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ENERGY CONSUMPTION OF BATTERY- ELECTRIC BUSES: REVIEW OF INFLUENTIAL PARAMETERS AND MODELLING APPROACHES

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Abstract: The electrification of public transportation fleets worldwide can pose a challenge to multiple stakeholders, such as the fleet operator or the operator of the local electrical grid. One of the important prerequisites for the successful integration of these fleets into the existing system is the knowledge of the energy consumption of the buses during their trips. The energy consumption varies depending on multiple factors such as the vehicle or route-related parameters, operational, and environmental parameters. This paper gives an overview of the latest research regarding these influential factors. Another essential prerequisite for the implementation of intelligent management systems for electric bus fleets is the forecasting of energy consumption. Researchers take different approaches to tackle this issue. A review of the latest research considering empirical approaches, physical models, regression, and machine learning is also provided in this paper. The findings of this paper provide a quick overview of different aspects of the energy consumption of electric buses and can therefore support other researchers or decision-makers in their work.

Keywords: energy consumption, electric buses, influential factors, modelling approaches

INTRODUCTION

The need to reduce the emissions caused by transportation is leading to the electrification of public transportation systems worldwide. The growing number of electric buses on the streets, however, brings numerous challenges for different stakeholders. When considering the operators of electrical grids, the challenges can be grid congestion, grid instability, or power quality issues, depending on the local grid infrastructure [1]–[3]. This is not unexpected, knowing that the charging power of electric buses usually lies in the range of 100 – 400 kW per bus, depending on the charging infrastructure and charging concept. The operators of electric fleets face other challenges. The total cost of ownership for electric buses is higher than the one for conventional buses [4]. The electrification of the fleets therefore comes with significant economic costs. Further challenges for the operator have an organizational and technical nature. The electric buses need to be integrated into existing operation and disposition plans. Compared to conventional buses, electric buses have shorter ranges and longer refuelling (charging) times, due to the limited battery capacity. On the other hand, the energy consumption (EC) itself is highly dependent on multiple internal and external factors. These new characteristics have to be considered in the existing management systems to provide uninterruptible and optimal operation [5], [6]. However, with the development of different kinds of route and charging management systems, the electric bus fleets also provide several opportunities. With intelligent route and charging scheduling the operation cost can be reduced and at the same time eventual grid problems can be tackled [7], [8], especially considering the available flexibility of electric bus depots [9]. This flexibility can be used in virtual power plants [10], for optimal energy purchase in auction bids [11], or even for the provision of grid services [12].

However, various criteria need to be fulfilled to implement the previously mentioned intelligent management systems. One of the core prerequisites is the understanding and prediction of the EC of electric buses during their trips [13], [14]. There is a wide range of different factors that show an impact on the EC. This paper offers an overview of findings regarding these influential factors provided in other studies with the goal of a more profound understanding of EC. When it comes to predicting the EC, the researchers take different approaches, from empirical and physical models to regression analysis and machine learning. This paper provides an overview of the models proposed so far.

The potential papers relevant to the review were identified using the database Scopus and the following keywords: electric buses and energy (or electricity) consumption. This resulted in 331 relevant papers. In the next step, the abstracts of these papers were screened. Papers dealing with the topic of battery electric buses in the context of the

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measured EC, parameters impacting the EC, and models for EC (physical, regression, or machine learning) were chosen for further analysis. Papers focusing on hybrid, supercapacitor, or trolleybuses were not considered. A significant number of papers focus on topics such as greenhouse gas (GHG) emissions, comparison of different bus types, economic and lifecycle aspects, or charging management while considering the EC rather as an input or marginal subtopic. These papers are not included in the further analysis. Additionally, although the topic of eco-driving is shortly addressed in the context of the driving style, further analysis does not include a detailed overview of this topic. Considering the mentioned criteria, 63 papers were chosen for a detailed analysis, as presented in the following sections.

The contributions of this paper can be summarized as follows:

- classification of influential parameters on the EC based on findings in research papers,
- review of four different approaches to EC modelling,
- review of previously suggested regression models for EC forecasting.

