Use of machine learning based digital twins on vehicle emissions tests.

Eduardo Tomanik
Surface Phenomena Laboratory, Escola Politecnica, USP, Brazil.

Victor Tomanik
Dentsu, Brazil.

Bernardo Tormos
Instituto Universitario CMT - Motores Termicos, Universitat Politècnica de València, Spain.

ABSTRACT

Emission tests generate a huge amount of measurement data but are usually evaluated only regarding the accumulated value according to the emission homologation limits. In this work, a Random Forest machine leaning code was used to create a vehicle digital twin able to predict an output of interest, e.g., instantaneous fuel consumption. The digital twin, after being trained on measurements from the FTP-75 cold start, was able to predict with good accuracy, not only the accumulated values but also the instantaneous values of fuel consumption and CO_2 emissions. A first exercise on a hybrid vehicle showed some potential, but more work is needed to reproduce some of the parameters of interest.

INTRODUCTION

Standard vehicle emission tests (e.g., FTP75, NEDC) are composed by complex velocity transients that demand that the powertrain be optimized not only for stationary engine operation regimes but especially for transient ones. The introduction of Real Drive Emissions enlarged the test envelope to cover almost infinite and unpredictable engine regimes and transients. Such transient tests are expensive and complex to analyze.

Artificial Intelligence (AI) tools, machine learning and especially digital twins are being developed and used on fields as diverse as bank credit scoring, personal targeting interests, image recognition and industrial predictive maintenance. Indeed, machine learning can be applied to any complex system with available sources of large data, cause-effect or at least inputs influencing the output ("target" in the AI jargon). AI literature and tools are abundant and constantly being updated, for more theoretical introduction, the readers are encouraged to see references [1-3].

Most AI-based computing platforms implement the so-called top-down approach, reproducing human decision-making processes to solve a specific task. See Figure 1. Major steps include collecting and preparing data, which involves some data organization and cleaning of spurious or irrelevant information; training the model: a sub-set of historical data is used to train the model; testing the model: data not used for training are input and the model is validated if it can predict the target value. If successful, the model can be used to make analysis, predictions and help optimizations. In opposition to usual physic computer simulations, AI usually demands relatively little computer coding, instead the AI program is "trained" by existent data in a way that somehow mimics a sophisticate statistical approach.

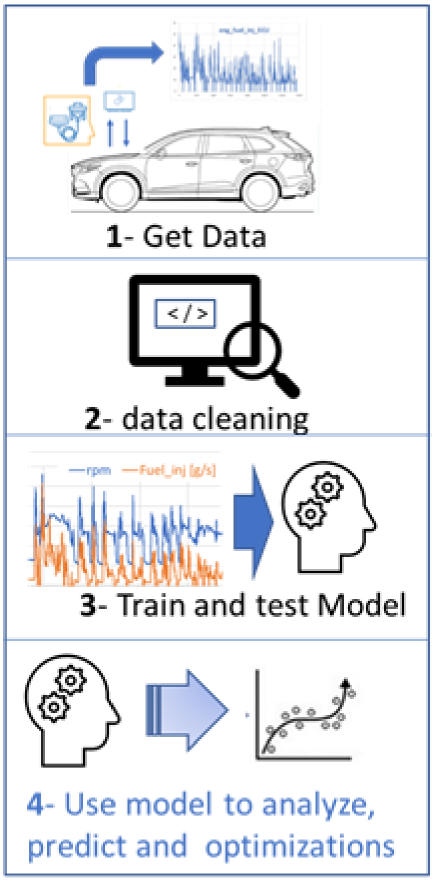

Figure 1- Overview of a machine learning model.

DIGITAL TWIN FOR TRANSIENT TESTS

Digital twin can be defined as digital representation of a real-world physical product, system, or process that can be used as the effectively indistinguishable digital counterpart of it for practical purposes, such as simulation, testing etc. Several authors [3-9] have explored the use of AI to analyze and predict fuel consumption and other parameters. On previous author works [10-11] data from the Downloadable Dynamometer Database, Argonne National Laboratory [12,13] were used to develop tribological and supervised machine learning models to predict instantaneous fuel consumption on emission transient cycles. The developed Random Forest and Neural Network models used dynamometer and/or vehicle Engine Control Unit (ECU) or OBD data from a given test and then were used to predict the output for different tests. See figure 2 and 3.

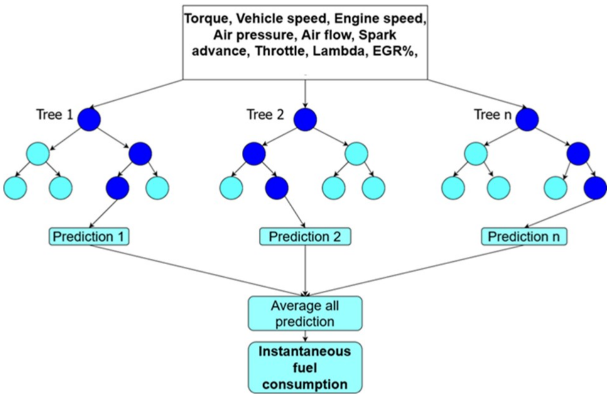

Figure 2- Scheme of the Random Forest model.

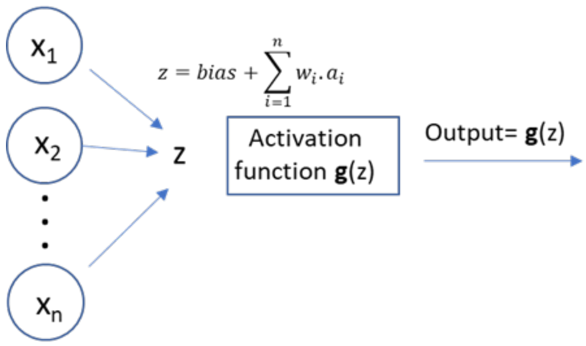

Figure 3- Numerical process in each tree node.

