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Data driven Energy Economy Prediction for electricity buses Using Machine Learning

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Abstract:

Electrification of transportation systems is increasing; in particular city buses raise enormous potential. Deep understanding of real- world driving data is essential for vehicle design and fleet operation. Various technological aspects must be considered to run alternative power trains efficiently. Uncertainty about energy demand results in conservative design which implies inefficiency and high costs. Both, industry, and academia miss analytical solutions to solve this problem due to complexity and interrelation of parameters. Precise energy demand prediction enables significant cost reduction by optimized operations. This paper aims at increased transparency of battery electric buses' (BEB) energy economy. We introduce novel sets of explanatory variables to characterize speed profiles, which we utilize in powerful machine learning methods. We develop and comprehensively assess 5 different algorithms regarding prediction accuracy, robustness, and overall applicability. Achieving a prediction accuracy of more than 94%, our models performed excellent in combination with the sophisticated selection of features. The presented methodology bears enormous potential for manufacturers, fleet operators and communities to transform mobility and thus pave the way for sustainable, public transportation..

Keywords: *Battery Electric Bus, Heat Ventilation Air Condition, Support Vector Machine, Unified Modeling Language, Multi Variate Regression, Artificial Neural Network, Convolution Neural Network, Battery electric vehicles.*

1. INTRODUCTION

Traffic causes approximately 25% of greenhouse gas (GHG) emissions in Europe, and this percentage is increasing. Therefore, widespread electrification of the mobility sector is one of the most positive actions that can be taken in relation to climate change and sustainability. It seems clear that electric buses, because of their low pollutant emissions, are set to play a key role in the public urban transportation of the future. Although the initial investment in electrification may be high - e.g. purchase costs of BEBs are up to twice as high as those of Diesel buses- it is quickly amortizedbecausetheinherentefficiency ofelectric vehicles farexceeds thatof internal combustion engine vehicles up to 77%and thus operationalrespectively life cycle costs are significantly lower. In addition, electrification of the power train brings many other advantages, such as a reduced noise level or pollution. On the downside, the battery charging time of an electric bus is significantly longer than the refueling time of a diesel bus, while the opposite is true for the range. Ultimately, widespread electrification of the the mobility sector is one of the most positive actions that can be takenintermsofclimatechangeandsustainability,butmoreresearch is needed to ensure efficient operation, as it also poses significant challenges. The starting point for this study was a problem proposed bySeville'spublicbusoperator.Inshort,theywantedtoreplacetheir diesel fleet with all-electric vehicles, but first they had to size the vehicles' batteries and determine the best charging locations around the city. In practice, this means using computers to predict consumption on each route. Unfortunately, this can currently only be done with complex physical models that require long simulation times, or with data-driven models that are less computationally intensive once trained, but require numerous driving, mechanical, and road measurements as inputs. This is where the present research comes in. In this paper we use the bus operator's database and a physics-based model of soon-to-be deployed electric buses to develop data-driven models that predict the energy requirements of the vehicles. others, what distinguishes our contribution from previous data-driven approaches is the small number of physical variables involved: we show that, to accurately predict the consumption on a route using machine learning, we only need to know the instantaneous speed of the vehicle and the number of passengers on the bus. Specifically, our approach consists of three steps:

1) We calculate the energy consumed by the bus on each route using a physics-based model, including the bus's own weight and the weight of its payload. Both variables are taken from the operator's database.

2) We extract a comprehensive set of time and frequency features from the speed signal.

3)We train machine learning regression models to predict the energy consumption from bus payload mass and the above set of features, and identify those with the best predictive value. Interestingly, the feature that turns out to be the most relevant, i.e., the spectral entropy of velocity has so far gone unnoticed in this field of research. Ultimately, our results are useful for planning the transition from a conventional to a green bus fleet, and even for adding new functionalities that will be useful to planners: for example, the algorithms may be run on the battery management systems to provide an alternative way of monitoring the current state of charge of the batteries. The paper is structured as follows. Secondly, our material, methodology and methods are explained in Section II. Experimental results are presented and discussed insection III. Finally, section IVconclude and our

Objectiveoftheproject:

Electrification of transportation systems is increasing, in particular city buses raise enormous potential. Deep understanding of real- world driving data is essential for vehicle design and fleet operation. Various technological aspects must be considered to run alternative power trains efficiently. Uncertainty about energy demand results in conservative design which implies inefficiency and high costs. Both, industry,andacademiamissanalyticalsolutionstosolvethisproblem due to complexity and interrelation of parameters. Precise energy demand prediction enables significant cost reduction by optimized operations. This paper aims at increased transparency of battery electric buses' (BEB) energy economy. We introduce novel sets of explanatory variables to characterize speed profiles, which we utilize in powerful machine learning methods. We develop and comprehensively assess 5 different algorithms regarding prediction accuracy,robustness,andoverallapplicability.Achievingaprediction accuracy of more than 94%, our models performed excellent in combination with the sophisticated selection of features. The presented methodology bears enormous potential for manufacturers, fleet operators and communities to transform mobility and thus pave the way for sustainable, public transportation.

2. LITERATURESURVEY

Gasoline compression ignition approach to efficient, clean and affordable future engines

Controllingtheoxidesofnitrogen (NOx) and particulate matter(PM) emissions is one of the vital goals of compression ignition (CI) engines. Implementing stringent emissions regulations has motivated researchers to adopt various strategies for controlling emissions. Gasoline compression ignition (GCI) has emerged as a prime technologytocontrolemissionsandincrease engineefficiency,while using low octane gasoline as fuel in CI engines. Preheated air, hot exhaust gas recirculation (EGR), and negative valve overlap, are required to manage the combustion instabilities in theGCIengines. However thesetechniqueshavenotbeenusedinthisstudyinorderto reduce system complexity. Low octane test fuel was prepared (G80) by blending 80 % v/v gasoline and 20 % v/v diesel. This study involvedexperimentsto evaluate theeffects ofmain injectiontiming, split injection quantities (10–30 %), and engine load (brake mean effective pressure (BMEP): 3–5 bar) on a two cylinderGCIengine's performance, combustion, cyclic variability, emissions, and particulates. Conventional diesel combustion (CDC) mode experimentswere performed usingdiesel.Theresultsindicated a5 % higher brake thermal efficiency (BTE) and comparable exhaust gas temperature (EGT) for the GCI mode compared to the baseline CDC mode.GCIcombustionwith lowsplitratioshowed higherincylinder pressure than CDC mode. Baseline CDC mode showed < 3 % coefficient of variation ofindicated mean effective pressureandpeak pressure, whereas these parameters varied from 1 % to 9 % in theGCI mode. GCI mode engine exhibited ∼60 and 50 % lower NOx andPMemissions than baseline diesel mode engine. The double injection strategy improved GCI engine's performance and emission characteristics.

Energy consumption of an electric and an internal combustion passengercar.Acomparative case study from real world data on the Erfurt circuit in German

This paper presents the measured energy consumption of a range of "fuel efficient" vehicles over a 57 mile urban/extra-urban route. The results show that on average the electric vehicles used the least amount of energy (0.62 MJ/km average), followed by the hybrid vehicles(1.14MJ/km),andinternalcombustionenginevehicles(1.68 MJ/km). Estimates of CO_2 emissions finds that hybrids gave the lowestCO_2emissions,witharoundhalfofthevehiclesemittingless than 70 g CO_2/km. The most efficient diesel combustion engine vehicles emitted about80g CO_2/kmbut the majorityexceeded 110g CO_2/km.Themajorityofelectricvehicles emitted70–110gCO_2/km assuming a UK grid average emissions factor of 542 g CO_2/km.Highlights The energy consumption of 51 "fuel efficient" vehicles was measured.On average, electric vehicles used the least amountofenergy,thenhybrids,thenICEvehicles.EstimatesofCO_2 emissions found that hybrids had the lowest CO_2 emissions.