After the introduction, the analysis of different influential factors is provided in Section 1. Section 2 focuses on four different modelling approaches: empirical, physical, regression, and machine learning. The summary of the main findings and future work are provided in Section 3.

1. FACTORS IMPACTING THE EC OF ELECTRIC BUSES

Several parameters show an impact on the EC of electric buses. Abdelaty and Mohamed classify 25 different parameters into various subcategories and four main categories: vehicular, operational, topological, and external [15]. Xu et al. analyse the EC based on the road, driver, vehicle, and ambient factors [16]. Based on the proposed classification in [15] and [16], and thorough literature research, this paper proposes a more compact classification, which focuses on the most considered parameters in other studies. The proposed classification is given in Figure 1. The parameters can be divided into vehicle and route-related parameters, as well as operational and environmental parameters.

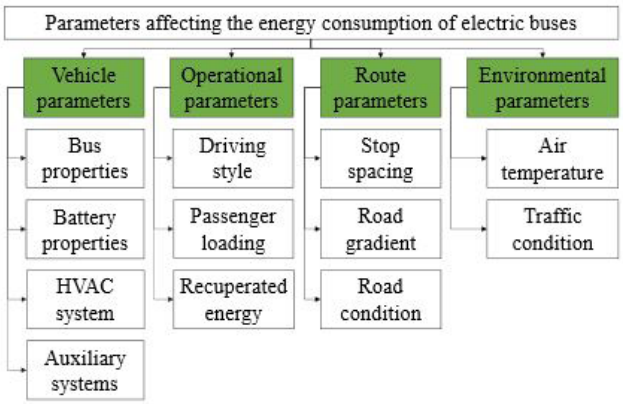


Figure 1: Classification of parameters affecting the energy consumption of electric buses

1.1. Vehicle-related parameters

The vehicle-related parameters include all technical characteristics of the bus, battery, HVAC system, and additional auxiliary systems. When observing the bus itself, these are the powertrain components (inverter, motor, gearbox), vehicle mass, or the frontal area of the bus [17]–[20]. Battery parameters affecting the EC are the battery temperature and internal resistance [21], [22]. The impact of HVAC on the EC of the bus can be significant [23]–[28]. The intelligent control of HVAC operation can therefore contribute to reduced EC [29], [30]. Depending on the geographical position and climate conditions in the area, the energy needed for heating or cooling of the passenger cabin can be more dominant [26]. Auxiliary systems including the pneumatic, electric, and hydraulic auxiliaries can also have a significant impact on the EC [22], [31]–[33].

1.2. Operational parameters

The operational parameters include the driving style, passenger loading, initial state of charge (SoC), and recuperated energy via braking. The driving style, meaning the driving aggressiveness when accelerating or decelerating, leads to an increase in the total EC [22], [32], [34]–[36]. Interestingly, the impact seems to be bigger for diesel buses than for electric ones [37]. Optimization of the driving behavior and the so-called eco-driving can help reduce the EC [34], [38]. The impact of initial SoC (SoC at the beginning of the trip) on the EC has been analyzed in only a few studies [15], [39]–[41]. Vepsäläinen indicated that the initial SoC impacts the EC by affecting the energy regeneration [39]. However, the impact is significant only when the charge is over 90%. Abdelaty et al. found that initial SoC has a great impact on the EC, with an increase in the initial state of charge by 10% causing the increase of EC by 0.124 kWh/km [15]. Perugu et al. used real measured data to show a general trend of lower EC at higher SoC levels [41]. The energy loss due to cornering and tire slip during the trip can also have an impact on the total EC. Beckers et al. show that for buses driving in a city environment, the relative contribution of these cornering losses can even be as high as 5.8% [42]. Passenger loading has been shown to have an impact on the EC of buses [43], [44]. Kivekäs et al. show that one passenger increase in the average number of passengers increased the consumption by approximately 0.013 kWh/km [43]. Anttila et al. confirm these findings and show that the EC per passenger is below 0.02 kWh/km, measured with a payload of 40 passengers [44]. The number of passengers also affects the energy necessary for heating and cooling with HVAC [31]. Energy recuperated or regenerated via braking directly impacts the total EC on the trip [17], [24], [41], [44], [45]. Besides the road slope, parameters such as the rolling resistance coefficient, initial SoC, or the headwind show a high correlation with the regenerated energy [39]. Additionally, the weather

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conditions, especially cold temperatures and wet streets lead to a decrease in regenerated energy [45].