In the current work, the less CPU intensive Random Forest machine learning developed in [11] was applied to predict transient cycles in 4 vehicles:

- 2018 Toyota Camry, tested at ANL using ECU and dynamometer data.
- Brazilian Flex-Fuel car, only ECU data.
- Brazilian Truck RDE test, only OBD data.
- Hybrid vehicle, tested at ANL, ECU and dynamometer data.

The work is part of the development of a digital twin able to support analysis, predictions, and optimizations of vehicle powertrain parameters of interest using mostly data from the vehicle ECU or OBD under RDE tests. In the current stage, the digital twin still needs to be supervised, i.e., data cleaning and selection of the parameters used during the training are done under human supervising. Future work intends to develop data clustering routines, see as example [14].

USE OF ECU, OBD DATA

It is mandatory that all new vehicles have an ECU (or OBD) reading and controlling engine parameters. Using a simple datalogger, detailed and instantaneous readings can be carried out in real time at a much lower cost than engine or car dynamometer tests. On Board Monitoring (OBM) is indeed an application of such approach, when real time data from ECU and the aftertreatment is used to monitor emissions as well as indicating need of maintenance etc.

Dynamometer measured fuel consumption and ECU fuel rate correlated quite well, as expected. Figure 4 compares dynamometer equipment measurements with the vehicle reading ECU on tests done at the Argonne National Laboratory (ANL) database. There are some delays between measurement and cylinder injection as well other instantaneous variations, but such differences almost disappear when the original 10Hz acquisition rate is averaged to 1Hz.

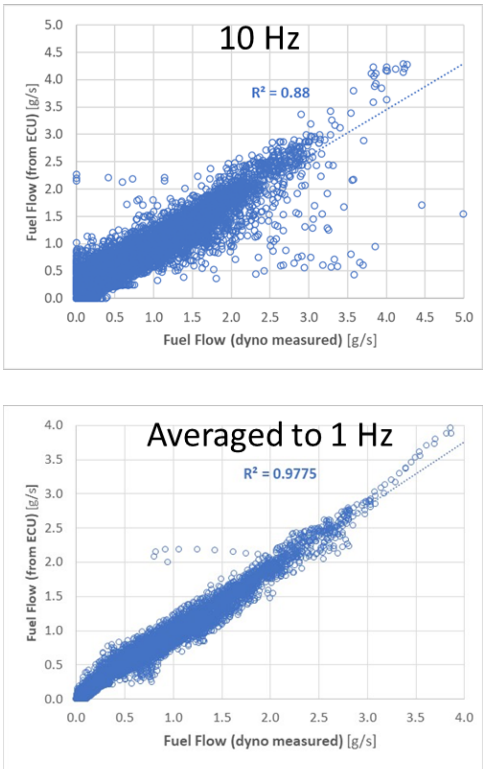

Figure 4- Fuel Flow, ECU data versus Dynamometer measurements.

EMISSION TEST, ECU AND DYNAMOMETER DATA

As first example to demonstrate the developed digital twin, test data from the 2018 Toyota Camry available on the downloadable dynamometer database - Argonne National Laboratory [12-13] was used. The original datasets contain 104 parameters, including ecu readings and dynamometer measurements. For input in the model, no filter was applied in the data, except erasing the readings before and after test and the stop phase in the cold start.

2.5 DOHC I4 engine, Atkison Cycle, naturally aspirated, Port and direction Injection, 8-speed automatic transmission.

Figure 5- Vehicle on chassis dynamometer test [12]

In addition to the ECU data, car acceleration was derived from car speed and included in the datasets for input in the digital twin. Instantaneous ECU Fuel rate (PFI+GDI) or measured CO_2 were used as output to be predicted.

Three data sets were considered: FTP 75 cold start, NEDC and to illustrate the model limitations, a steady state engine mapping. See figures 6-8. Notice that:
- the engine mapping is, of course, very different. Car speed and consequently engine rpm were kept constant during relative long periods; engine reached 6500rpm while in the transient cycles was most of the time lower than 3000rpm.
- Oil temperature varies along the cold start, it was relative constant in the NEDC, and reached peaks around 120°C during the engine mapping.
- CO_2 followed the trends of fuel rate, but it less “noisy”.

