DATA RELIABLE ENERGY PREDICTION FOR ELECTRIC BUSES USING ARTIFICIAL NEURAL NETWORK

[1]Adapa venkata chaitanya [2]Dr. Nagesh Babu Dasari [3] DR. Pucha Venkata Subbarama Sarma

[1]M. Tech Scholar, Dept. of CSE, St. Ann's College of Engineering & Technology, Chirala.
[2]Associate Professor, Dept. of CSE, St. Ann's College of Engineering & Technology, Chirala.
[3]Associate Professor, Dept. of CSE, St. Ann's College of Engineering & Technology, Chirala.
e-mail: drdasarinagesh@gmail.com

ABSTRACT: Reliable and accurate estimation of an electric bus's instantaneous energy consumption is critical in evaluating energy impacts of planning and control of electric bus operations. The developed machine learning-based long short-term memory (LSTM) and artificial neural network (ANN) models to estimate. We introduce a data driven approach for characterization and predictive classification of electric city buses by powerful machine learning algorithms. These challenges encompass critical factors such as range anxiety charge rate optimization and the longevity of energy storage in EVs. By analyzing existing literature, we delve into the role that AI can play in tackling these challenges and enabling efficient energy management in EMS. This paper aims to systematically review the existing application of machine learning methods on power system resilience enhancement to expand the interest of researchers and scholars in this topic and to jointly promote the application of artificial intelligence in the field of power systems. Unlike these studies this article estimates the energy consumption of all the electric buses that circulate in the city of Santiago Chile during the studied period using full disaggregated GPS data and empirical measurements on some sensitized electric buses. The neural network is employed to learn the current driving information and main knowledge after the simplified correlation of characteristic parameters and meanwhile the genetic algorithm is adopted to optimize the initial weight and thresholds of networks. This analysis allows decision-makers to target investment by determining the buses with higher energy consumption savings in the face of budget constraints.

INDEX TERMS: Driving condition prediction, Markov chain, neural network, principal component analysis, energy managemen, Deep Learning, Machine Learning, Power System Control, Resilience,.

INTRODUCTION

Electrification of public transportation is a promising approach to reduce greenhouse gas emissions used by transportation sector [1]. Recent studies investigated various operation strategies to improve energy consumption of electric buses, including eco-driving at signalized intersections, vehicle dynamic management, and energy management control [2].The availability of infrastructure vehicle autonomy and secure operation transform public transport into a green fleet, alternatively powered vehicles have to be carefully designed and their use case specified accurately [3]. Electric Mobility Service (EMS) refers to the use of electric powered vehicles, including E-bikes, E-scooters, Hybrid Electric Vehicle (HEV), and Plug-in Hybrid Electric Vehicle (PHEV), for transportation needs. EMS has rapidly transformed the transportation landscape, offering sustainable alternatives to traditional combustion engine vehicles [4]. AI technologies, such as machine learning (ML), there have been great breakthroughs in data resolution, learning and computing power [5]. Machine learning methods have been widely applied in power system operation and planning such as load and wind speed forecasting demand response fault detection, stability assessment stability control and restoration [6]. Nowadays several cities are transitioning to greener bus fleets and in Santiago the number of electric buses in operation on RED will continue to increase in the coming years large share of electric buses impacts some key performance indicators of a public transport system [7]. The clustering analysis is conducted to find the characteristic parameters of transportation information and the Markov chain model is built to identify the transportation pattern stochastic approach is proposed to construct the power management algorithm, in which the power demand is modeled as a MC process and estimated based on different driving cycles, then the control scenarios are generated in a stochastic MPC framework [8].

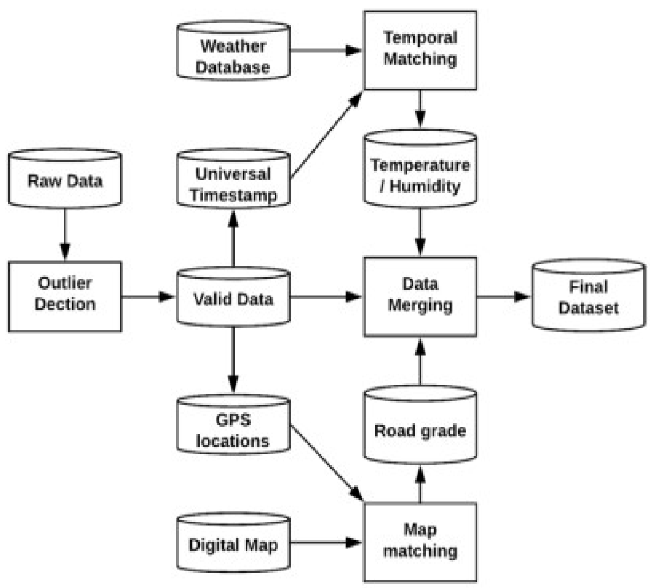

Figure 1. Flowchart of electric bus driving, operating, and environment data infusion.