1.3. Route-related parameters

The nature of the route has a further impact on the EC. The stop spacing, meaning the number of stops per km, can have a great impact on the EC [20], [22], [43]. An additional route-related parameter influencing the EC is the road grade [46]. According to Abdelaty et al., the road grade has the most significant impact on the EC, with an increase in the road grade of 1% leading to an increase of EC by 0.380 kWh/km [15]. Depending on the road surface type and condition (dry or wet), the rolling resistance coefficient (RRC) changes, which directly impacts the EC [17], [33]. The RRC can have a great impact on the total EC as well as on the recuperated energy in particular [39]. Ma et al. show that the mentioned route characteristics, including stops and road characteristics, show a high contribution factor on the EC of 57% [47].

1.4. Environmental parameters

Another category of relevant parameters is the environment, such as the ambient temperature or traffic conditions. The ambient temperature has a direct impact on the HVAC and has been shown to have one of the biggest impacts on the EC in several studies [16], [20], [22], [39], [40], [48], [49]. The traffic is correlated with the operational parameters such as the driving style, passenger load, and vehicle speed [35], [41], [50]. During commute hours, which usually indicates traffic congestion, the EC is higher [41], [50]. The impact of the traffic conditions can be seen when comparing the electric buses in urban and rural areas. Buses consume more energy along routes that encounter high levels of traffic, such as in urban city areas. Intercity buses, on the other hand, benefit from reduced EC [31].

2. MODELLING APPROACHES TO EC

When it comes to analysing the EC of electric buses, the researchers take different approaches. The empirical approach is the simplest one. In this case, the EC is based on experiences with the bus fleets in the analysed area. This very basic approach makes it convenient for first rough estimations. On the other hand, this approach can result in a big discrepancy between the models and the reality. It is not well suited for forecasting EC for real-time intelligent management systems, since it does not consider the current conditions. Physical models on the other side represent the opposite. Depending on the complexity, they can model the vehicle, battery, and auxiliary system with different grades of detail. Physical models can be very exact; however, they also require higher computation time. An additional challenge when using these kinds of models is the availability of the input data such as the technical characteristics of the buses or the passenger and speed profiles for the trips. Researchers often use parameters from the literature, which can again lead to discrepancy with reality. Data-driven approaches do not model the buses and therefore do not require their detailed technical characteristics. Those are regression models and models based on machine learning. They, however, require large amounts of real data for training and validation, which are not always available.

2.1. Empirical approach

As already stated, the empirical approach to modelling the EC is the simplest approach. In this case, the researchers usually take average or worst-case consumption and use these values in their models. This approach is sufficient for the first rough estimation and can be helpful when making the first design decision for entire fleets or depots. However, as already stated, it is not suited for detailed analysis or real-time management systems. The basis for this approach is

Table 1: Summary of studies showing real measured energy consumption for longer time period and for large fleets

	Measurement duration (time or covered distance)	Location	Bus type	Energy consumption (EC)
Vepsäläinen et al. [22]	21 months	Finland	12 m	0.4 – 1.4 kWh/km
Vehviläinen et al. [26]	3 years	Finland	12 m	1.1 – 2.5 kWh/km
He et al. [51]	880 km	China	12 m	1.7 – 4.1 kWh/km
He et al. [51]	870 km	China	10 m	1.2 – 2.9 kWh/km
Perugu et al. [41]	1 year	USA	12 m	1.4 – 1.8 kWh/km*
Perugu et al. [41]	1 year	USA	18 m	1.9 – 2.5 kWh/km*
Chen et al. [52]	2600 operation hours	USA	10 m	0.8 – 2.6 kWh/km
Lin et al. [53]	8 months	Taiwan	12 m	0.98 – 1.56 kWh/km **
Nan et al. [38]	3 months	China	-	0.73 – 0.85 kWh/km
Alarrouqi et al. [54]	7 months	Qatar	11 & 12 m	0.7 – 1.5 kWh/km
Jahic et al. [49]	13 months	Germany	12 m	0.58 – 1.8 kWh/km
Jahic et al. [49]	13 months	Germany	18 m	0.99 – 2.42 kWh/km

