causing the deviation from ideal. In fact, the requirement on the slip-ratio being zero is a very conservative and rough approach. Any information on the optimal slip ratio for the particular road will help a better tracking performance and less load on the actuators.
Transfer function of the MFC is derived having the torque (or current) as input and angular velocity difference of the wheel as output finding (1).

\[
\frac{\omega_{\text{diff}}(s)}{I_{\text{ref}}(s)} = \frac{K(J_m - J_f)}{s^2\tau_r^2 + (J_m + J_f)\tau_r s + (J_m + J_f) + K_{\text{MFC}}\tau_r K(J_m - J_f)}
\]

Using the characteristic equation of the transfer function in (1), absolute stability condition in (2) can be derived.

\[
K_{\text{MFC}} \leq \frac{J_m(\tau_2 - \tau_3)}{4\tau_1^2\tau_3 K\Delta}
\]

\(\Delta\) is the uncertainty between the real and the model values of the vehicle inertia described by equation (3).

\[
J_{\text{r}} = \frac{J_m}{1 + \Delta}
\]

As it can be seen, the MFC gain is an upper bounded variable and it depends on the vehicle inertia \(J_m\), motor time constant \(\tau_1\), motor gain \(K\), high-pass filter constant \(\tau_2\) and most importantly the uncertainty in the vehicle inertia denoted by \(\Delta\). From here, it can be understood that the classical MFC uses a predefined \(K_{\text{MFC}}\) gain value which may not be the optimal value for the particular situation.

**B. Slip Ratio Controller (SRC)**

Slip ratio controller structures in literature has two versions:

(I) SRC with road condition estimator using a free wheel to estimate mu-lambda characteristics accordingly.

(II) SRC with fuzzy system to estimate the optimum lambda value using the mu-lambda curve slope (a), mu and lambda at particular point.

In the analysis here, the second type of SRC with fuzzy system will be examined. The closed block diagram of SRC as it appears in [4] and corresponding expanded diagram in simplified form is given in Figure 3. As it can be seen from Fig 3, system uses an optimal slip ratio estimator (i.e. fuzzy inference) and tries controlling the ratio directly. Since the slip ratio is more directly addressed in SRC and dynamically included with the estimation here, SRC is a much finer method compared to MFC.

In fact, SRC system main control structure can be examined in more detail showing five main parts: (i) EV-motor for the plant to be controlled, (ii) driving observer, (iii) road condition estimator, (iv) slip ratio estimator, and (v) controller having PI action. From the motor-EV section of the model the transfer function can be obtained having the current as input and velocity difference as the output in (4) to compare with MFC’s transfer function (1).

\[
\frac{V_{\text{diff}}(s)}{I(s)} = \frac{r_{\lambda}}{s^2(\tau_m s + 1)(M_r^2(1-\lambda) + J_f)}
\]

However, in order to assess the closed-loop stability of SRC structure, using equation (4), transfer function from optimum slip ratio reference input to resultant slip ratio, hence \(\lambda(s)/\lambda_{\text{opt}}(s)\), is calculated. For derivation of the closed loop transfer function the block diagram in Fig 4 is considered.

In the analysis here, the second type of SRC with fuzzy system will be examined. The closed block diagram of SRC as it appears in [4] and corresponding expanded diagram in simplified form is given in Figure 3. As it can be seen from Fig 3, system uses an optimal slip ratio estimator (i.e. fuzzy inference) and tries controlling the ratio directly. Since the slip ratio is more directly addressed in SRC and dynamically included with the estimation here, SRC is a much finer method compared to MFC.
Using (6) and re-arranging the relation, finally (7) is obtained that can be used to define the stability conditions on SRC.

\[
\frac{\lambda(s)}{\lambda_{opt}(s)} = \frac{K(1 + \tau s)\lambda_0}{s[(\tau_m s + 1)(s(1 + KR) + 1)] C}
\]

(7)

in which \( C \) is taken as \((Mf_r^2(1 - \lambda) + J_f)\sqrt{\nu_0}\). The stability condition using the characteristic equation in (7) can be seen in (8):

\[
1 + KR + \tau_m \geq 2\sqrt{\tau_m}
\]

(8)

C. Maximum Transmissible Torque Estimation (MTTE)

Maximum transmissible torque estimation method does not require the chassis or wheel velocity measurements. The main part of the structure is based upon the observed driving force. The block diagram of MTTE is given in Fig 5. MTTE is a structure employing an observer for obtaining the driving force \( F_d \) and then uses this estimation to calculate the maximum allowable torque. One of the advantages of MTTE is that it uses the ratio of accelerations of the chassis and the wheel as a relaxation variable, \( \alpha \), and tries to keep the ratio as close as possible to unity. This means that since the accelerations of the vehicle chassis and the wheels are not allowed to deviate too much, then the speeds would not be so different from each other, thus ensuring a low slip ratio, \( \lambda \).

