Revolutionizing Heavy Vehicle Fuel Efficiency: A Distance-Based Machine Learning Approach

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ABSTRACT:"Emphasizing the significance of fuel consumption across all vehicle lifecycle stages, this paper proposes a data summarization strategy centered on distance rather than conventional time intervals for crafting personalized machine learning models. The focus is on optimizing fuel consumption in heavy vehicles using machine learning techniques. The effectiveness of a methodology aimed at reducing fuel consumption in heavy-duty vehicles (HDVs) is detailed and assessed through simulations and real-world HDV experiments. The suggested model can be easily tailored and implemented for each vehicle within a fleet to enhance overall fuel efficiency. Furthermore, the study demonstrates the reliability of simulations for direct application to real HDVs. Notably, in scenarios where speed variation range was limited, the proposed method exhibited an average improvement of approximately 3 percentage points over standard predictive cruise control (PCC) across identical road profiles."

KEYWORDS: Artificial Neural Networks (ANN),fuelconsumptionoptimization,data summarization, HeavyVehicles.

I. INTRODUCTION

The average fuel consumption for vehicles isneededandcrucialalloverthephasesoftheir life-cycle. These models are importanttothemanufacturestobuildthepartsofvehiclesaccordingly,regulatorsandconsumers[1].Inordertodealwithincreasingly strict limitations on greenhousegasemissions,andthelikelyincreasein(fossil)fuelprices,heavy-dutyvehicle(HDV) manufacturers are under pressure toreduce fuel consumption.

Moreover,thecompetitivenatureoftheHDVmarketalsoforcesmanufacturerstodevelop fuel-efficient vehicles [2]. On a flatroad, driving with constant speed (standardcruise control) is the optimal solution to theproblem of minimizing the fuel consumptionwith a constraint on travelling time. Speedprofile optimization is an effective approachfor reducing the fuel consumption of a singleHDV.Thisapproachcanalsobeusedinotherapplicationssuchasin HDVplatooning[3].

In general, every customer wants to use lessfuelforthevehicleswithmoreprofit.Ingeneral, techniques used to develop modelsfor fuel consumption fall under three maincategories:•Physics-basedmodels,whichare derived from an indepthunderstandingofthephysicalsystem.Thesemodelsdescribe the dynamics of the components ofthe vehicle at each time step using detailedmathematicalequations.

• Machine learning models, which are data-drivenandrepresentanabstractmappingfrom an input space consisting of a selectedsetofpredictorstoanoutputspacethatrepresentsthetargetoutput,inthiscaseaveragefuelconsumption.•Statisticalmodels,whichareals odata-drivenandestablish a mapping between the probabilitydistributionofaselectedsetofpredictorsandthe target outcome

It is common to formulate the speed profileoptimization problem as an optimal controlproblem[4].Inthisformulation,theoptimizationiscarriedout(duringdriving)

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with respect to fuel consumption, and withconstraintsontravellingtime,numberofgearshifts, and the allowed speed range forthevehicle.Thesemethods,whichareusuallyreferredtoaspredictivecruisecontrol, allow the vehicle to deviate from thecruise control's set speed based on the slopeangleof theroad ahead.

Severalpreviousmodelsforbothinstantaneous and average fuel consumptionhave been proposed. Physics-based modelsare best suited for predicting instantaneousfuel consumption because they can capturethedynamicsofthebehaviorofthesystemat different time steps [5]. Machine learningmodels are not able to predict instantaneousfuelconsumptionwithahighlevelofaccuracy because of the difficulty associatedwithidentifyingpatternsininstantaneousdata.However,thesemodelsareabletoidentifyandlearntrendsinaveragefuelconsumption withanadequatelevelofaccuracy.