*Recalculated from kWh/mile **Recalculated from km/kWh

the experience gathered by observing the existing fleets. Depending on the bus types, or the geographical position, the experiences show different ranges of measured EC. Table 1 gives an overview of several studies offering insight into real-measured EC for longer time and large fleets. As can be seen, the experience shows a wide range of possible EC, from the smallest measured EC of 0.4 kWh/km to the highest one of 4.1 kWh/km. This emphasizes, once more, the withdrawal of using the empirical approach when aiming for detailed and accurate analysis. This approach does not consider the current conditions and especially volatile parameters from the operational and environmental category, which makes it not suitable for real-time usage. Another disadvantage of this approach is limited transferability. Since it is based on experience values, it can be transferable only to fleets that operate in similar conditions, such as fleet composition, geographical position, weather conditions, or road topology.

2.2. Physical models

Physical models calculate the energy needed to operate the bus, considering the power needed for the vehicle motion and the power consumed by auxiliaries. A variety of different physical models with different grades of detail have been proposed so far. When it comes to the power consumed for the vehicle motion, the most common approach is the longitudinal model of the vehicle [3], [15], [17], [18], [20], [24], [31], [33], [34], [47], [46], [55]–[61]. This model relies on Newton's second law of motion and calculates the traction force F_t based on the rolling resistance F_r, aerodynamic drag resistance F_{aero}, grade resistance F_g, and acceleration force of the vehicle F_a, as summarized in (1) – (5). The graphical representation of the mentioned forces is provided in Figure 2. The rolling resistance F_r is the result of the friction between the tires and the road and is based on the coefficient of rolling resistance C_r, vehicle mass m, road gradient α, and the gravitational force g. The aerodynamic resistance F_{aero} depends on the frontal area of the bus A_f, air density ρ, aerodynamic drag coefficient C_d, and the velocity of the bus v. The grade resistance F_g depends on the road gradient α, the vehicle mass m, and the gravitational force g, whereas the acceleration force depends on the vehicle mass m and the acceleration rate a.

$$F_t = F_r + F_{aero} + F_g + F_a \quad (1)$$

$$F_r = m \cdot C_r \cdot g \cdot \cos\alpha \quad (2)$$

$$F_{aero} = 0.5 \cdot \rho \cdot A_f \cdot C_d \cdot v^2 \quad (3)$$

$$F_g = m \cdot g \cdot \sin\alpha \quad (4)$$

$$F_a = m \cdot a \quad (5)$$

The electrical DC power needed from the battery is directly dependent on the tractive force F_t, velocity of the vehicle v, and the efficiency η, as shown in (6).