Using (6) and re-arranging the relation, finally (7) is obtained that can be used to define the stability conditions on SRC.

In order to compare these three TCS in a systematically reasonable manner, we have selected four criteria indicating the performance of a TCS: (i) time averaged total deviation of slip ratio from zero (i.e. the ideal value), (ii) the max torque of the motor during TCS in action, (iii) the normalised area under the torque-time graph showing the correction effort and energy consumption, (iv) gap metric to assess the stability under worst cases of deviation from the nominal system parameters. The study also reflects different torque demand profiles of several traffic and conditions: (i) flowing traffic: continuous torque requirement, (ii) road with inclination: torque requirement like ramp function, (iii) city traffic: stop-and-go pattern torque requirement. According to road profiles and the traffic conditions, torque inputs shown in Fig 6 are used for all the simulations.

![Fig 5. MTTE structure in closed form](image)

![Fig 6. Torque inputs used in simulations (in terms of motor control current, Amperes) as a common basis, reflecting several traffic conditions and road profiles.](image)

### TABLE I. PHYSICAL PARAMETERS OF EV FOR COMPARISON

<table>
<thead>
<tr>
<th>System Parameter</th>
<th>Values</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>( J_w ): moment of inertia for the wheel</td>
<td>0.6</td>
<td>kg.m²</td>
</tr>
<tr>
<td>( r ): wheel radius</td>
<td>0.28</td>
<td>m</td>
</tr>
<tr>
<td>( \tau_1 ): Time constant for electric motor</td>
<td>0.05</td>
<td>sec</td>
</tr>
<tr>
<td>( \tau_2 ): Time constant for high pass filter</td>
<td>1000</td>
<td>sec</td>
</tr>
<tr>
<td>( M ): Vehicle mass</td>
<td>1400</td>
<td>kg</td>
</tr>
<tr>
<td>( m ): Wheel mass</td>
<td>40</td>
<td>kg</td>
</tr>
</tbody>
</table>

Performances of MFC, SRC and MTTE systems without using ARTE module is shown through Fig 7-9 having wheel, chassis velocities, slip-ratios and torque effort by the motor under different traffic and road conditions i.e. constant torque demand, ramping torque demand with interruptions and stop-and-go city traffic conditions or in other words unpredictable torque demand.

A quantitative way to compare several TCS structures under different road and traffic conditions the results in Fig 7-9 are summarized in proposed performance criteria and shown in Table II. From the graphs and Table II, it is first observed that the SRC system is the most successful method in keeping the slip ratio close to zero except stop-and-go condition. However, when the peak torque value and average torque effort is considered MTTE seems to be more

![Fig 7-9 having wheel, chassis velocities, slip-ratios and torque effort by the motor under different traffic and road conditions i.e. constant torque demand, ramping torque demand with interruptions and stop-and-go city traffic conditions or in other words unpredictable torque demand.](image)
convenient since it can provide good slip-ratio control without much torque effort except stop-and-go scenario. For example, considering the comparison between SRC and MTTE structures, it can be considered an insignificant benefit having the average slip ratio reduce from 0.0752 to 0.0469 but spending the double effort in terms of torque since SRC output is almost double of MTTE torque effort. In addition to this, MTTE does not need to measure the chassis velocity, therefore it can be considered as a more energy efficient TCS structure.

<table>
<thead>
<tr>
<th>Traffic-Road Condition</th>
<th>TCS Structure</th>
<th>Time-averaged slip ratio deviation</th>
<th>Max torque during operation</th>
<th>Normalized area of torque-time graph</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant torque</td>
<td>MFC</td>
<td>0.8455</td>
<td>2776</td>
<td>453.29</td>
</tr>
<tr>
<td></td>
<td>SRC</td>
<td>0.0469</td>
<td>600</td>
<td>506.93</td>
</tr>
<tr>
<td></td>
<td>MTTE</td>
<td>0.0752</td>
<td>300</td>
<td>299.43</td>
</tr>
<tr>
<td>Ramp torque</td>
<td>MFC</td>
<td>0.7952</td>
<td>3024</td>
<td>505.083</td>
</tr>
<tr>
<td></td>
<td>SRC</td>
<td>0.0435</td>
<td>1052</td>
<td>379.09</td>
</tr>
<tr>
<td></td>
<td>MTTE</td>
<td>0.0590</td>
<td>540</td>
<td>234.19</td>
</tr>
<tr>
<td>Stop-and-go</td>
<td>MFC</td>
<td>0.7529</td>
<td>5124</td>
<td>323.39</td>
</tr>
<tr>
<td></td>
<td>SRC</td>
<td>0.0345</td>
<td>497.28</td>
<td>53.47</td>
</tr>
<tr>
<td></td>
<td>MTTE</td>
<td>0.0237</td>
<td>440</td>
<td>113.24</td>
</tr>
</tbody>
</table>