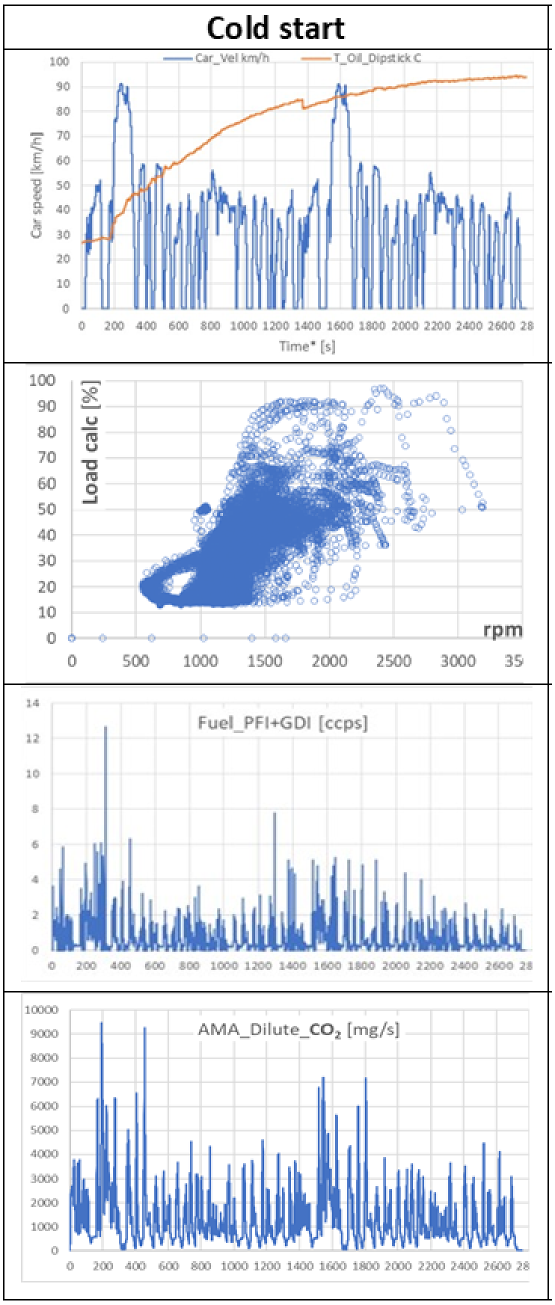

Figure 6- FTP 75 Cold start. From top to bottom: car speed and oil temperature; engine load and speed (rpm); instantaneous fuel rate (PFI+GDI); and the measured CO_2 mass flow.

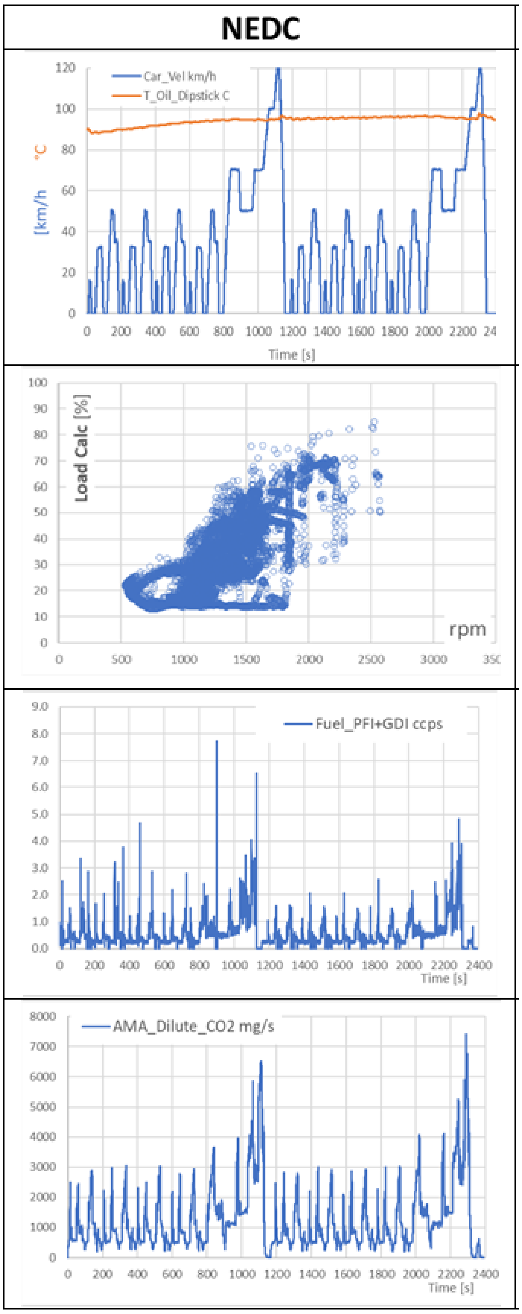

Figure 7. NEDC cycle. From top to bottom: car speed and oil temperature; engine load and speed (rpm); instantaneous fuel rate (PFI+GDI); and the measured CO_2 mass flow.

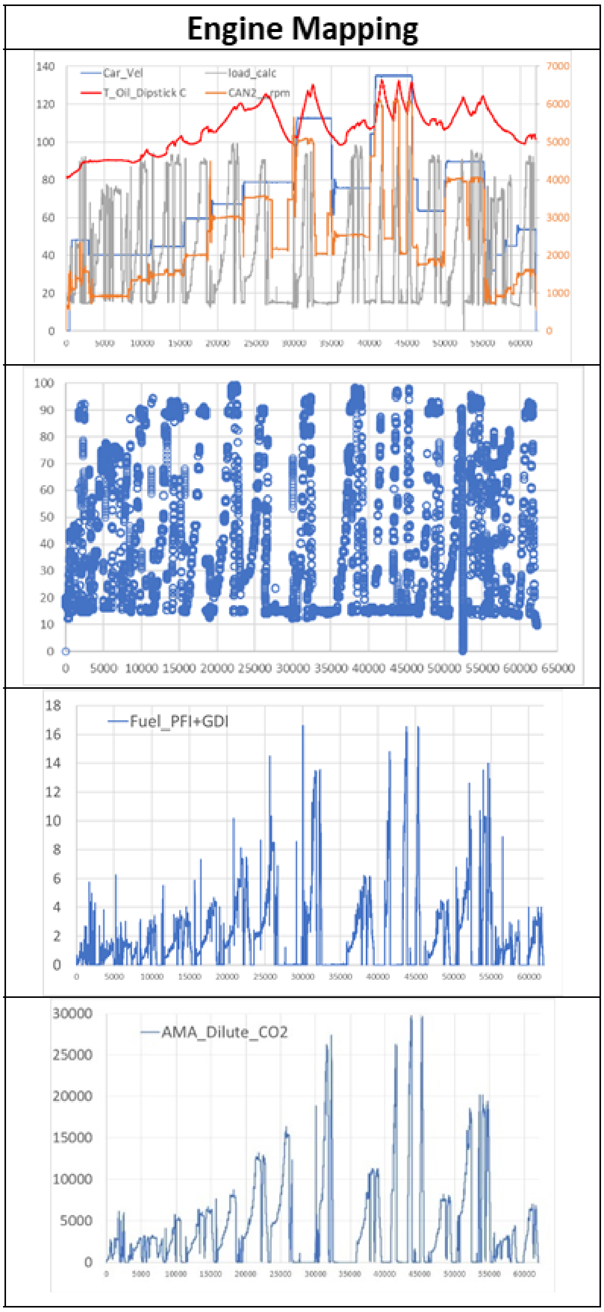

Figure 8- Engine mapping. From TOP to BOTTOM: car speed, oil temperature, engine load and speed (rpm) along the test; engine load and rpm, instantaneous fuel rate (PFI+GDI) and the measured CO_2 mass flow.