Lifecycle cost assessment and carbon dioxide emissions of diesel, natural gas, hybrid electric, fuel cell hybrid and electric transit buses

This paper evaluates thelifecycle costs and carbon dioxide emissions of different types of city buses. The simulation models of thedifferent powertrains were developed in the Autonomies vehicle simulation software. The carbon dioxide emissions were calculated both for the bus operation and for the fuel and energy pathways from well to tank. Two different operating environment case scenarioswere used for the primary energy sources, which were Finland and California (USA). The fuel and energy pathways were selected appropriately in relation to the operating environment. The lifecycle costs take into account the purchase, operating, maintenance, and possible carbon emission costs. Based on the simulation results, the energy efficiency of city buses can be significantly improved by the alternative power train technologies. Hybrid buses have moderately lower carbon dioxide emissions during the service life than diesel buses whereas fully-electric buses have potential to significantly reduce carbon dioxide emissions, by

up to 75%. The lifecycle cost analysis indicates that diesel hybrid buses are already competitive with diesel and natural gas buses. The high costs of fuel cell and batterysystems arethemajorchallengesfor thefuel cell hybridbuses in order to reduce lifecycle costs to more competitive levels

Cost analysis of plug-in hybrid electric vehicles including maintenance & repair costs and resale values

This paper analyses the cost competitiveness of different electrified propulsiontechnologies for the German auto market in 2020. Several types of hybrid electric vehicles including parallel hybrids (with and without external charging) and a serial range extended electricvehicle are compared to a conventional car with SI engine, a full battery electric vehicle and a hydrogen powered fuel cell vehicle. Special focus lies on the maintenance and repair cost and theexpected resale value of alternative vehicles, which have been integrated within one extensive total cost of ownership model. The assessment shows that the current TCO gaps for alternative drive trains will decrease significantly by 2020 mainly driven by the reduction in production cost. Furthermore, hybrid electric vehicles will profit from lower maintenance and repair cost and a higher expected resale value compared to conventional cars. Therefore, hybrid electric vehicles will be an attractive option in particular for users with high annual mileages, who can benefit from the low operating cost of EVs in combination with unlimited driving range. The analysis concludes that there will not be one dominant power train design in the midterm future. Hence, automakers have tomanage a wide portfolio of competing drive train architectures,which will increase the risk and complexity of strategic decisions.

Electricity system and emission impact of direct and indirect electrification of heavy duty transportation
Widespread adoption of alternative fuel vehicles in the heavy-duty transportation sector could significantly mitigate carbon emissions of this important sector.However,the extent ofemission reductionsand their feasibility will depend on the carbon intensity of the electricity system, alternative fuel vehicle technologies and vehicle charging profiles. Utilizing a capacity expansion and dispatch model, thisstudycompares alternativepathways for decarbonizingtheelectricity and heavy duty transportation sector to 2060. Scenarios with battery electricvehicles,withthreealternativechargingprofiles,andfuelcell vehicles are compared with 0 and 150 $/to 2 carbon taxes. Results showthatadoptionofalternativefuelvehiclesintheabsenceof

Life cycle assessment of battery electric vehicles: Implications of future electricity mix and different battery end-of-life management
The environmental performance of battery electric vehicles (BEV) is influenced by their battery size and charging electricity source. Therefore, assessing their environmental performance shouldconsider changes in the electricity sector and refurbishment of their batteries. This study conducts a scenario-based life cycle assessment (LCA) of three different scenarios combining four key parameters: futurechangesinthechargingelectricitymix,batteryefficiencyfade, battery refurbishment, and recycling for their collective importanceon the life-cycle environmental performance of a BEV. The system boundary covers all the life-cycle stages of the BEV and includes battery refurbishment, except for its second use stage. Therefurbished battery was modelled considering refurbishedcomponents and a 50% cell conversation rate for the second life of 5 years. The results found a 9.4% reduction in climate impacts when future changes (i.e., increase in the share of renewable energy) in the charging electricity are
considered. Recycling reduced the BEV climate impacts by approximately 8.3%, and a reduction smaller than 1% was observed for battery refurbishment. However, the battery efficiency fade increases the BEV energy consumption, which results in a 7.4 to8.1%riseinuse-stageclimateimpacts.Therefore,itisvitaltoinclude battery efficiency fade and changes to the electricity sector when estimating the use stage impacts of BEVs; without this, LCA results couldbeunreliable.The sensitivityanalysis showed the possibilityof a higher reduction in the BEV climate impacts for longer second lifespans (>5 years) and higher cell conversation rates (>50%). BEV and battery production are the most critical stages for all the other impact categories assessed, specifically contributing more than 90% to mineral resource scarcity. However, recycling and battery refurbishment can reduce the burden of the different impactcategories considered. Therefore, manufacturers should design BEV battery packs while considering recycling and refurbishment.