$$P_{DC} = \frac{v \cdot F_t}{\eta} \quad (6)$$

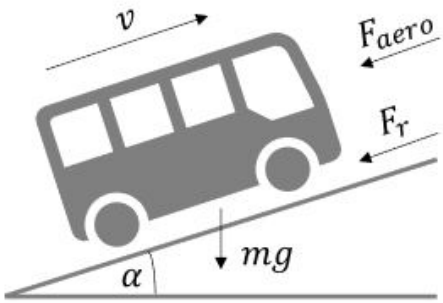


Figure 2: Forces acting on the bus during its movement

The calculation of the traction force requires knowledge of the parameters mentioned in (1) – (5). They, however, show different levels of volatility. The frontal area of the vehicle is a known constant parameter. Air density and aerodynamic drag coefficient show very low volatility based on the wind direction and weather conditions. However, other parameters such as vehicle mass and velocity, as well as the rolling resistance coefficient show high volatility. Researchers take different approaches when defining these parameters, usually focusing on the vehicle mass and velocity. The vehicle mass can be divided into the curb weight of the empty vehicle and the mass added due to passengers. The curb weight is a known parameter, whereas the passengers' mass changes during the trip. Some studies use average estimated values for the passengers' mass [17], [18], [31], [56] while others create a passenger load profile, either measured or estimated, to take the mass volatility into account [20], [24], [47], [57], [59]. The velocity of the vehicle is another parameter often modelled in different grades of detail. Study [18] uses simple continuous speed profiles, studies [24], [55], [56] use full synthetic speed profiles, while studies [3], [17], [34], [47], [57], [60] analyse measured speed profiles. In fact, to tackle this problem, Kivekäs et al. propose a driving cycle synthetization method for generating a large number of driving cycles with varying speeds and passenger profiles [43]. These can be used as inputs for physical models.

While some researchers only consider the mentioned longitudinal model when modelling the EC, others additionally consider the power consumption of different auxiliaries P_{aux}. These include heating and cooling, ventilation, lighting, doors, wipers, hydraulics, etc. [15], [18], [20], [24], [31], [33], [57], [58]. Some studies provide an extensive heat flow model of the vehicle in order to have a more exact consideration of the HVAC system [18], [24], [31], [58].

Further models often included when using the physical approach are the battery model, with some including the energy recuperated during the driving [31], [34].

2.3. Regression models

Regression models provide a function that describes the relationship between one or more independent variables

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X and one dependent variable, in this case EC, as shown in (7). The goal is to estimate the parameters b_i for each variable X_i to best fit the data and minimize the error ε, where i is the total number of considered variables.

$$EC = f\left(X_i, b_i\right) + \varepsilon \tag{7}$$

Different studies have analysed and included different independent variables, as summarized in Table 2, focusing on linear as well as nonlinear models. Abdelaty et al. investigate the impact of vehicular, operational, topological, and external parameters on the EC of electric buses [15]. Furthermore, they use multiple linear regression to analyse the impact of the following parameters on the EC: road grade, the initial state of charge, road condition, passenger loading, driver aggressiveness, average speed, HVAC, and stop density. The same authors use the existing prediction model in an open-source low-resolution data-based framework to estimate the EC [66]. Vepsäläinen et al. use multiple linear regression to identify the operation factors that cause variation in EC and in the internal resistance of the battery [22]. The correlation between the consumption and the following parameters was analysed: battery and ambient temperature, the auxiliary power of the air compressor, DC devices, heat pump, and power steering, idle time, stops per kilometer, driving aggressiveness, and vehicle velocity. For the linear regression model, they chose the auxiliary power of DC devices, ambient temperature, number of stops per kilometer, and driving aggressiveness. Pamula and Pamula propose a deep learning network as well as a multiple linear regression model to predict the EC between two stops based on the following parameters: distance between stops, travel time, elevation difference, and weather conditions [46]. In another study, Pamula and Pamula use the same principle and extend the model by adding another parameter, the hour of traveling [62]. Ji et al. propose a multivariate nonlinear regression model to estimate the total EC on the trip level [48]. They analyse the impact of travel distance, curb weight, travel time, ambient temperature, and the duration of the AC system in the energized state. Vehviläinen et al. collected and analysed weather and electric city bus data to understand the effects of temperature and weather conditions on the EC [26]. They use simple linear regression to express the EC as the function of the ambient temperature. Bie et al. propose an optimization method for scheduling electric buses while considering stochastic volatility in trip travel time and EC [40]. They use a regression model for the calculation of EC based on three parameters: battery SoC at the departure time, trip travel time, and average temperature. Jiang et al. propose two probabilistic models, based on Bayesian and quantile regression, to estimate the EC [64]. They use the intensity of the speed, braking, slow-driving, and temperature for their estimate. The mentioned features can be calculated based on the vehicle speed and air temperature. Xing et al. use different methods to estimate the EC of electric buses, including multivariate nonlinear regression [63]. Their model uses the following parameters: initial SoC, average vehicle speed, trip time, and operation of air conditioning. Jiang et al. propose a hybrid approach for the prediction of EC on a trip level by combining physical modelling with Gaussian processing regression [67]. In their case, the physically modelled parameters such as vehicle speed, travel time, motor power, and auxiliary power are combined with data-driven parameters such as bus number, departure day of the week, departure time, traffic