Before running the model, a Pearson correlation table is calculated to help the selection of input parameters. See Figure 9. Parameter influence depends on the cycle, oil temperature e.g., had no influence on the NEDC cycle, while as expected, acceleration had not in the engine mapping. Engine load and speed are the more influent parameters.

Fuel Rate

	Cold Start	NEDC	Engine Mapping
Car_Vel	0.29	0.61	0.26
Acc	0.62	0.48	0.00
rpm	0.73	0.77	0.50
Load	0.88	0.93	0.72
T_oil	0.19	0.08	0.35

CO_2

	Cold Start	NEDC	Engine Mapping
Car_Vel	0.44	0.69	0.26
Acc	0.58	0.43	0.00
rpm	0.88	0.86	0.49
Load	0.90	0.94	0.72
T_oil	0.19	0.10	0.27

1.00
0.80
0.60
0.40
0.20
0.00

Figure 9- Pearson correlation for fuel rate and CO_2 for the different tests.

As usual on machine learning, a random subset containing 75% of the data, including the output, was used to train the model. The trained model is then validated using the other 25% data subset. The “trained” digital twin was later applied to predict the output, instantaneous fuel rate or CO_2 for other cycles. CO_2 emissions was selected for this first study as it correlates directly with fuel consumption and does not depend on the aftertreatment temperature and efficiency, similar approach can be used for the other gases.

To evaluate model performance, two indicators were used: R^2 and the difference between model and “real” of the accumulated value along the cycle. Tables 1 and 2 summarize the performance indicators. Trained with the cold start, model performance to predict the fuel consumption and CO_2 along the NEDC cycle was good. See figures 11-14. However, as expected, notice that using the steady state engine mapping (with only the short transients from one regime to the other) to train the digital twin make it unable to adequately predict the transient NEDC cycle. See figure 15.

Table 1 - Instantaneous Fuel Rate (PFI + GDI) as output

CYCLE	training	testing		predicting the NEDC cycle	
	R^2	R^2	Δ%	R^2	Δ%
FTP75 cold start	0.90	0.96	+0.04	0.89	0.5
NEDC	0.94	0.98	-0.10	N.A.	N.A.
engine mapping	0.99	1.00	0.00	0.64	12.0

Table 2 - Instantaneous CO_2 as output

CYCLE	training	testing		predicting the NEDC cycle	
	R^2	R^2	Δ%	R^2	Δ%
FTP75 cold start	0.99	1.0	-0.2	0.95	0.8
NEDC	1.00	1.00	-0.04	N.A.	N.A.
engine mapping	1.00	1.00	0.03	0.84	1.5

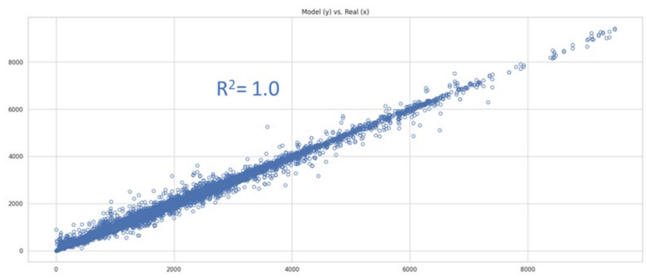

Figure 10- Model vs. Measured CO_2 along the Cold Start

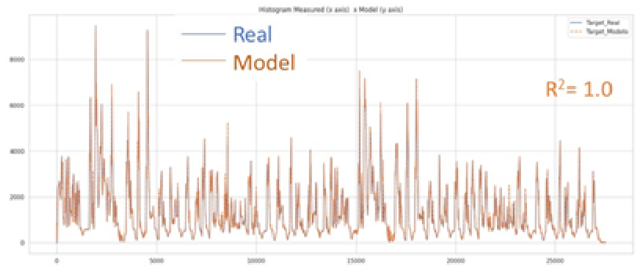

Figure 11- Model vs. Measured- CO_2 along the Cold Start

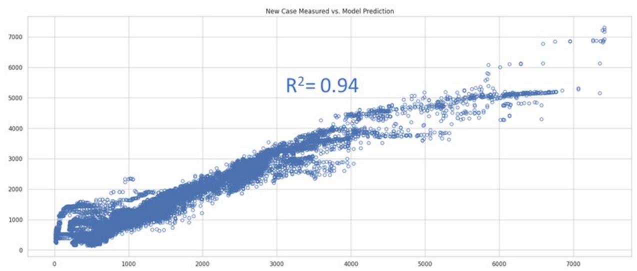

Figure 12- CO_2 along the NEDC, measured and the model (trained with the Cold Start) predictions.

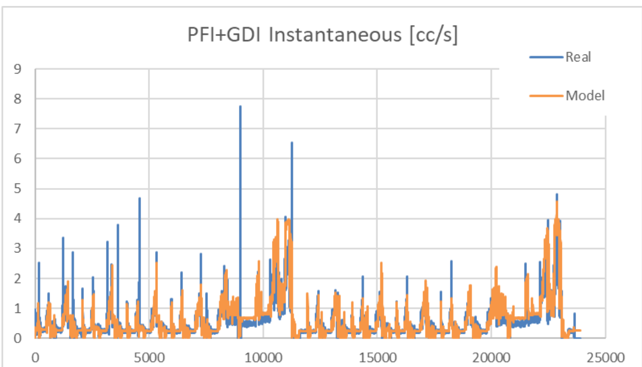

Figure 13- Fuel consumption along the NEDC, measured and the model (trained with the cold start) predictions. R^2= 0.89.