3. PROPOSEDMETHODOLOGY

In this paper we use the bus operator's database and a physics-based model of soon-to be deployed electric buses to develop data-driven modelsthatpredictthe energy requirements of thevehicles.Amongst others, what distinguishes our contribution from previous data driven approaches is the small number of physical variables involved: we show that, to accurately predict the consumption on a route using machine learning, we only need to know the instantaneous speed of thevehicleandthenumberofpassengers onthebus.Specifically,our approach consists of three steps:

1) We calculate the energy consumed by the bus on each route usinga physics-based model, validated by the vehicle manufacturer, that uses speed and mass as inputs, including the bus's own weight andthe weight of its payload. Both variables are taken from theoperator's database.
2) We extract a comprehensive set of time and frequency features from the speed signal.
3) Wetrain machinelearningregression models to predict theenergy consumption from bus payload mass and the above set of features, and identify those with the best predictive value. Interestingly, the feature that turns out tobe the most relevant,i.e., the spectral entropy ofvelocity, has so far gone unnoticed in this field of research.

Advantages:

1) WeproposeascalableandefficienthybridizationMachineLearning models for exactpredictions.

2) We conducted several hybridizations of genetic algorithm with filter and embedded feature selection methods, in the data pre- processing phase of Random Forest and Multivariate Linear Regression (MLR) predictive model, with the aim of improving its performance

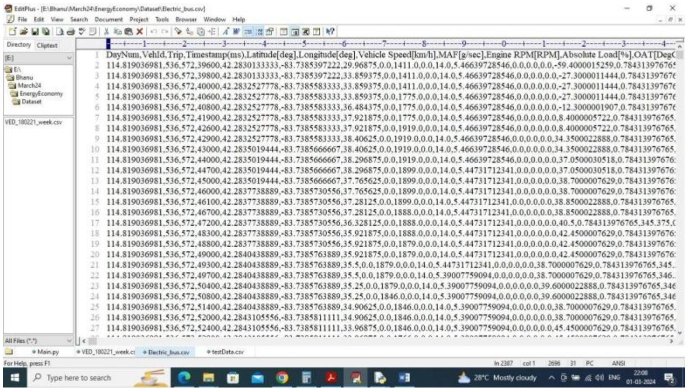
EXPERIMENTALANALYSIS

DataDrivenEnergyEconomyPredictionforElectricCityBuses Using Machine Learning.

Now-a-days all vehicles are running on battery power but recharging batterywill take more time comparingto refuelingfuel. So, author of this paper employing machine and deep learning algorithms topredict energy consumption between routes and based on predicted energy then refueling can be schedule with nearest service station. Selected features will get trained with various machine learning algorithms like Linear Regression, Random Forest, SVM, ANN, Gaussian regression process. Each algorithm performance isevaluatedintermsofR2SCORE,RMSE(rootmeansquareerror)and MAP (mean absolute error).

RMSEandMAPrefers to difference between originaltest values and predicted test values so the lower the RMSE and MAP the better isthealgorithm.AmongallalgorithmsLinear Regressionisgiving high R2SCORE

To train above algorithms author has used Real Vehicle dataset from some company but not publish on internet so we downloaded vehicle energy consumption dataset from KAGGLE repository. In below screen showing dataset details.

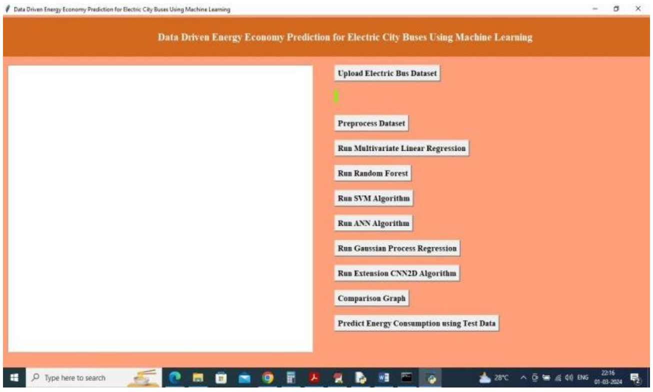


In above dataset screen first row contains dataset column names and remaining rows contains data set values and by using above data set will train and test all algorithm performances