1. RELATED WORKS

Technological progress promoted machine learning algorithms in almost any field of research and the prediction of energy demand for battery electric vehicles (BEVs) in general and battery electric buses (BEBs) in particular, have been thoroughly investigated [9]. We focus on data based approaches for driving profile characterization and energy demand classification of public transportataset [10].We conducted a systematic search of peer-reviewed research publications to

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collect studies that employed AI approaches to address issues related to energy management in EMS. Our screening process involved a thorough review to identify papers that addressed the structural challenges of EMS energy management and utilized AI methods [12]. Machine learning methods have been widely applied in power system operation and planning such as load and wind speed forecasting, demand response, fault detection, stability assessment, stability control and restoration [13]. The up-to-date ML techniques enhancing power system resilience is limited. These methods identify highly complex relationships between different variables and the measurement of consumption, generally through Machine Learning (ML) models [14]. Its conclusions are strongly dependent on the available data set more difficult to perform. Machine learning algorithms in particular NNs, can extract nonlinear laws from the training data and can be well-suited for prediction of future driving conditions thereafter. NN can effectively fit random nonlinear data and features self-learning capability after proper parameter tuning [15].

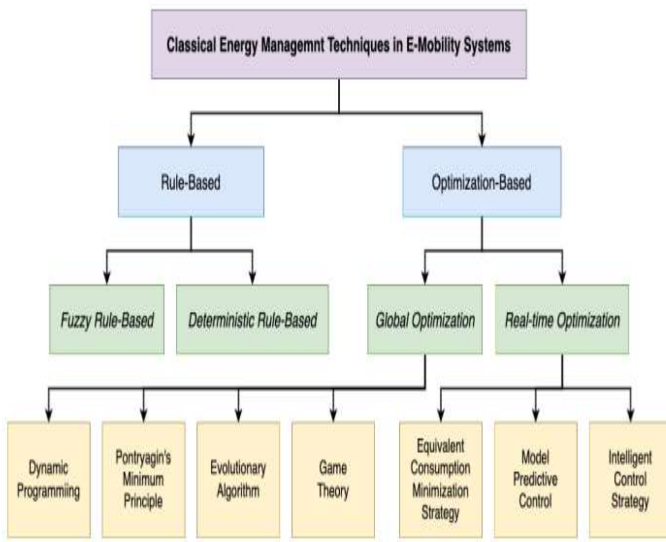

Figure. 2. Hierarchical categorization of classical EMS.

2. SYSTEM ARCHITECTURE

We aim to improve prediction performance of black-box microscopic energy prediction models for electric buses utilize physical knowledge to select predicting variables and explore various data-driven methods, including artificial neural network (ANN) and long short-term memory (LSTM) to estimate energy consumption under real-world driving conditions in a mountainous region [16]. Closing the gap and removing the lack of trust into new technologies is key to transform future mobility. The motivation is obviously not only for academia but also for the economy and society. All this said and all mentioned studies build the base for our research [17]. Rule-based methods have been widely employed in early HEVs due to their simplicity and feasibility methods focus on coordinating the operation of the internal combustion engine to improve fuel economy and emission performance by transferring the working points of the engine from low to high-efficiency zones [18].

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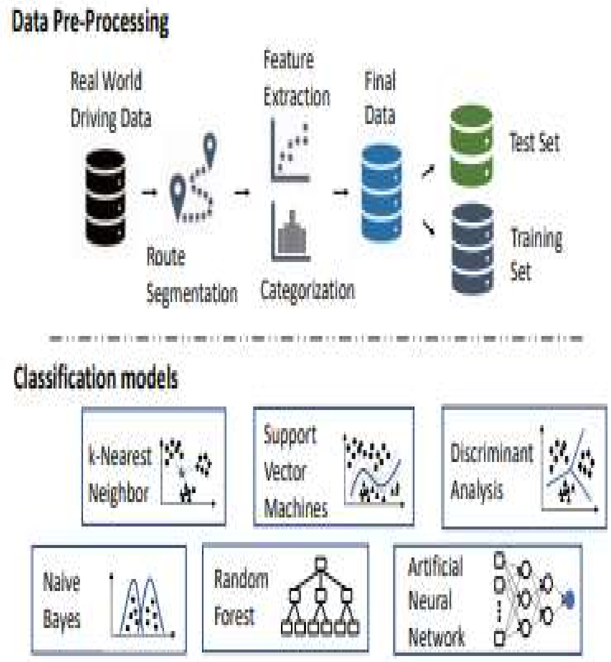

