RELIABLE VEHICULAR CONSUMPTION PREDICTION BASED ON MACHINE LEARNING

Michail Masikos, Konstantinos Demestichas, Evgenia Adamopoulou, Michael Theologou[*]

Abstract: A robust prediction model is developed for reliably estimating vehicular consumption. This model is distinguished from other models proposed so far for the following reasons: it detects the factors contributing into vehicular consumption, it applies machine learning functionality for approximating the nonlinearities and the specificities between the contributing factors, and it is capable of implicitly adapting to the characteristics of the vehicle, the road network and the contextual conditions through its learning process. The authors validated its efficiency by applying it on measurements collected during a data acquisition campaign, which was performed by a fully electric vehicle (FEV) in an urban road network.

Key words: *MLP, consumption model, context-aware prediction, FEV*

Received: October 23, 2013 **DOI:** 10.14311/NNW.2014.24.019
Revised and accepted: July 18, 2014

1. Introduction

Nowadays, there is a growing interest in reliably estimating a vehicle's energy consumption (either fuel or electrical consumption) towards a specific destination. The pre-trip knowledge of the expected energy consumption along a route may affect the decision of selecting a particular route among the available ones considering the constantly rising price of energy, as well as due to ecological reasons [2, 4, 5]. Furthermore, such knowledge is necessary in order to calculate the reachability of a destination before settling towards it. The outcome of this calculation is very important especially in cases of vehicles consuming alternative fuels, which have limited reserves and certain restrictions regarding their refuelling process. For example, the FEVs' recharging process is significantly time consuming, while the compressed natural gas (CNG) vehicles' refuelling network is very limited. Thus, the accuracy and reliability of the energy consumption estimation is of high significance when planning the routing and refuelling strategies of such vehicles.

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Several techniques have been proposed for vehicular energy consumption estimation. In [8] authors formulated a fuel consumption model using only engine efficiency characteristics as part of an ecological vehicle control system. An ecological route search mechanism that generates routes requiring the least amount of fuel by considering many factors such as traffic information, geographic information, and vehicle parameters is introduced in [11]. Another analytical model is presented in [12] where link energy consumption is calculated based on the actual power needed to overcome the driving resistance for each link using link travel speeds and volume/capacity-ratios. In all these studies, authors try to develop a deterministic formula for fuel consumption estimation adopting a different factor analysis. However, the complexity and the nonlinearities prevailing in the relations between the factors contributing in vehicular consumption impose a lower bound in the estimation error of these models.

In order to overcome this limitation, we propose a prediction model based on machine learning (ML) functionality. ML involves searching a very large space of possible hypotheses to determine one that best fits the observed data. Then, this optimal hypothesis can be used to estimate the energy consumptions in case of future and possibly yet unseen contextual instances. ML functionality has already been applied successfully in a model predicting the torque and brake-specific fuel consumption of a gasoline engine (the rate of fuel consumption divided by the power produced) [9]. The spark advance, the throttle position and the engine speed constitute the inputs of the artificial neural network (ANN) based formulation developed in the context of this study. In a similar manner, the make of car, the engine style, the weight of car, the vehicle type and the transmission system type are used as input information for an ANN based predictive system introduced in [19]. The developed model comprises three parts (i.e. the information acquisition system, the fuel consumption forecasting algorithm and the performance evaluation process) and provides reliable forecasts of the vehicular consumption rates in different environments (city, highway or mixed mode). Although the implementation of ML functionality proved to be successful in the reviewed studies, exploiting the average rates that are generated by these models (i.e. the brake specific fuel consumption and the fuel consumption rates in city, highway or mixed mode) can lead only to a rough estimation of the expected vehicular consumption along a specific road segment. Thus, the present paper proposes the development of a ML based model that estimates directly the vehicular consumption along a specific road segment based on the current contextual instance.

The rest of this paper is organized as follows. In Section 2, the proposed model for vehicular consumption prediction is introduced. Section 3 presents the contextual parameters identified as major contributors in vehicular consumption. Section 4 describes the validation process and analyzes the generated results. Finally, Section 5 summarizes the work and concludes the paper.