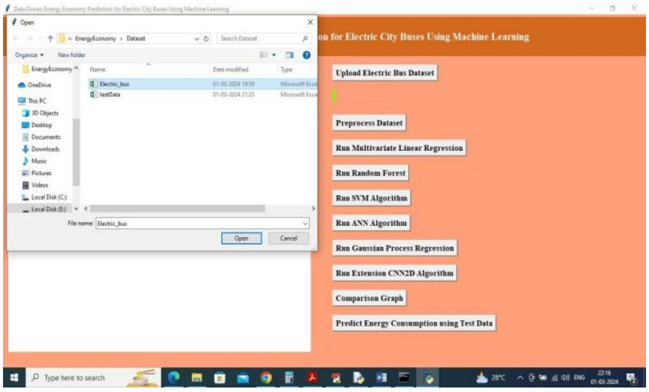
In propose paper author has used all traditional machine learning algorithms so as extension we have experimented with advance CNN2D (convolution neural network) which will filtered data setwith multiple layers and neurons which can help in better prediction of energy consumption while increasing R2SCORE and reducing RMSE and MAP.

SCREENSHOTS

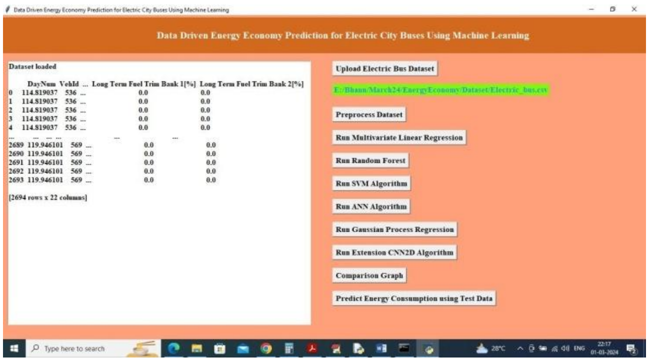
Torunprojectdoubleclickonrun.batfiletogetbelow screen



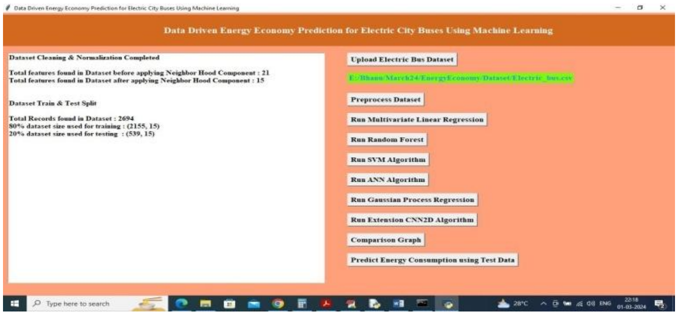
In above screen click on 'Upload Electric Bus Datasets button to upload data set and get below page



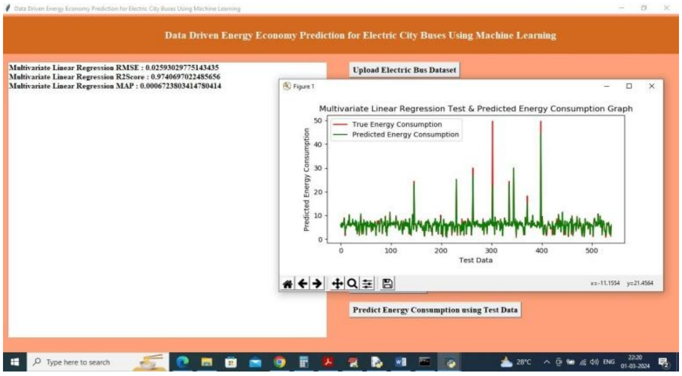
In above screen selecting and uploading data set and then click on 'Open'button to load data set and get below page



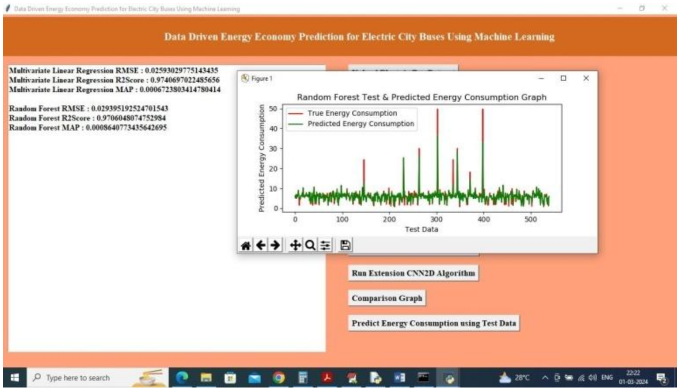
In above screen data set loaded and now click on ‘Pre-process Dataset’ button to clean dataset and then select features using neighbor hood and then split to train and test