Previouslyproposedmachinelearningmodels for average fuel consumption use asetofpredictorsthatarecollectedoveratime period to predict the corresponding fuelconsumption in terms of either gallons permileorlitersperkilometer.Whilestillfocusing on average fuel consumption, ourproposed approach differs from that used inprevious models because the input space ofthe predictors is quantized with respect to afixeddistanceasopposedtoafixedtimeperiod. Intheproposedmodel,allthepredictors are aggregated with respect to afixedwindowthatrepresentsthedistancetraveled by the vehicle thereby providing abetter mapping from the input space to theoutputspaceofthemodel.Incontrast,previous machine learning models must notonly learn the patterns in the input data butalsoperformaconversionfromthetimebasedscaleoftheinputdomaintothe distance-basedscaleoftheoutputdomain(i.e.,averagefuel consumption).

II. LITERATURESURVEY

S. Wickramanayake and H. D. Bandara, et.al. [6] arranged Fuel utilization forecast ofarmadavehiclesexploitationAI.Theytrained an ability to display andanticipatethefuelutilizationissignificantin improvingefficiencyofvehiclesandforestallingoffensiveexercisesinarmadathe board. Fuel utilization of a vehicle reliesuponafewinteriorcomponentslikedistance,vehiclequalities,anddriverconduct,conjointlyasoutsidefactorslikestreetconditions, traffic,and climate.

L. Wang, A. Duran, J. Gonder, and K. Kelly,et.al.[7]createdDisplayingsubstantial/ mediumdutyfuelutilizationupheld drive cycle properties. They trainedvariouswaysforforeseeingweighty/mediumdutyvehiclefuelutilizationuphelddriving cycledata.Apolynomial model, a recorder fake neural netmodel,apolynomialneuralorganizationmodel,andavariableaccommodativerelapse splines (MARS) model were createdand checked exploitation data gathered fromskeletontestingperformedonapackageconveyance diesel truck operational over theextraordinarymodernDieselTruck(HHDDT),cityterritorygenuineVehicleCycle(CSHVC),newworkCompositeCycle(NYCC),andwaterpoweredhalfbreed vehicle (HHV) drive cycles. H. Almer,et.al.[8],comparestheaccuracyoftheproposedfuelconsumptionmodelswithrespect to input data collected at 1 minuteand 10 minute intervals and concludes thatthe 10 minute interval yields more accuratemodels.Vehicleweightisnottypically available as a standard sensor and the weightwas estimated using the suspension. In thispaper, we also use vehicle speed and roadgradetoderivethepredictorsoftheproposedmodel.G.Fontaras,R.Luz,K.

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Anagnostopoulus,D.Savvidis,S.Hausberger,andM.Rexeis,et.al.[9]utilized perception gas outflows from hdv ineurope-a test confirmation of develop of thearrangedmethodologicalapproach.Asshownbythem,theEuropeanCommissioninjointcoordinatedeffortwithgenuineObligation Vehicle makes, the city CollegeofInnovationandcompletelytotallyextraordinarycounselingandinvestigationbodies hasbeensettingupabeginnerauthoritative system for perception and newsgasemanationsfromgenuineObligation Vehicles(HDVs) in Europe.

H. A. Rakha, K. Ahn, K. Moran, B. Saerens,and E. Van den Bulck, et al. [10] proposed amethodtocalibratetheVT-CPFMmodelparameters for passenger cars by using USEPAcityandhighwaycyclesandfueleconomy ratings. Unfortunately, there wereno currently available public driving cyclesand fuel economy ratings reported for HDT.The model parameters calibrated under onescenario might require recalibration for newscenarios,which istime-consuming.

III. METHODOLOGY

ThearchitectureofHeavyVehiclesFuelConsumptionOptimizationusingMachineLearning ModelisrepresentedinbelowFig. 1.Themodelisdevelopedby usingdutycycles collected from a single truck, with anapproximate mass of 8, 700 kg exposed to avarietyoftransientsincludingbothurbanand highway traffic in the Indianapolis area.DatawascollectedusingtheSAEJ1939standardforserialcontrolandcommunicationsinheavydutyvehiclenetworks.