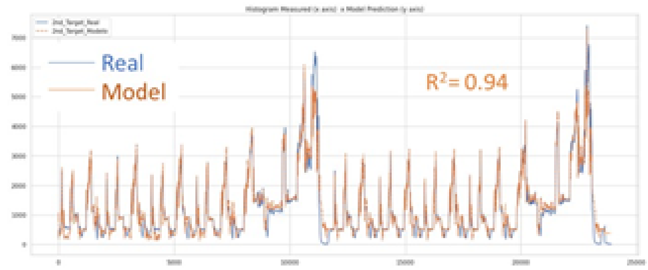

Figure 14- CO_2 along the NEDC, measured and the model (trained with the cold start) predictions.

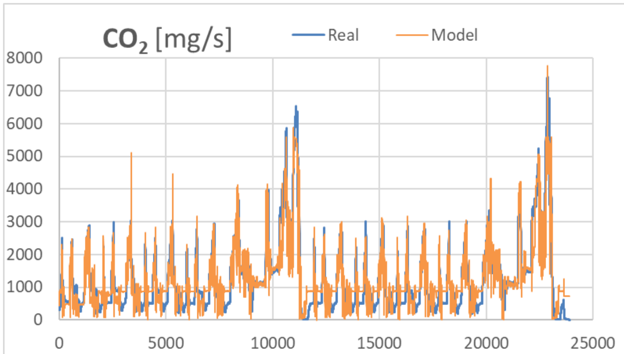

Figure 15- NEDC cycle prediction for instantaneous CO_2 using the engine mapping for training. R^2= 0.84.

BRAZILIAN FLEX-FUEL CAR TEST

Test data from a flex-fuel car, weighting 1350 kg with a 1.4l TDI engine was used. The test was run with the Brazilian E22 gasoline (LHV = 39.32 MJ/kg, density = 0.743 kg/l). In addition to the usual cold start, hot start and highway, another cycle reproducing the highway, but starting at lower temperature was included. See figure 16.

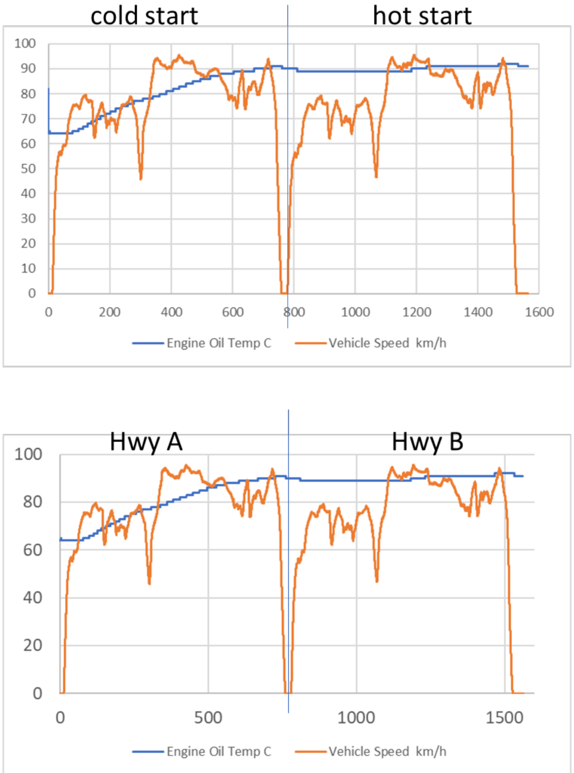

Figure 16- Emission test on the Flex-Fuel car.

For this case, only ECU data was used. Figure 17 shows the Pearson correlation for the different cycles.

	Cold start	Hot start	HwyA	HwyB		
km/h	0.43	0.42	0.22	0.49		scale
rpm	0.72	0.72	0.44	0.59		1.0
torque	0.91	0.95	0.93	0.96		0.8
Throttle %	0.87	0.92	0.88	0.92		0.6
T_cooling	0.30	0.12	0.06	0.20		0.4
T_oil	0.37	0.01	0.04	0.10		0.2
Car_accel	0.53	0.61	0.58	0.50		0.0

Figure 17- Pearson Correlation

Figures 18 and 19 show the model prediction for the cold start. Despite Cooling and oil temperature were relevant for the cold start, they were not for the other cycles. Including the temperatures during the training, improved the model accuracy for the cold start but jeopardized it for the other cycles. As example, the error for the cycle accumulated fuel consumption was 3.1% when including the temperatures but reduced to 0.3% on the Hwy B. See figure 20.

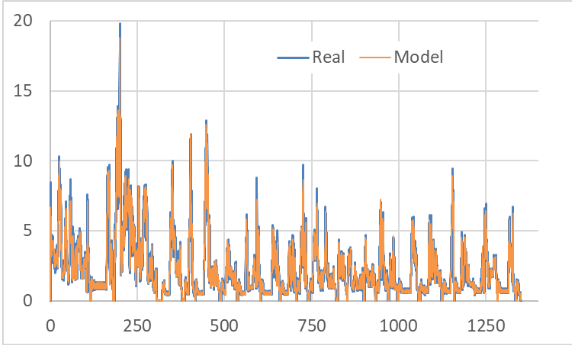

Figure 18- Fuel consumption, model vs. ECU reading, cold start.