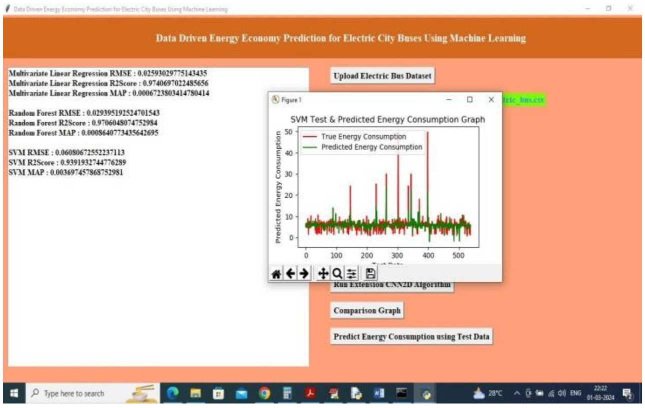
Inabove screen can see before applyingneighborhooddataset having 21featuresandafterapplying,wegot15selectedrelevantfeatures and then can see train and test dataset size and now click on ‘Run Multivariate Linear Regression’ button to train model and get below page



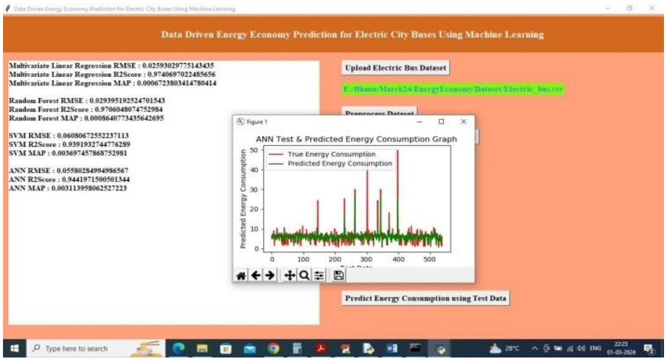
In above screen Linear Regression got 97% R2Score and can see RMSEandMAPerrorvaluesandingraph x-axisrepresentsTestdata and y-axis represents energy consumption values where green line represents predicted energy and red line represents True energy test datavalues and can see both lines are fully overlapping with tiny gap so we can say linear regression is accurate and now click on ‘Run Random Forest’ button to get below output



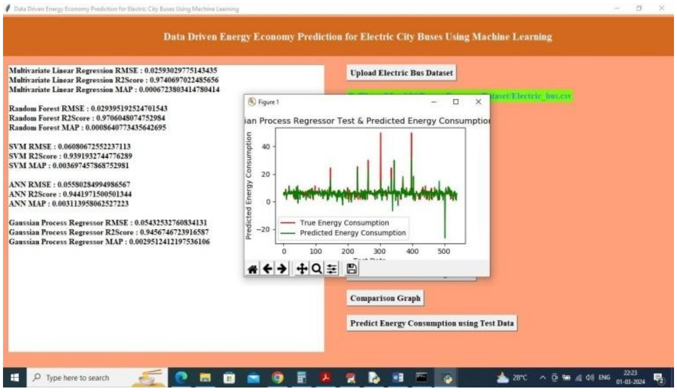
In above screen Random Forest also got same 97% score but error values are high and now run SVM algorithm



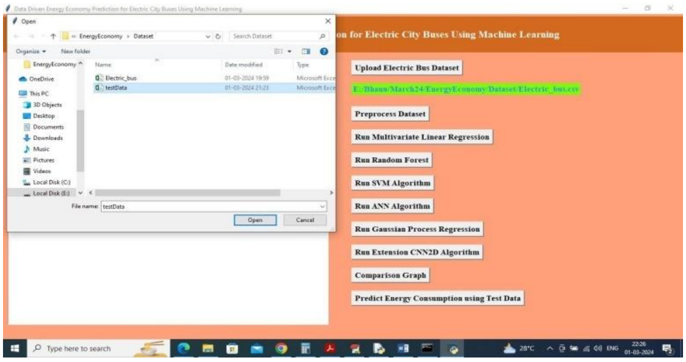
In above screen can see SVM performance output and now click on ‘Run ANN algorithm’ button to get below output