III. ACOUSTIC ROAD-TYPE ESTIMATION (ARTE) SYSTEM

ARTE system is designed as a low-cost solution to uncertainty in estimation of road-tire interaction in terms of friction force or mu-lambda relationship. The system collects acoustic data from the tire-road interaction area using a cardioid microphone and the data is processed to classify the road type giving important information on which mu-lambda profile should be selected at particular time in order to produce a better optimal lambda value or a better motor-EV model since it inherently uses a road-tire model which is assumed to remain constant. When the reality does not match the assumed model, the system performance is subdued. The main objective of using ARTE is to prevent the system failure due to faulty model assumptions. It can be also seen from the perspective of uncertain systems. Integrating ARTE the bounds of uncertainty in the system becomes narrower allowing the system control the traction force much better with a more robust structure. Here, the system will be introduced in three parts: (a) data collection set-up and pre-processing, (b) feature extraction and selection, (c) road type estimation using artificial neural networks. A block-diagram of ARTE is given in Fig 10.

![Block diagram of acoustic road type estimation system](Fig 10)

**A. Data Collection set-up and pre-processing**

Acoustic data was collected by using a Full Electric Vehicle located at Mechatronics Education and Research Centre, ITU, a DC-AC converter, a DPA 4012 cardioid microphone, a generic microphone amplifier, a laptop which has Pentium(R) Dual-Core CPU T4200 2 GHz processor. Gold Wave program was employed as data acquisition and pre-processing environment. The data collection included four
types of road: asphalt, gravel, snowy and stony as shown in Figure 11. Electric vehicle provided more quite environment compared to vehicles with internal combustion engine, therefore the method was more applicable. In addition to this, a foam rubber shield was used to suppress the wind noise. Figure 11 also shows cardioid microphone pattern which indicates graphical representation of microphone’s directionality. This pattern shows that the acoustic data is picked up mostly the front but to a lesser extend the side as well. The data was collected at relatively low-speeds from 10-30 km/h and was kept constant during the data collection. In general, the road-tire friction estimation systems require variable speed profile for the estimation process as stated in [9], however, ARTE does not require this. In fact, it works much better in constant speed profiles.

In addition to this, the effective separability supplied by the selected feature vector space is measured using Kullback-Leibler distance for calculating the distances between asphalt, snow, stone and gravel data clusters. Taking the stony road as the benchmark, the distances between the stone and asphalt is 936.58, stone and snow is 971.88 and stone-gravel is 928.13. These K-L distances show that the clusters are separable after the most significant digit. Based on this rough analysis of separability and optimizing the feature vectors on inter-class separability and intra-class coherence, artificial neural network is trained for classification which is detailed in next section.

Thirty samples were taken from each record of data at intervals of 0.1 seconds randomly. In order to represent the road surface conditions as acoustic signature, a feature vector had to be determined. Classical audio signal processing techniques are implemented such as linear predictive coding coefficients (LPC), power spectrums and cepstrums for determining the best feature vector for representing the data. The elements of the feature vector are selected among the features or coefficients with the minimum variance intra-class coherence and maximum distance criteria for inter-class separability. At first, 10 coefficients from LPC analysis, 5 coefficients from power spectrum and cepstrums are selected giving total feature vector dimension of 20. Then, the feature vector was trimmed using a least variance approach considering intra-class values. After this pruning process the features providing a coherent class representation remained as 3 LPC, 2 power spectrum coefficient and 2 cepstrums values giving a feature vector of seven elements per data. The variance values of selected feature vector elements are given in Fig 13.

B. Feature Extraction and Selection
The acoustic signals acquired by the cardioid microphone can be seen in Fig 12 for asphalt, snow, gravel and stony road in order to have an idea on the raw-format data collected by ARTE.

C. Road Type Estimation
Using the selected feature vector, an artificial neural network was trained and tested on acoustic data off-line. The ANN uses Levenberg-Marquardt learning and having 4 layers with hidden layers including [4:3:2] neurons in order. The structure is a MLP network and back-propagation is used. After 18 epochs, the ANN converged to performance criteria of mean square error. The regression results showed that ANN can identify the test data with a regression coefficient of 0.91. The coefficient can be increased if the bias in

Fig 11. (1) Data collection set-up behind the electric vehicle, (2) microphone set-up and (3) cardioid response

Fig 12. Raw acoustic signals obtained by ARTE for asphalt, snowy road, stony road and gravel

Fig 13. Variance values of selected feature vector elements
feature vector space is removed. In fact the results shown here is one of the worst, better performances are obtained giving regression coefficients above 0.95 however with further manipulation on feature space. The correct classification rate was always higher than 85%. In order to see the performance of the ANN classifier more clearly, the confusion table showing the false negatives (FN), false positives (FP), true negatives (TN) and true positives are shown in Table III. The classes that are particularly more difficult to separate consist of snow and stone.