Table 2: Overview of parameters affecting the energy consumption of electric buses as analysed in different regression studies

	Vehicle and battery	HVAC	Auxiliary	Driving style	Passenger load	Trip duration	Initial SoC	Vehicle speed	Stops spacing	Road gradient	Road condition	Air temperature
Abdelaty et al. [15]	-	x	-	x	x	-	x	x	x	x	x	-
Vepsäläinen et al. [22]	-	-	x	x	-	-	-	-	x	-	-	x
Pamula et al. [46]	-	-	-	-	-	x	-	-	x	x	-	x
Pamula et al. [62]	-	-	-	-	*	x	-	-	x	x	-	x
Ji et al. [48]	x	x	-	-	-	-	-	-	-	-	-	x
Vehviläinen et al. [26]	-	-	-	-	-	-	-	-	-	-	-	x
Bie et al. [40]	-	-	-	-	-	x	x	-	-	-	-	x
Xing et al. [63]	-	x	-	-	-	x	x	x	-	-	-	-
Jiang et al. [64]	-	-	-	-	-	-	-	x	-	-	-	x
Qin et al. [65]	-	x	-	-	-	x	-	-	-	-	-	x
Xu et al. [16]	x	-	-	x	x	x	-	x	-	-	-	x

* Passenger load is considered indirectly by considering the hours of travelling

condition level, ambient temperature, and accumulated mileage. Sennefelder et al. propose a multiple linear regression model for EC prediction based on 40 features of the measured speed profile [68]. Qin et al. use support vector machine regression and a grey wolf optimization algorithm to estimate the EC based on SoC, travel time, air temperature, and air-conditioning operation time [65]. Xu et al. propose three regression models, including the elastic net (linear regression), gaussian process regression, and light gradient boosting [16]. They use 18 different features related to the road, driver, vehicle, and ambient factors. Table 3 gives an overview of regression models used in the literature. The coefficients b_i represent the weight of particular parameters denoting their relative contribution to the overall prediction. As can be seen, researchers used different parameters to predict the EC, such as: road grade GR, driving aggressiveness D_{agg}, road condition R_C, power of the HVAC system $HVAC$, passenger load P_L, stops density per km S_D, average speed v_a, initial SoC SoC_i, length of the trip L, ambient temperature T_a, optimal operating temperature T_o, DC converter power P_{dc}, distance between stops d, travel time between stops Δt, elevation difference between stops Δh, weather code w, hour code tph, total curb weight of the bus M, total travel time t_t, operation time of the AC system of each trip t_a.

2.4. Machine learning models

Another data-driven approach for the estimation of EC is machine learning. Lin et al. collected 10s data from a bus on one line in Taiwan, for a period of 8 months [53]. They use this data to construct analytical models to forecast the EC of the bus using decision trees and the random forest method. The analysis indicates that the vehicle and motor speed, as well as the total voltage, have the greatest impact on the EC. Whereas the forecasting shows good results for one analysed route, applying the same parameters for another bus on another route had significantly less success with the forecast. The parameters therefore needed to be adjusted for each route and bus. Li et al. propose a physical and data-driven fusion model for electric bus EC estimation [21]. The basic EC of the electric bus was modelled by a simplified physical model. For other factors such as the velocity variance, velocity average, acceleration and deceleration, and ambient temperature, the data-driven model was selected. Finally, the two models are fused to estimate vehicle EC using the decision tree modelling approach. Abdelaty and Mohamed developed a deep learning neural network (DLNN) model to predict the consumed energy based on bus and route-related parameters, driver aggressiveness, and environmental parameters [69]. They modelled 10,800 scenarios varying 10 parameters. The road gradient had the biggest influence on the EC, followed by the initial SoC, the deceleration rate, and the average speed. In contrast, the HVAC had the lowest importance among all the used parameters. This might be attributed to the fact that the HVAC input was assumed to be constant based on ambient temperature. In another study, Abdelaty et al. extend their previous work and analyse and compare different methods for the prediction of EC of electric buses, including multiple linear regression, interpolation method, and DLNN [75]. Gao et al. used a wavelet neural network (WNN) to predict the EC based on the following factors: travel date (working day or weekend), travel weather condition (temperature, haze, or rain), length of the travel path, vehicle air conditioning, and vehicle running limit policy [70]. Xing et al. use long-short-term memory (LSTM) and convolutional neural network (CNN) to predict the EC of electric buses by observing