2. Prediction Model

The first step in designing a learning system involves choosing the training experience through which the system will learn. Herein, we propose to exploit training data collected by vehicles while travelling along everyday routes (i.e. energy con-

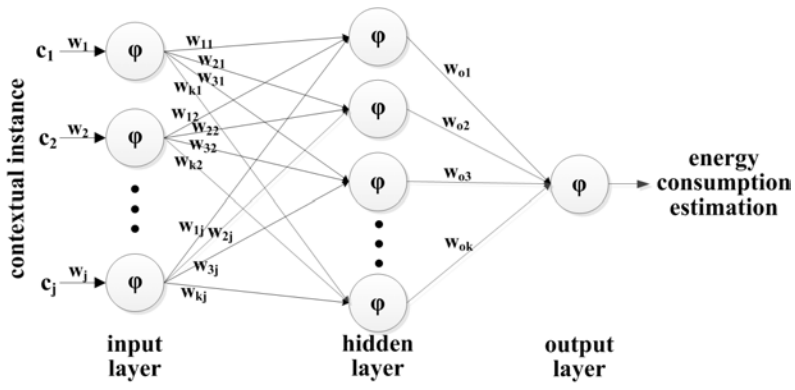

Fig. 1 *The MLP network used for energy consumption prediction.*

sumption along road segments, together with contextual attributes such as weather characteristics). In this way, the developed system tries to infer the relations underlying real collected data and, subsequently, after training, it is rendered capable of running in an autonomous fashion. The second step involves selecting the target function of the learning system. Here, as target function, we choose a function f that calculates the energy consumed after travelling a road segment based on the current context ($f : C \to \mathbb{R}$). Next step involves choosing an ideal representation $\hat{f}$ for the target function. Considering that the energy consumption calculated by the target function is a real value and that the relations dominating among the context factors are non-linear, we propose the use of artificial neural networks, and specifically multilayer perceptrons (MLP), for representing the target function.

MLPs are proved to be an effective tool in several application areas. According to the literature survey conducted in [20], which evaluates the recent applications of artificial intelligence-based modelling studies in the environmental engineering field, the three-layer feed-forward and back-propagation MLP networks are considered as one of the simplest and the most widely used ML networks. Their performance either in estimating the effectiveness of various biological and chemical treatment processes or in forecasting the levels of various air pollutants (e.g. NO_2, SO_2, etc.) or in modelling the weight of solid waste generation is proved to be significant. Quite astonishing is also the performance of the ML based model that is proposed in [3] as a tool for measuring the speech quality in Voice over Internet Protocol (VoIP) networks. Other application areas where the usage of MLP networks resulted in significant performance results include photovoltaic power plant ouput prediction models [17], time series forecasting in stock markets [15], prediction of shear strength of reinforced concrete beams [1] and prediction of monthly natural gas consumption [13]. In addition to the previously cited achievements, the application of MLP techniques in image processing technology gave also a major boost to the successful interpretation of medical images and the early diagnosis of serious diseases [6]. Thus, the reported prediction capabilities of the MLP networks render their usage a quite promising solution in environmental applications, and herein we employ them for reliably estimating vehicular consumption.

The structure of the designed MLP is depicted in Fig. 1 and consists of the input layer, one hidden layer and the output layer. According to the MLP network structure, the representation $\hat{f}$ for the target function can be written in the following nested form:

$$\hat{f}(\vec{c}, \vec{w}) = \phi \left(\sum_k w_{ok} \phi \left(\sum_j w_{kj} \phi(w_j c_j) \right) \right) \tag{1}$$

where $\phi(.)$ is a sigmoid activation function, w_{ok} is the synaptic weight from neuron k in the hidden layer to the single output neuron o, w_{kj} is the synaptic weight from neuron j in the input layer to the neuron k in the hidden layer and c_j is the jth element of the input vector $\vec{c}$.

The sigmoid activation function $\phi(.)$ applied to the MLP network is:

$$\phi_j(u_j(n)) = \alpha \cdot tanh(b \cdot u_j(n)), \qquad (a, b) > 0 \tag{2}$$

i.e. the hyperbolic tangent function where a and b are constants and u_j is the weighted sum of all synaptic inputs of neuron j.

The design of the learning system is completed with the adoption of a learning algorithm. The most widespread choice in case of MLPs is the backpropagation algorithm [18], which searches the space of possible hypotheses using gradient descent to iteratively reduce the error in the network fit to the training dataset. However, in order to accelerate the typically slow rate of convergence experienced with the method of gradient descent, we propose the use of the conjugate gradient descent method [14] that handles the supervised learning as a numerical optimization problem. The objective of the learning process is to adjust the weights of the MLP network to minimize the average squared error energy function E_{av} over all (N) examples of the training set:

$$E_{av} = \frac{1}{N} \sum_{n=1}^{N} E(n) = \frac{1}{N} \sum_{n=1}^{N} \frac{1}{2} e_o^2(n) = \frac{1}{N} \sum_{n=1}^{N} \frac{1}{2} (d_o(n) - y_o(n))^2 \tag{3}$$

where e_o is the error signal at the output neuron, d_o is the desired response of the output neuron and y_o is the function signal appearing at the output neuron.