<table>
<thead>
<tr>
<th>Traffic-Road Condition</th>
<th>TCS</th>
<th>Slip ratio deviation</th>
<th>Max torque correction</th>
<th>Normalized area of torque-time graph</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant torque</td>
<td>MFC</td>
<td>0.9724</td>
<td>3003.3</td>
<td>2820</td>
</tr>
<tr>
<td></td>
<td>SRC</td>
<td>0.0162</td>
<td>56</td>
<td>15.024</td>
</tr>
<tr>
<td></td>
<td>MTTE</td>
<td>0.0001037</td>
<td>10.48</td>
<td>5.52</td>
</tr>
<tr>
<td>Ramp torque</td>
<td>MFC</td>
<td>0.9303</td>
<td>5235.2</td>
<td>2124.5</td>
</tr>
<tr>
<td></td>
<td>SRC</td>
<td>0.0196</td>
<td>54</td>
<td>21.95</td>
</tr>
<tr>
<td></td>
<td>MTTE</td>
<td>0.0001618</td>
<td>10.485</td>
<td>10.48</td>
</tr>
<tr>
<td>Stop-and-go</td>
<td>MFC</td>
<td>0.9255</td>
<td>5595.1</td>
<td>1399.5</td>
</tr>
<tr>
<td></td>
<td>SRC</td>
<td>0.0196</td>
<td>54</td>
<td>21.95</td>
</tr>
<tr>
<td></td>
<td>MTTE</td>
<td>0.0001</td>
<td>10.48</td>
<td>5.52</td>
</tr>
</tbody>
</table>

IV. RESULTS ON EVALUATION OF TCS WITH ARTE

ARTE system with trained ANN classifier is integrated in all TCS structures examined in this work. The integration was performed as follows: For MFC, the total inertia of the vehicle used in the model is updated according to the estimated value of lambda in \( J = J_w + Mr^2 (1 - \lambda) \). In the SRC structure, the integration is straightforward since the estimated optimum lambda by ARTE is directly needed in the algorithm as the reference signal. Last, the MTTE system uses the estimated result in updating the \( \alpha \) coefficient used to calculate the maximum torque. It should be noted as well that the ARTE system uses the ANN-classifier results of the road types and matches them with pre-loaded mu-lambda curves for the estimation of the optimal lambda for each road condition.

The evaluation was performed in a set of simulated tests. The simulations mainly consist of road scenarios where different mu-lambda characteristics and dynamic torque-demands may occur. The ARTE module is integrated in MFC to update the reference model, in SRC as the reference optimal slip ratio source and in MTTE to update the relaxation factor. The main mechanism behind why ARTE helps improving the TCS performance is that it reduces the uncertainty sources or narrows down the uncertainty bounds in the systems. The performance criteria measured on all TCS structures with ARTE module is given in Table III and Figure 14 –16. As it can be seen from the table and the figures, the slip ratio is reduced to a level very close to zero especially when MTTE is integrated with ARTE. It was also observed that although ARTE helped MFC system to have a less angular velocity difference between the model and the real vehicle the slip ratio did not reflect any further improvement. The SRC system also benefited from ARTE however the average torque values were still high compared to MTTE. As a result, it can be concluded that MTTE with ARTE is the best TCS structure of all since the slip ratio has reduced dramatically without increasing the torque correction effort.
V. CONCLUSION

In this work, three different TCS structures proposed for electric vehicles with in-wheel-motor configuration are re-examined and compared in terms of their robustness, energy efficiency, and accuracy in reaching control targets. New stability conditions and transfer functions are derived for MFC, SRC and MTTE to examine dynamic behaviour more closely. Next, the performances of these TCS structures are calculated using the same vehicle physical parameters in three different road-traffic conditions requiring different torque demands. Finally, after understanding more about the system dynamics of TCS, it is thought that if any method or estimation process could supply a dynamic measurement of road conditions such as optimum slip ratio or the uncertainty bound, then TCS performances could get better. Following this approach, a low-cost road-type estimation system is proposed based on acoustic data collected from the vicinity of interface between the road and the tire. The design of acoustic road-type estimation (ARTE) system is given including data collection set-up, feature extraction process and classification. Finally ARTE system is integrated in all three TCS structures for supplying the uncertainty bounds in the system or the optimum lambda value. It was found that, based on the simulation tests, ARTE system is able to improve the performances of SRC and MTTE greatly while it does not necessarily improve the performance of MFC.

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