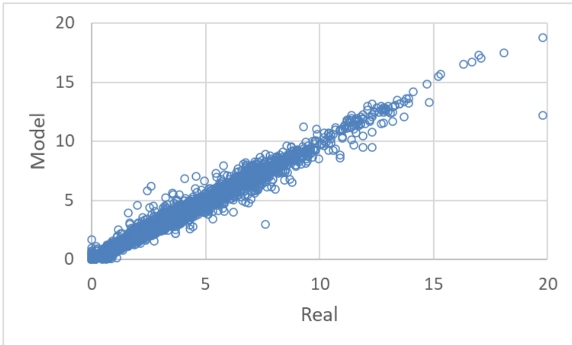

Figure 19- Fuel consumption, model vs. ECU reading, cold start.

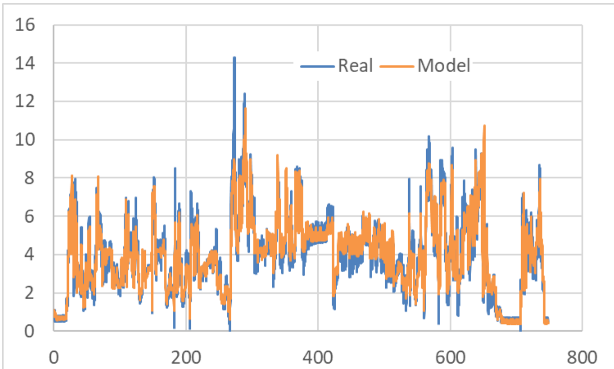

Figure 20- Instantaneous Fuel Consumption, Flex Fuel Car - Predictions for Hwy_B using the cold start for training.

TRUCK RDE TEST

Brazilian RDE test of a N3 class truck was used. Figures 21 shows truck speed and altitude. Similar approach describe on the previous car cases was used. Figures 22 and 23 show the trained digital win versus the measurement. The case is discussed on more details in [11] including use of shorter durations and fewer input parameters.

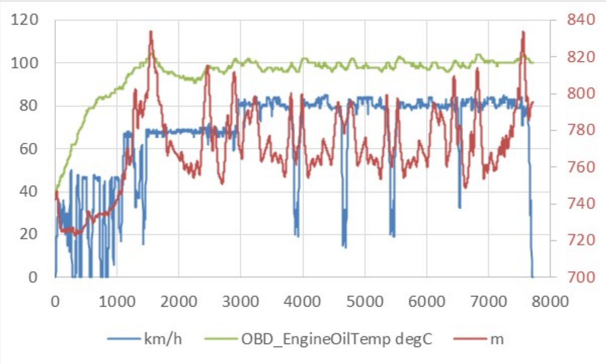

Figure 21- Truck RDE test. Vehicle speed [km/h], T_oil [°C] and altitude (m) along the test.

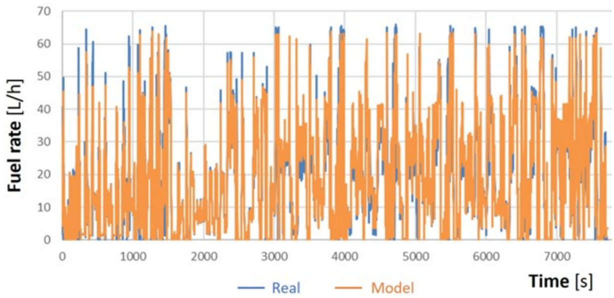

Figure 22- Truck RDE test. Fuel rate.

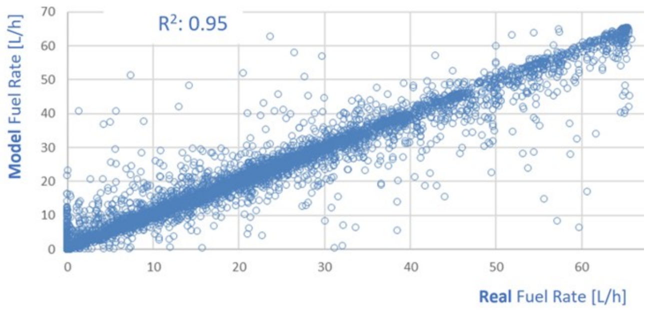

Figure 23- Fuel rate, ECU vs. model.

HYBRID VEHICLE

Hybrid vehicles are more complex to model. Powertrain usage depends on battery status, engine temperature and several other OEM and user strategies e.g., making the car sporty or more economical. Anyway, as long as the digital twin was trained correctly, it should be able to reproduce the vehicle performance and support analysis and optimizations.

As first exercise of using the developed model on a hybrid vehicle, data from 2019 Acura MDX Sport Hybrid from [15] was used. Table 3 summarizes the main vehicle characteristics.

Table 3 – 2019 Acura hybrid main characteristics [15]

all wheel drive (SH-AWD) hybrid architecture	
Transmission:	7-speed dual clutch
ICE	3.0 liter, V6, Port Injection
	192kW, 296Nm
HV Battery	Lithium-ion 260V, 1.3kwh, Air cooled
Front Motor	DC brushless, permanent magnet, single motor
	35kW, 148Nm, 7950 rpm (max)
Rear Twin Motor Unit	DC brushless, permanent magnet motors
	27kW, 73Nm, 11,000 rpm (max)

The ANL test data for this vehicle contains more than 200 parameters including status of the individual battery cells, if the head light is on etc. For this first study, instantaneous motor electrical power (front + rear) was chosen as parameter as target (i.e., to be predicted). Figure 24 shows car speed and the High Voltage Battery SoC (Status of Charge) percentage during the FTP75 cycle.