The conjugate gradient descent method tries to iteratively minimize the quadratic part of the Taylor series expansion of E_{av} (eq. 4) and is briefly described by the set of equations (5)-(9):

$$E_{av}(w(n)) + g^T(n)\Delta w(n) + \frac{1}{2}\Delta w^T(n) H(n) \Delta w(n) \tag{4}$$

$$s(0) = r(0) = -g(0) \tag{5}$$

$$w(n+1) = w(n) + \eta(n) s(n) \tag{6}$$

$$r(n+1) = -g(n+1) \tag{7}$$

$$\beta(n+1) = max(\frac{r^T(n+1) \cdot (r(n+1) - r(n))}{r^T(n) \cdot r(n)}, 0) \tag{8}$$

$$s(n+1) = r(n+1) + \beta(n+1)s(n) \tag{9}$$

where $g(n)$ is the local gradient vector and $H(n)$ is the local Hessian matrix.

The result of the learning process is finding the hypothesis that best fits the observed data and thus reliably predicts the vehicle's energy consumption (according to the inductive learning hypothesis).

3. Measurements

A data acquisition campaign was carefully planned and conducted in order to generate the necessary dataset for verifying and validating the proposed model. The objective of the planning was twofold: first, to collect a number of consumption measurements corresponding to several contextual instances and generate an efficient training dataset; and, second, to define validation routes and generate the appropriate validation dataset. The campaign was performed by a FEV [16] in the town of Chieri, Turin area, Italy (approx. 1275km travelled). The training instances were recorded by an on-board computer connected both to the vehicle's controller area network bus socket and to external sensors (i.e. GPS, temperature and humidity sensors).

Five groups of context parameters have been detected as contributors to vehicular consumption, namely the *Vehicle Context*, the *Traffic Context*, the *Road Context*, the *Weather Context* and the *Driver Profile*. The *Vehicle Context* includes the vehicle characteristics that affect the vehicular consumption in a direct (e.g. the usage of electric auxiliaries or the vehicle gross weight) or in an indirect manner (e.g. the battery's state-of-charge or state-of-health indicators). The *Traffic Context* describes the traffic conditions prevailing in the considered road segment at a given point in time. In general, traffic density, velocity and flow constitute the macroscopic parameters used for describing the traffic status of a specific road segment. Several complicated models have been developed for identifying traffic congestion based on them (such as [10]) or on traffic images' processing (for instance, [7]). As using one of them would result in increased complexity, the periodic trends of the traffic conditions (recurrent traffic) are identified in the proposed model by considering the time window (i.e. the month of the year, the day of the week and the hour of the day) when the vehicle travels along the road segment. The *Road Context* refers to structural characteristics of the road segment that affect directly (e.g. moving uphill leads to increased consumption) or indirectly (e.g. travelling along a highway at high speed leads to increased consumption) the vehicular consumption. The *Weather Context*, on the other hand, describes the weather conditions that affect indirectly the vehicular consumption (e.g. electric auxiliaries that consume energy are turned on during warm or rainy days). Finally, describing the *Driver Profile* is not straightforward, as it refers to the current driving attitude of the driver (e.g. aggressive driving vs. eco-driving). Authors propose the comparison of the driver's average consumption rate (calculated by the vehicle's trip computer) with the vehicle's nominal average consumption rate (specified by the vehicle manufacturer) as the proper parameter for adequately describing the *Driver Profile*.

According to the previous analysis, each instance of contextual attributes comprises observed values of the following set of variables:

$$\overrightarrow{C} = (h_b, l_b, \overrightarrow{s}_{aux}, w_v, t_d, t_{mo}, t_{hr}, \theta_{rs}, \kappa_{rs}, T, RH, \bar{c}_d) \tag{10}$$

where h_b and l_b are the battery's state-of-health and state-of-charge, respectively, $\overrightarrow{s}_{aux}$ is the vector describing the status of the vehicle's electric auxiliaries, w_v is the vehicle's weight, t_d is the current day of the week, t_{mo} is the current month, t_{hr} is the current hour of the day, θ_{rs} is the slope of the road segment, κ_{rs} is the class of the road segment, T is the temperature, RH is the relative humidity and $\bar{c}_d$ is the driver's average consumption rate calculated by the vehicle's trip computer.

4. Experimental Results

After training the learning system with the collected measurements, we proceeded to its functional performance evaluation. The proposed system's performance is evaluated with actual measurements collected while travelling on a set of validation routes (approx. 551km travelled). More specifically, the target of the evaluation process is twofold, i.e. the validation of the system's reliability and the verification of the system's superiority against a reference model.