Severalprocessingstepswereneededinorderto generatethepredictorsofthemodel.Thesepredictorsarederivedfromtwo measurements, namely, road grade andtransmissionoutputspeed.Thefirstprocessingstepconsistedofdownsampling theroadgradeandobtainingthevehiclespeedfromthe transmissionoutputspeed.The road grade was measured using an on-board inclinometer and down-sampled to 1Hz.

In order to reduce the noise in the variable, amoving average low pass filter was appliedtothevehiclespeedobtainedandthevariable was down-sampled from 50 Hz to 1Hz. The purpose of the second processingstep was to derive the synthetic duty cycles.Towards this objective,the duty cycles intherealdataweresplitintosegmentsdefinedbyintervalsbetweenconsecutivevehiclestops.

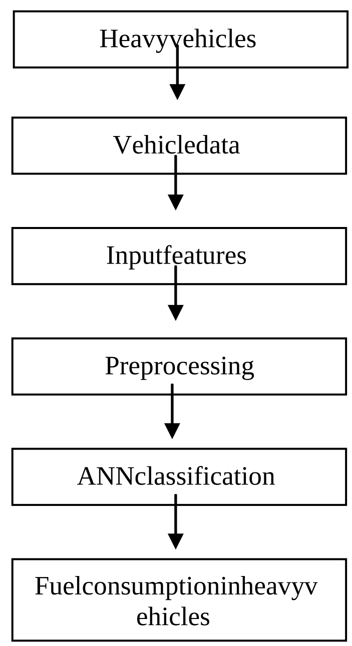

Fig.1:SYSTEMARCHITECTURE

Consider the problem of reducing the fuelconsumptionofanHDV,movingfromagiven start point to a given end point, in acase where the road profile (here representedas a composite Bezier curve) is known. Inorder to evaluate a speed profile in a realHDV,asimilarprocedureisused:Theoptimized speed profile is again used as alook-up table from which the HDV receivesa desired speed based on its current positionalongtheroad.

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The speed profile optimization is carried outinsimulationusingArtificialNeuralNetworks(ANN)withrespecttofuelconsumption only. Moreover, the optimizedspeed profile must fulfill certain constraints,namely(i)theinstantaneousmaximumspeed must not exceed an upper limit (thespeed limit), (ii) the instantaneous minimumspeedshouldbeaboveauser-definedlimitto ensure that the vehicle does not affect thetraffic negatively, and (iii) the average speedshouldnot bebelow acertain threshold.

Dataset will be divided into 80% and 20%format,80%willbeusedtotrainANNmodel and 20% will be used to test ANNmodel. Using this model we can create ANNobject and then feed train and test data tobuildANNmodel.PredictAverageFuelConsumption:-Using thismodulewewilluploadnewtestdataandthen ANNwillapply train model on that test data to predictaveragefuelconsumptionforthattestrecords Fuel Consumption Graph: Using thismodule we will plot fuel consumption graphforeach test record.

Predict Average Fuel Consumption modulewill upload new test data and then ANN willapply train model on that test data to predictaveragefuelconsumptionforthattestrecords.

IV. RESULTANALYSIS

The model is developed by using duty cyclescollectedfromasingletruck,withanapproximate mass of 8, 700 kg exposed to avarietyoftransientsincludingbothurbanand highway traffic in the Indianapolis area.DatawascollectedusingtheSAEJ1939standardforserialcontrolandcommunicationsinheavydutyvehiclenetworks.Twelvedriverswereaskedtoexhibitgoodorbadbehaviorovertwodifferentroutes.Driversexhibitinggoodbehavioranticipatedbrakingandallowedthe vehicle to coast when possible. Some driversparticipated more than others and as a resultthe distribution of drivers and routes is notuniformacross the data set.

Whencoupledwiththedifferenceinstandarddeviationoftheaveragefuelconsumptionforthe1 kmandthe5kmwindows (Table II), this trend indicates thataggregating the input and output data over 5kmprovidesastableprofileforthefuelconsumption of the vehicle over the routesandthisprofiledoesnotnecessitateextensive learning. It was found that the tripdistance is an important indicator and thatpredicting fuel consumption over long routesegments for small vehicles in urban areashasbetteraccuracy.Webelievethatextendingthedatacollectionintervalpromotes a linear relationship between fuelconsumptionanddistancetraveled.Whilethisapproachyieldsgoodaveragefuelconsumption prediction over long distances,point-wise predicted fuel consumption maynotadequatelytrack actual values.