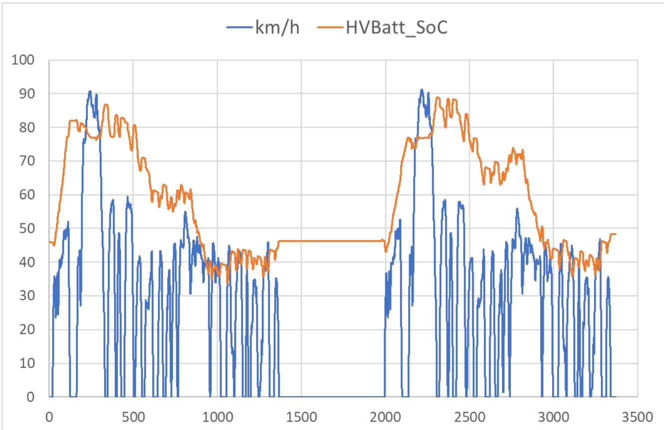

Figure 24- Car Speed and High Voltage Battery SoC (Status of Charge) percentage. FTP75 cycle

Figure 25 shows the Pearson correlations on the three studied tests: FTP75 hot and cold phases and the more aggressive US06. Car acceleration was the parameter with major influence, maybe due to the sporty characteristic of the vehicle. Somehow surprisingly Battery Status of Charge (SoC) was not found to be influent.

	cold	hot	US06	
Car speed	0.07	0.07	0.09	1.0
Car acc.	0.56	0.59	0.56	0.8
ICE rpm	0.17	0.18	0.30	0.6
ICE torque target	0.23	0.20	0.50	0.4
Fuel Flow	0.24	0.22	0.41	0.2
T_oil	0.16	0.10	0.06	0.0
Battery SoC	0.03	0.04	0.02	

Figure 25- Pearson correlation for the Instantaneous electrical power (front + rear motors)

The model was able to reproduce the output for the same cycle that it was trained. But not to predict other cycle than the one it was trained. See table 4. Figure 26 compares as example the model predictions for the instantaneous motor electrical power for the FTP75 hot phase, when trained with the cold start phase. Positive values, i.e., when the electrical power is actuating was relatively well reproduced, but not when the battery is being charged (negative values). Predictions for the US06 were completely inadequate using the Random Forest model

Table 4- Predictions for the instantaneous electrical power.

CYCLE	training	testing		predicting the cycle	
	R^2	R^2	Δ%		R^2
cold start	0.96	0.99	-0.4	hot	0.73
				US 06	0.19
hot start	0.95	0.98	3.5	US 06	0.06
US 06	0.94	0.98	3.7	-	-

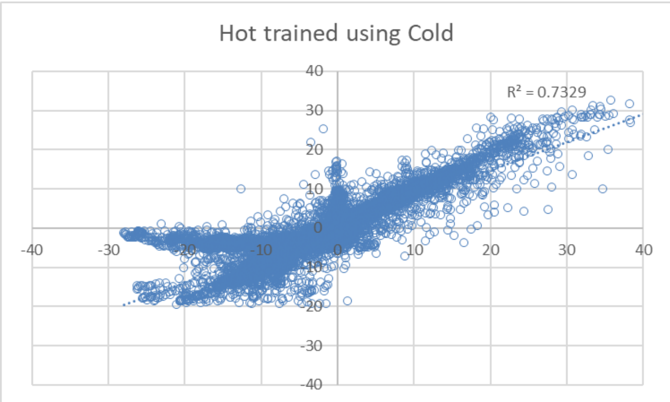

Figure 26- Instantaneous motor electrical power in kW, model predictions in the Y axis, ECU reading on X axis. Hot start with the model trained with the cold one.

HYBRID VEHICLE - USING NEURAL NETWORK TO PREDICT US06 CYCLE.

The same Random Forest model used to the other cases failed to accurately predict the US06 cycle, when trained with the milder FTP 75 cycles. To overcome such limitation, the more complex Artificial Neural Network, ANN, model from University of Patras was used. Much better results were obtained. See table 5 and figures 27 and 28.

The Patras ANN has four hidden layers with 50, 50, 50 and 50 neurons respectively. The loss function is the ‘mean squared error’, the optimization algorithm is the ‘Adam’, the activation function for hidden layers is ReLU, and for the output layer is the linear. To avoid overfitting several methods applied during the training such as early stopping, and feature scaling can be used. Early stopping method stops the training after some number of optimization steps not leading to decreased validation loss. Feature scaling can be done for the whole dataset during the preprocessing stage, and it means that every feature in the dataset is scaled independently in the range 0-1.

Table 5- ANN predictions for the instantaneous electrical power.

CYCLE	testing		predicting the cycle	
	R^2	MAE [kW]		R^2
cold + hot start	0.87	3.3	US06	0.84

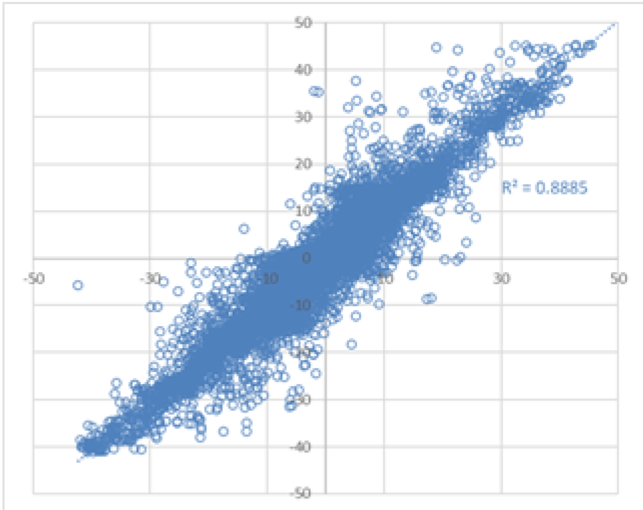

Figure 27- Instantaneous motor electrical power in kW, Patras ANN model. Predictions for the US06 with the model trained with the FTP75 (cold and hot).