Fig. 2 depicts the results extracted for validating the proposed model's reliability. The horizontal axis represents the actual energy consumption values measured

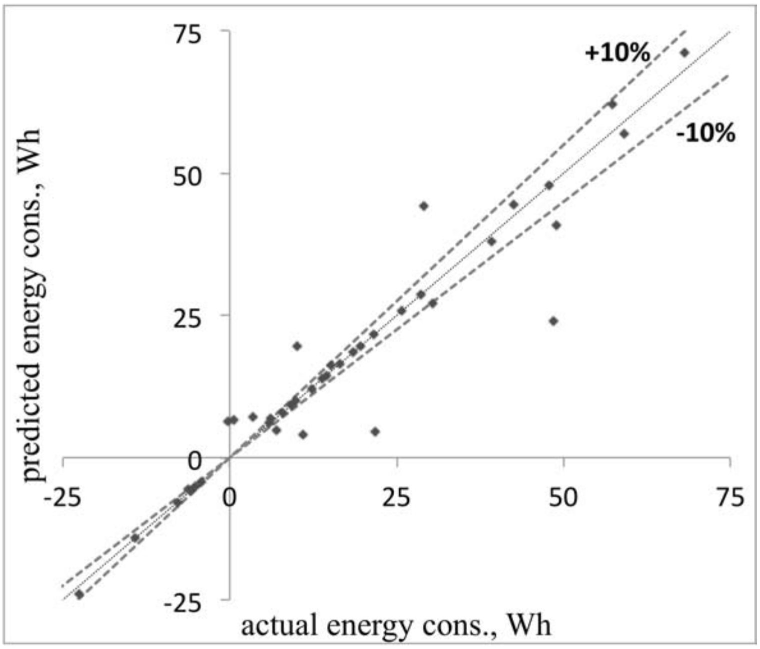

Fig. 2 *Estimation accuracy of the proposed prediction model.*

on the validation routes, while the vertical axis represents the values predicted beforehand through our model. Obviously, the closer the scattered points are to the 1:1 line (45-degree line) the better the prediction accuracy. According to these results, the proposed prediction model is quite accurate and reliable and provides only few energy consumption estimations deviating more than $\pm 10\%$. In other words, the majority of the validation points are quite close to the 45-degree line.

In the next diagram (Fig. 3), the corresponding performance of a reference model is depicted, for comparison purposes. As a reference model, we consider a system that estimates the energy consumption by multiplying the vehicle's average consumption rate per length unit with the length of the route. In the case of our testing vehicle [16], the average consumption rate per length unit is calculated by dividing the values for the battery's nominal capacity and the vehicle's range that are provided by the manufacturer ($22kWh/140km \approx 157Wh/km$). According to the validation results depicted in Fig. 3, the deviation between the reference model's predictions and the measured consumptions is more than 10% in the large majority of the tests. Thus, the reference model is not as accurate as the model proposed in the present paper.

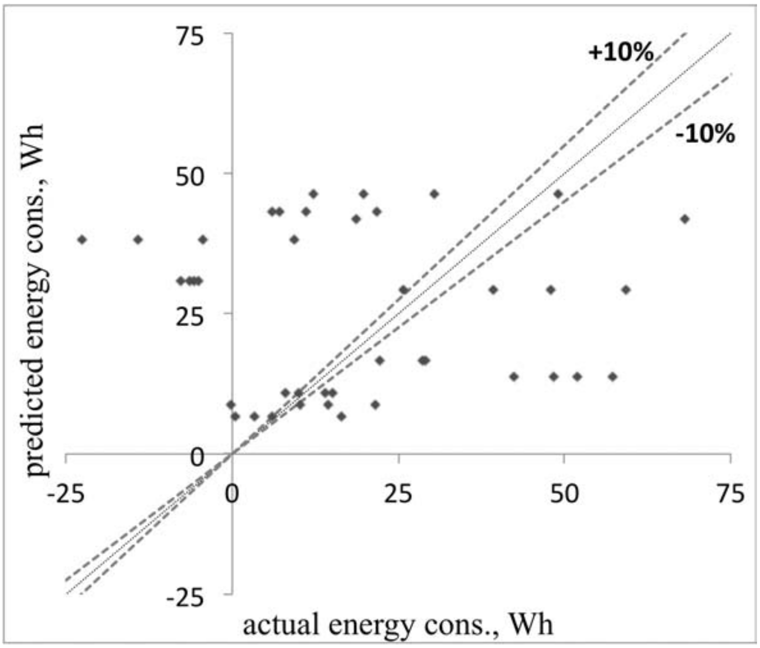

Fig. 3 *Estimation accuracy of the reference model.*

In order to further verify this conclusion, we generate the stem diagram presented in Fig. 4. This figure is a comparative diagram of the estimation error for the proposed MLP model and the reference model. The vertical axis represents the measured estimation error for each model, while the horizontal axis corresponds to distinct validation tests. It should be mentioned that the scale of the vertical axis is limited to ±100%, although some error values cannot be bounded by these limits. This restriction, however, is necessary in order to make the diagram more readable, without significant loss of information. Based on the generated diagram, the proposed vehicular consumption model outperforms the considered reference model as it presents lower estimation error in almost all of the examined tests.