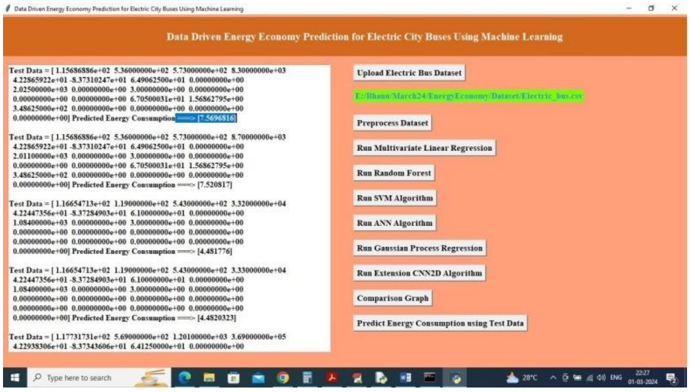
Inabovescreen canseeANNoutputandnowclickon‘RunGaussian Process’ button to get below output



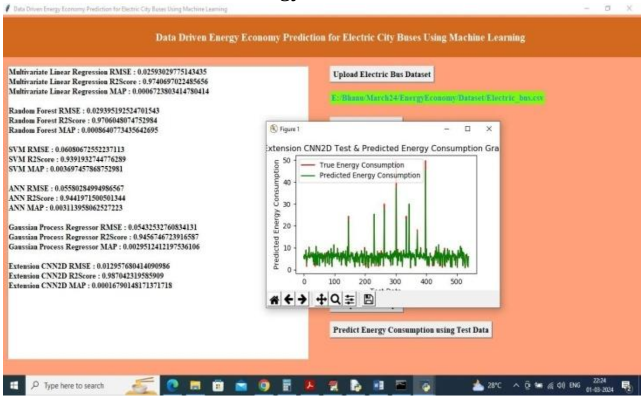
Inabovescreen can seeGaussian Process Regressionoutputandnow click on ‘Run Extension CNN2D algorithm’ button to get below output high R2 and less RMSE error and now click on ‘Predict Energy Consumption using Test Data’ button to upload test data and get belowpage



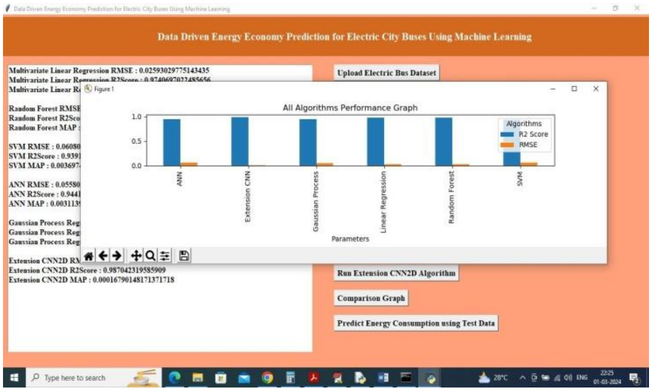
In above screen selecting and uploading test data file and then click on ‘Open’ button to get below output



In above screen in square bracket can see vehicle energy Test dataand then after = ➔arrow symbol can see predicted energy consumption.



In above screen extension CNN2D got highest R2SCORE as 98%and now click on 'Comparison Graph'button to get below graph



In above screen x-axis represents algorithm names and y-axis represents R2SCORE and RMSE and blue line represents R2score andorangebarrepresentsRMSEandcanseeextensionCNN2dgot

Focusing on the "Vehicle Routing Problem," this study emphasizes the importance of knowing route energy demands for optimal battery sizing,operatingmodes,andchargingstrategies.Understandingthese factors helps fleet operators mitigate risks and ensure reliable, cost- effective services.A key contribution is the identification of novel predictive features, particularly the spectral entropy of velocity profiles, which captures crucial energy-related information.

Future research will extend this methodology to other transport sectors, considering factors like seasonal variations, road types, and operational conditions. Expanding predictive analytics to includepeak power and battery demands will further refine fleet electrification strategies.

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