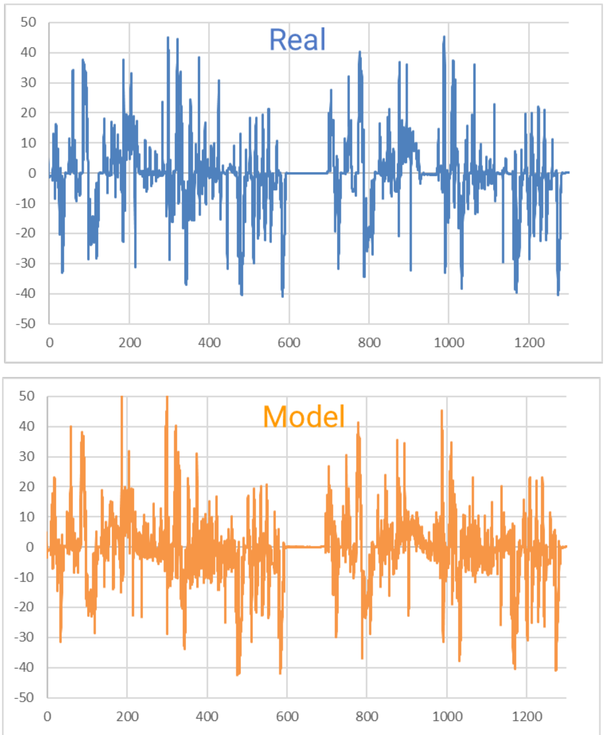

Figure 28- Instantaneous motor electrical power in kW, along the US06 cycle. Patras ANN model trained with the FTP75 (cold and hot).

CONCLUSIONS

The developed RF model was able to predict with good accuracy the instantaneous fuel consumption and CO_2 emissions for conventional ICE vehicles.

Model accuracy depends on a proper selection of input parameters and that the "experimental space" of the cycle to be predicted be relatively covered during the training. As obvious example, using a steady state engine map for training, makes the digital twin unable to predict a transient cycle.

A first exercise on a hybrid vehicle showed some potential, but the RF model failed to predict the more aggressive US06 cycle, probably because the cycles used for trained do not include the conditions faced in the US06 cycle. A more refined ANN model showed much better results.

The approach described in this work opens opportunity to less costly vehicle transient tests. Automated selection of the input parameters as well as data cleaning are needed for a more robust model and are planned.

ACKNOWLEDGMENTS: the authors would like to thank to Ioannis Tselios, Anastasios Zavos and Pantelis Nikolakopoulos from the Machine Design Laboratory, Department of Mechanical Engineering and Aeronautics, University of Patras, Greece for the valuable discussions and for the ANN modeling of the Hybrid vehicle.

REFERENCES

1. Machine Learning - A Probabilistic Perspective by Kevin P. Murphy. The MIT press, 2012. ISBN 9780262018029
2. Sarker, I.H. Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN Comput. Sci.* **2021**, *2*, 160.
3. Ho, T. Random decision forests. In Proceedings of the 3rd International Conference on Document Analysis and Recognition, Montreal, QC, Canada, 14–16 August 1995; pp. 278–282.
4. Hien, N.L.H.; Kor, A.L. Analysis and prediction model of fuel consumption and carbon dioxide emissions of light-duty vehicles. *Appl. Sci.* **2022**.
5. Katreddi, S.; Thiruvengadam, A. Trip based modeling of fuel consumption in modern heavy-duty vehicles using artificial intelligence. *Energies* **2021**.
6. Gong, J.; Shang, J.; Li, L.; Zhang, C.; He, J.; Ma, J. A Comparative Study on Fuel Consumption Prediction Methods of Heavy-Duty Diesel Trucks Considering 21 Influencing Factors. *Energies* **2021**.
7. He, Y.; Rutland, C. Application of artificial neural networks in engine modelling. *Int. J. Engine Res.* **2005**.
8. Ziółkowski, J.; Oszczypała, M.; Małachowski, J.; Szkutnik-Rogoż, J. Use of Artificial Neural Networks to Predict Fuel Consumption on the Basis of Technical Parameters of Vehicles. *Energies* **2021.**
9. Perrotta, F.; Parry, T.; Neves, L. Application of machine learning for fuel consumption modelling of trucks. In Proceedings of the 2017 IEEE International Conference on Big Data, Boston, MA, USA, 11–14 December 2017; pp. 3810–3815.
10. Tomanik, E., Tomanik, V., Morais, P. Use of tribological and AI models on vehicle emission tests to predict fuel savings through lower oil viscosity, SAE Technical Paper (2021-36-0038) **2021**.
11. Tomanik, E.; Jimenez-Reyes, A.J.; Tomanik, V.; Tormos, B. Machine-Learning-Based Digital Twins for Transient Vehicle Cycles and Their Potential for Predicting Fuel Consumption. Vehicles **2023**.
12. Downloadable Dynamometer Database—Argonne National Laboratory. Available online: https://www.anl.gov/es/downloadable-dynamometer-database (accessed on 22 March 2023).
13. Overview of the ANL Chassis Dynamometer Test Facilities and Methodology. Available online: https://anl.app.box.com/s/5tlld40tjhhhtoj2tg0n4y3fkwdbs4m3 (accessed on 22 March 2023).
14. Krysmon, S.; Claßen, J.; Pischinger, S.; Trendafilov, G.; Düzgün, M.; Dorscheidt, F. RDE Calibration—Evaluating Fundamentals of Clustering Approaches to Support the Calibration Process. Vehicles 2023
15. https://www.anl.gov/taps/d3-2019-acura-mdx-sport-hybrid (accessed on 22 March 2023).