Table 3: Regression models for the prediction of energy consumption used in literature

	Regression model
Abdelaty et al. [15]	$EC= b_0+b_1 \cdot GR+ b_2 \cdot D_{agg}+b_3 \cdot RC+b_4 \cdot HVAC+b_5 \cdot P_L+b_6 \cdot S_D+b_7 \cdot v_a+b_8 \cdot S_o C_i+b_9 \cdot L$
Vepsäläinen et al. [22]	$EC= b_0+b_1 \cdot \lvert 20\text{-}T_a \rvert + b_2 \cdot P_{dc}+b_3 \cdot S_D+ b_4 \cdot D_{agg}$
Pamula et al. [46]	$EC= b_0 \cdot d_n+b_1 \cdot \Delta t+ b_2 \cdot \Delta h+b_3 \cdot w$
Pamula et al. [62]	$EC= b_0 \cdot d_n+b_1 \cdot \Delta t+ b_2 \cdot \Delta h+b_3 \cdot w+b_4 \cdot tph$
Ji et al. [48]	$EC=EC_1+ EC_2$ *where* $\ln EC_1=b_0 \cdot \ln L+b_1 \cdot \ln M+ b_2 \cdot \ln t_t+b_3 \cdot \lvert T_a\text{-}T_o \rvert$ and $EC= \begin{cases} b_4 \cdot t_a, \text{ if AC system in cooling mode} \\ b_5 \cdot t_a, \text{ if AC system in heating mode} \end{cases}$
Vehviläinen et al. [26]	$EC= \begin{cases} b_o \cdot T_a^3+b_1 \cdot T_a^2+b_2 \cdot T_a, \text{ if } T_a \geq 0^oC \\ b_3 \cdot T_a, \text{ if } T_a < 0^oC \end{cases}$
Bie et al. [40]	$EC= b_0 \cdot SoC_i+b_1 \cdot t_t+ b_2 \cdot T_a$
Xing et al. [63]	$EC = b_o + b_1 \cdot \ln\left(\frac{1-SoC_i}{100}\right) + b_2 \cdot t + b_3 \cdot v_a^2 + b_4 \cdot v_a + b_5 \cdot t_a^2 + b_6 \cdot t_a$
Jiang et al. [64]*	$EC= b_0+b_1 \cdot I_{spd}+ b_2 \cdot I_{brk}+b_3 \cdot I_{slw}+ b_4 \cdot I_{tmp}$

* Features I_{spd}, I_{brk}, I_{slw}, and I_{tmp} are physically interpretable based on V_a and T_a