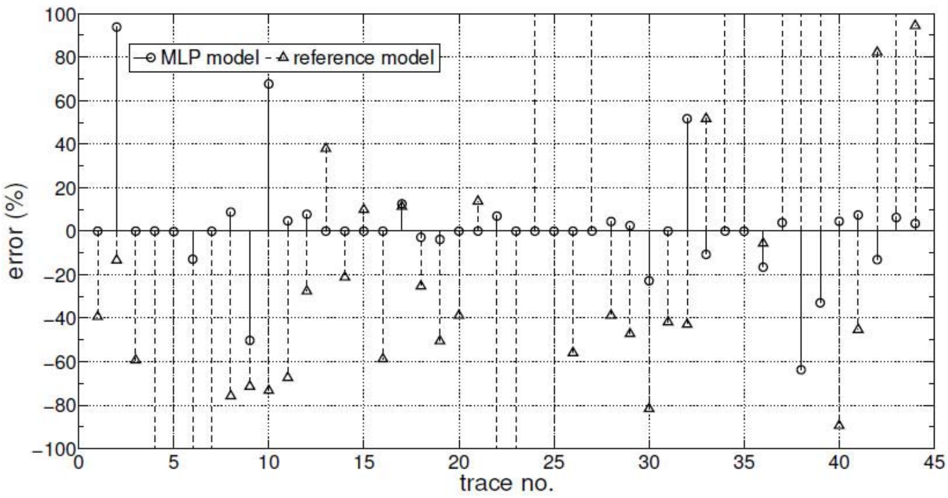

Fig. 4 *Comparative stem diagram of the estimation error for the proposed MLP model and the reference model.*

Finally, in order to quantify the comparison of results between the proposed model and the reference model, the mean percentage error (MPE) and the mean absolute percentage error (MAPE) performance indicators are calculated for both models. Thus, the MPE of the proposed prediction model is 1.22%, which means that it produces very slight overestimations, while the MAPE is 12.36%. On the other hand, the MPE of the reference model is -66.07% (meaning that it features severe negative bias, i.e. produces underestimations) and the MAPE is 189.59%. This means that our model achieves an improvement for the MPE of more than 50 times over the conventional system, and of more than 15 times for the MAPE. This outcome can be attributed to the fact that the conventional system, in contrast to the developed learning system, cannot accurately predict neither the incurred negative consumptions (i.e. the FEV may generate energy while braking) nor the different consumptions occuring when travelling through the same route in different contextual conditions (e.g. different traffic conditions).

5. Conclusion

A context-aware model for predicting vehicular energy consumption is presented in the current paper. The proposed model implements ML functionality and performs energy consumption estimations based on previously collected experience.

The initial results extracted after applying the proposed model on real measurements collected using a FEV are quite promising. In particular, the achieved estimation error of 12.36% on average (less than 10% in the majority of the tests) renders the introduced model quite reliable for predicting vehicular consumption. Furthermore, the introduced model is suitable for supporting a destination reachability assessment tool, because on average it does not understimate the vehicular consumption (as indicated by the computed MPE value of 1.22%).

On the other hand, the present paper uses the same validation dataset in order to evaluate the performance of a reference model. According to the computed MPE value of -66.07%, the reference model severely underestimates the vehicular consumption and, therefore, it is not safe to use it for assessing destination reachability. After the evaluation of the reference model, the extracted results are also compared against the corresponding ones generated by the proposed model. Such a comparison is allowed as the same validation dataset is used for both model evaluations. Thus, the comparison of the MAPE indicators computed for the reference and the proposed models suggests that the latter outperforms the former (15 times better). This outcome is significant since it verifies the robustness of the proposed model, namely its capability of predicting different consumption values for the same road segment when the contextual parameters change (e.g. different traffic conditions).

Acknowledgement

This work has been performed under project EMERALD, which has received research funding from the European Commission's Seventh Framework Programme. This paper reflects only the authors' views, and the European Commission is not liable for any use that may be made of the information contained therein.

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