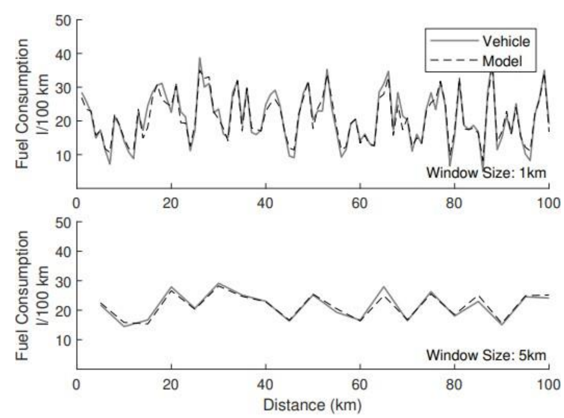

Fig.2:PREDICTEDVERSUSACTUAL FUELCONSUMPTION FROM FTS FOR A 1 KMWINDOW (TOP) AND 5 KM WINDOW(BOTTOM)

To illustrate this behavior, Fig. 2 shows thepredicted and actual fuel consumption overthe first 100 km of the test data set (Fts) forwindow sizes 1 km and 5 km. The 1 kmmodelisabletobettertrackfuelconsumption onaperwindow-basis.These standard deviations indicate that the modelsderivedusingtheproposedapproachare stable.

inordertogeneratetheoptimalspeedprofilesfor theHDV.First,however,theHDV'sfuelconsumptionwasmeasuredwhen driving with standard CC, with a setspeed of 80 km/h, on all 10 road sections soastogeneratethebaselinecaseagainstwhichtheoptimizedspeedprofileswerelatercompared.Next,thespeedprofileoptimization was executed, constraining theminimum average speed of the HDV to be ator above 80 km/h, the maximum speed to beat most 90 km/h, and the minimum speed tobeat least 60 km/h.

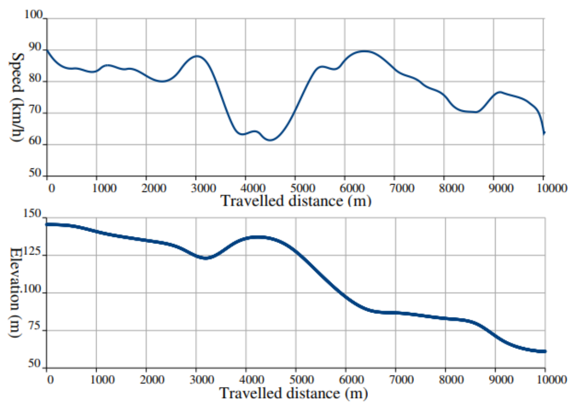

Fig.3:SPEEDOFVEHICLEANDELEVATIONOF ROAD WITH RESPECT TO TRAVELLEDDISTANCE

An example of an optimized speed profile,with its corresponding road profile, is shownin Fig. 3. In this case, the HDV speeds up (ata travelled distance of around 3 km) rightbeforeanuphillclimbwhichhelpsittoavoidexcessiveaccelerationtoreachthetop. Conversely, when driving through thedownhill parts of this road profile, the HDVstarts (attravelled distances ofaround4.5kmand8.5km,respectively)withalowspeed in order to avoid unnecessary brakingduringthedriving.Theoptimizedspeed profiles were then transferred to an HDV inorder to measure its fuel consumption as itfollowedthespeedprofilesoverthesame10 roadprofiles.Theproposedspeedprofileoptimizationalgorithmreducedthefuelconsumption of the HDV substantially, byaround 10.2% on average (over a total of 80km of highway). This saving was achievedwhile the HDV was driving at 77.9 km/h (onaverage)overthe8consideredroadprofiles.