Figure 3. Summary and overview of methodology

3. PROPOSED SYSTEM

The accurate prediction of power outage after disturbances and vulnerable areas plays an important role in power system restoration Part of the objectives of this work is to quantify the importance of different operational variables in the energy consumption of the network buses [19]. A Neural Network (NN) corresponds to a structure that seeks to replicate the behavior of the human brain by interconnecting a large number of neurons with each other from inputs and outputs [20]. Numerical simulations are performed to validate the effectiveness of the proposed fusion method by comparing with traditional prediction methods to further validate the performance and highlight the benefit of the proposed algorithm is conducted the prediction algorithm is applied to supply the reference for predictive energy management [21].`

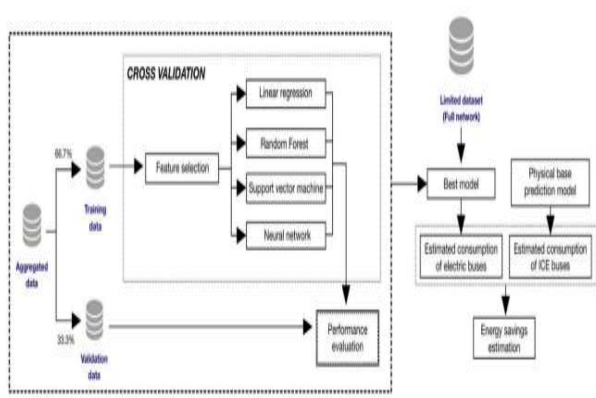

Figure. 4. Proposed Operation Scheme

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4. METHODOLOGIES

Based on the literature, conventional energy management methods for EVs are classified into two main categories: rule-based and optimization-based summary of the advantages and limitations of conventional methods[22].Rule-based methods have been widely employed in early HEVs due to their simplicity methods focus on coordinating the operation of the internal combustion engine to improve fuel economy and emission performance by transferring the working points of the engine from low to high-efficiency zones [23]. Optimization-based methods are categorized as global and real-time optimization methods. Various global optimization methods have been employed including dynamic programming, Pontryagin Minimum Principle (PMP), Evolutionary Algorithms, and Game Theory. Dynamic programming breaks down the decision process into discrete steps and has been used to solve the optimization problem of multi-step decision processes [24]. Parts of the network based on the prediction power flow profiles, including line active and reactive power flows, bus voltage magnitudes and angles, are collected as inputs for DBN to assess transient stability. Simulation results show that the out-performance of SVM-based method since SVM is sensitive to hyper-parameters

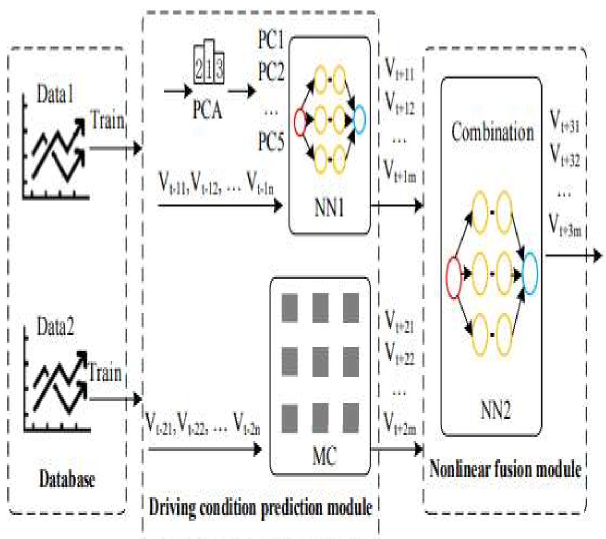

Figure 5. The working principle of the proposed fusion prediction method

5. GENETIC ALGORITHMS

The prediction process of driving condition, if several adjacent velocities are considered as the only input of NN1, they cannot truly reflect the characteristics of certain driving conditions, thus resulting in low prediction accuracy [23]. In contrast, if too many parameters are extracted, the computational intensity cannot be tolerated. The goal of genetic algorithms is to create optimal solutions to problems. Potential solutions to the problem to be solved are encoded as sequences of bits, characters or numbers [23].