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the consumption and the input parameters as a time series [63]. The input parameters used in their study are initial SoC, average vehicle speed, trip time, and operation of air conditioning. Chen et al. propose an LSTM and artificial neural network (ANN) to predict the EC of electric buses on a microscopic level with 1 Hz data resolution [52]. They analyse various configurations of the proposed networks, using different layer configurations and input parameters. The parameters involved in the analysis are instantaneous speed, acceleration, vehicle power and motor rotation speed, as well as time, road classification, ambient temperature, ambient humidity, and road grade. Nan et al. propose a hybrid method to predict the EC based on LSTM and extreme gradient boosting (XGB) [71]. The LSTM network is used to predict driving parameters on a microscopic level, including vehicle speed, acceleration, gas pedal position, and brake pedal position. In the second stage, the forecasted parameters are used to predict the EC based on XGB. The input variables included in the model are ambient temperature, traffic conditions, road characteristics, and driving behaviour characteristics. Pamula and Pamula compare different configurations and types of neural networks, such as deep learning networks with an autoencoder layer (DLNA) and a network of LSTM type [62]. They compare the EC prediction with the multiple linear regression approach while using the following input parameters: distance between stops, travel time, elevation difference, weather conditions, and hour of travel. Li et al. use a two-step methodology combining machine learning with stochastic speed profile generation and an EC calculation based on a physical model [72]. They use the stochastic random forest and k nearest neighbour algorithms to predict EC on a trip level based on three types of parameters: calculated based EC (physical model), kinematic factors (acceleration, speed), and external factors (departure time, departure day, air temperature, wet-dry conditions). Xu et al. compare EC models based on machine learning, LSTM, and XGB, with an improved physics-based power model using the input parameters speed, acceleration, and road grade [73]. They conclude that physics-based models can achieve similar accuracy as machine learning solutions, under the condition of limited data. Zhou et al. categorize the operation of electric buses into four states and use separate methods to predict the EC for each state [74]. For the state with the depressed accelerator pedal, they use multivariate linear regression. The states of the depressed brake pedal, vehicle sliding, and vehicle idle are modelled with LSTM. An overview of parameters considered in machine learning studies is given in Table 4.

3. CONCLUSION

Multiple parameters affect the EC of electric buses. This paper provides an overview of the latest research regarding these parameters and offers a classification into four categories: vehicle-related, operational, route-related, and environmental parameters.

To successfully integrate electric buses into existing fleet management systems, it is necessary to have extensive

Table 4: Overview of parameters affecting the energy consumption of electric buses as analysed in different machine learning models

	Vehicle and battery	HVAC	Driving style	Passenger load	Trip duration	Initial SoC	Vehicle speed	Motor speed	Stops spacing	Road gradient	Road condition	Air temperature
Lin et al. [53]	-	-	x	-	-	-	x	x	-	-	-	-
Li et al. [21]	-	-	x	-	-	-	x	-	-	-	-	x
Abdelaty et al. [69]	x	x	x	-	-	x	x	-	x	x	x	x
Gao et al. [70]	-	x	-	-	-	-	-	-	-	-	-	x
Xing et al. [63]	-	x	-	-	x	x	x	-	-	-	-	-
Chen et al. [52]	-	-	*	-	-	-	x	x	-	x	x	x
Nan et al. [71]	-	-	x	-	-	-	x	-	-	x	-	x
Pamula et al. [62]	-	-	-	**	x	-	-	-	x	x	-	x
Li et al. [72]***	-	-	-	-	-	-	x	-	-	-	x	x
Xu et al. [73]	-	-	-	-	-	-	x	-	-	x	-	-
Zhou et al. [74]	-	-	****	-	-	-	x	-	-	-	-	-

* Driving style includes the instantaneous acceleration of the vehicle
** Passenger load considered indirectly by considering the hour of travelling
*** The listed parameters are used for the part of the methodology which relies on machine learning.
**** Driving style includes the accelerator and brake pedal status

knowledge of the EC. This paper offers an overview of four different approaches to modelling and forecasting: an empirical approach, physical models, regression models, and machine learning. Each of the approaches has its advantages and disadvantages, as well as different types and fields of use. The empirical approach uses data gathered through measurements and usually relies on average values for EC. While it can be used for quick decisions and rough estimates, it is not appropriate for detailed modelling and real-time management. The physical approach uses an exact model of the vehicle and calculates the power necessary for the vehicle movement and the auxiliaries with different grades of detail. This approach can result in a very exact calculation of EC, but at the same time, it requires more computation time and the knowledge of multiple vehicle and route-related parameters. Especially for large heterogeneous fleets or fleets that still do not exist (yet to be purchased), the technical parameters of the vehicles are often not known and assumptions have to be made, which can lead to deviation in the resulting EC. Additionally, volatile parameters, such as the velocity profile of the vehicle or the passengers' flow, typically need to be assumed or simplified, which again leads to errors. Regression and machine learning, on the other hand, do not model the vehicle. These two approaches are based on the historical data. The goodness of the forecast is in this case typically related to the amount and resolution of the available historical data.

The overview provided in this paper can be used by other researchers or decisionmakers as a support in their work.

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