V. CONCLUSION

This paper introduces a method for optimizing fuel consumption in heavy vehicles using a machine learning model. The model provides a numeric value for the amount of fuel consumed, tailored to the specific characteristics of each vehicle. It can be easily customized and implemented for individual vehicles within a fleet, aiming to improve fuel efficiency across the entire fleet.

Various configurations of the model, including window sizes of 1, 2, and 5 kilometers, were tested. Results indicate that the 1 km window size yields the highest accuracy. The model demonstrates the ability to predict actual fuel consumption on a per-kilometer basis with a coefficient of determination (CD) of 0.91. This level of performance is comparable to physics-based models and surpasses previous machine learning models, which typically provide accurate results only for entire long-distance trips.

Additionally, the paper presents an optimization algorithm for speed profiles, which significantly reduces fuel consumption in heavy-duty vehicles (HDVs). On average, fuel consumption decreased by approximately 10.2% over an 80-kilometer highway stretch, with the HDV maintaining an average speed of 77.9 km/h across eight different road profiles.

VI. REFERENCES

[1] Jen-ChiunGuan,Bo-ChiuanChen,"AdaptivePowerManagementStrategyBasedonEquivalent Fuel ConsumptionMinimizationStrategyforaMild HybridElectric

ISSN PRINT 2319 1775 Online 2320 7876
Research Paper Journal Volume 11, Iss 12, 2022

Vehicle",2019IEEEVehiclePower and Propulsion Conference (VPPC),Year:2019

[2] XiXiong,ErdongXiao,LiJin,"AnalysisofaStochasticModelforCoordinated Platooning of Heavy-duty Vehicles", 2019 IEEE 58th ConferenceonDecisionandControl (CDC),Year:2019

[3] GustavLing,KlasLindsten,OskarLjungqvist,JohanLöfberg,ChristofferNorén, Christian A. Larsson, "Fuel-efficientModel Predictive Control for HeavyDuty Vehicle PlatooningusingNeuralNetworks", 2018 Annual American ControlConference(ACC), Year: 2018

[4] ChristosT.Krasopoulos,MinosE.Beniakar,AntoniosG.Kladas,"VelocityandTorqueLimit Profile Optimization ofElectricVehicleIncludingLimitedOverload",IEEETransactionsonIndustryApplications, Year: 2017, Volume:53,Issue: 4

[5] AtiwatSriwilai,WoraratanaPattaraprakorn,VivatChutiprapat,ChokechaiSansilah, PornrapeepatBhasaputra,"Thestudyontheeffectofelectriccartoenergy consumption inThailand",201613thInternationalConference on Electrical Engineering/Electronics, Computer, TelecommunicationsandInformationTechnology(ECTI-CON), Year: 2016

[6] S. Wickramanayake and H. D. Bandara,"Fuelconsumptionpredictionoffleet vehiclesusingmachinelearning:Acomparativestudy,"inMoratuwaEngineeringResearchConference(MERCon),2016.IEEE,2016,pp. 90–95.

[7] L. Wang, A. Duran, J. Gonder, and K.Kelly, "Modeling heavy/mediumduty fuelconsumptionbasedondrivecycleproperties,"SAETechnicalPaper,Tech. Rep.,2015

[8] H.Almer,"Machinelearningandstatisticalanalysisinfuelconsumption´prediction forheavyvehicles,"2015.

[9] G.Fontaras,R.Luz,K.Anagnostopoulus,D.Savvidis,S.Hausberger,andM.Rexeis,"Monitoringco2emissionsfromhdvineurope-an experimentalproofofconceptoftheproposed methodological approach," in 20thInternationalTransportandAirPollutionConference,2014.

[10] H. A. Rakha, K. Ahn, K. Moran,B.Saerens, and E. Van den Bulck, "VirginiaTechComprehensivePower-basedFuelconsumptionModel(VT-CPFM):modeldevelopmentandtesting,"TransportationResearchPartD:TransportEnvironment,vol.16, no. 7, pp. 492-503, 2011.