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An Auto-Encoder (AE) is a type of neural networks with the same number of neurons in both input and output layer [24]. It is mainly used for dimensionality reduction for better representation of data. Auto-Encoder is an unsupervised learning model and applies back propagation. The input and output layer consist of N nodes and hidden layer consist of K nodes. Hidden layer of AE is known as abstract layer. For a given training data set X with m samples, the encoder performs the mapping of input vector to hidden vector using mapping function.

Input: Dataset D= {x1, x2, ..…..xm} with m samples, number of hidden layers L
Output: Output of each hidden unit
Step 1: for l ∈[1, L] do
Step 2: initialize Wl= 0, Wl ’= 0, bl= 0, bl ’= 0
Step 3: define the l-th hidden layer representation vector hl= f(Wl hl-1+ bl)
Step 4: define the l-th hidden layer output xl’= f(Wl’hl+bl)
Step 5: while not stopping criterion do
Step 6: calculate hl from hl-1
Step 7: calculate yl
Step 8: calculate the loss function
Step 9: update layer parameters θl= (Wl, bl) and θl’= (Wl ’ , bl ’)
Step 10: end while
Step 11: end for
Step 12: Initialize (Wl+1, bl+1) at the supervised layer
Step 13: calculate the labels for each sample xi of the training dataset D
Step 14: perform BP in a supervised way to tune parameter of all layers;

6. EXPERIMENT RESULTS

We undertook a model selection process using a 10-fold cross-validation procedure to evaluate prediction performance based on different parameters and structures of ANN and LSTM models. The training process used 2,600 hours of operation data, i.e., 4 weeks of monitoring data from each season in 2019 and 2020. For each fold of cross-validation, Support vector machine and artificial neural network are the most popular approaches for single learning algorithm classifiers and number of comparative samples is less but the comparison result implies that Support Vector machine is by far the most common and considered single classification technique. Hybrid classifiers in intrusion detection have established in the mainstream study due to the performance accuracy in recent times Statistics shows hybrid classifiers have the highest number of articles used algorithms in each article and their performance in intrusion detection system.

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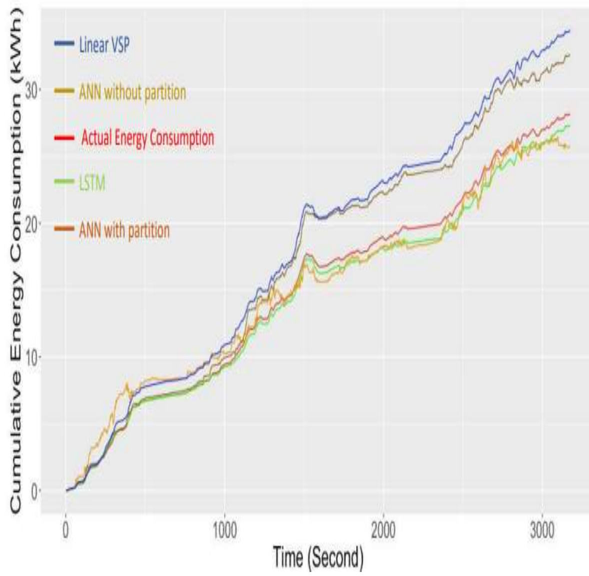

Figure. 6. Distribution of Single classifiers

7. CONCLUSION AND FUTURE WORK

We proposed machine learning-based LSTM and ANN models to estimate the instantaneous power and cumulative energy consumption of electric buses. The training, validation, and testing were done based on electric bus driving, road grade, and environment data in a long-term bus operation monitoring experiment in Chattanooga. We found a subset of 18 explanatory variables to be sufficient and the RF approach to be the most robust. As our main contribution, we state that both feature space reduction and investigating on new ones like velocity oscillation, spectral kurtosis and number of acceleration shifts leads to outstanding results when applying machine learning. The potential of ML-based power system resilience enhancement is analyzed based on the performance curve of a system after an event. Furthermore, there is a numerous amount of topics that require research attention in order to realize a resilient power system.

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