The Concept of a Cyber-Physical System for Intelligent Battery Health Assessment and Road Range Forecast

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Abstract

The use of up-to-date artificial intelligence systems to estimate and predict accurately the rechargeable battery life of modern electric cars is becoming a fairly common approach. After all, the incorrect and inadequate assessment of the electric car's operation affects the timeliness of its maintenance, which in turn impacts the overall service life of the most important mechanisms and parts of the car, in particular the engine and the battery. This article discusses the concept of using a cyber-physical system to predict the Road Range and the State of Health of an electric car based on the use of soft computing approaches (ANFIS). This made it possible to determine more accurately the individual Road Range and the State of Health indicators of an electric car depending on many parameters (temperature, driver's driving style and the current BMS indicators of the battery).

Keywords

State of Health, State of Charge, Battery Management System, Electric Vehicle, Neural Network, Internet of Things, Cyber-physical System, Soft Computing.

1. Introduction

Due to the significant exacerbation of energy and environmental problems associated with the use of internal combustion engines in vehicles, the development of new types of engines that use electric traction and are environmentally friendly has become quite important. This type of electric transport wins over ever more users every year: from ordinary owners of cars to owners of industrial electric trucks [1].

However, due to their growing popularity, electric cars have their own significant drawbacks. In particular, the main and principal disadvantages include the following:

- relatively sparse availability of charging stations, especially when it comes to long-distance travel;
- relatively long charging time. For example, the use of conventional ports with the J1772 interface makes it possible to charge batteries applying a current from 16A to 40A, which, depending on the EV battery capacity, will make it possible to obtain a State of Charge (SoC) value of 100% in about 5 to 10 hours.
- relatively short driving distance of the EV on a single charge. Depending on the design features of the battery and the value of its SoH, the ratio of 1% of the charge to the distance travelled can range from 0.3 to 4 [2]. For example, for a KIA Soul EV with SoH=100% and SoC=100%, this proprietary indicator will stand at 1.56. In other words, a new fully charged battery can cover approximately 156 km (provided the driving is moderate).

The most significant problem is the Road Range, and especially the correct prediction of the distance travelled by the EV's Battery Management System (BMS). It should be noted that regardless of the car brand and the type of batteries used, the forecast of the traveling distance (Road Range) can

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be very different even for the same cars [3]. In addition, manufacturers' BMS systems, depending on the forecasting algorithms used, can either overestimate the Road Range indicator (for example, Nissan LEAF) or underestimate it (for example, Ford Focus EV, KIA Soul EV). The predicted value of Road Range is influenced by such factors as SoH, SoC, kWh / 100km value (or driving style), car battery temperature, and ambient temperature. In the authors' opinion, enhancing the accuracy of driving range prediction based on the use of modern intelligent cyber-physical systems is therefore quite an important issue, solving of which will provide drivers with more reliable information.

2. Literature review and problem statement

At present, there are a number of studies that suggest the use of various methods and approaches to enhance the quality and reliability of forecasting the driving range of an electric vehicle. In studies [4], Fuzzy transformations were utilized and adapted for online use for the purpose of predicting the potential traveling distance. A Fuzzy transformation was demonstrated in a form that was suitable for use in an IoT network. The resulting form retains all the properties of the original Fuzzy transformation formula, which makes it possible to minimize computational needs.

The solution of the multi-criteria problem [5] of forecasting the Road Range with the maximum efficiency of the electric motor led to obtaining the optimal speeds and the maximum traveling time. In studies [5], two approaches to calculating target functions were considered, viz. the use of a constant battery voltage and the use of battery voltage depending on the state of charge.

In studies [6], a model was created for predicting traveling distance power consumption in order to improve the Road Range forecast based on the use of intelligent optimization methods with Fuzzy Logic, as well as genetic algorithms and neural networks. The experimental results of the research done demonstrate the efficiency of the proposed method that is based solely on historical data regarding power consumption. The mean absolute error (MAE) was 1.64 km and 1.95 km, respectively.

The method of assessing the real power consumption of driving electric vehicles [7] proposes an alternative mechanism for expanding the scope of estimates of power consumption by electric vehicles thus providing a basis for a comprehensive assessment of the environmental benefits of electric vehicles. Additionally, the studies indicate that there are many methods that can predict the traveling distance and there are many factors that affect the traveling distance prediction. However, current research cannot take into account both the accuracy and comprehensiveness of those methods.

The machine learning method was used for predicting the driving range of rechargeable battery-powered electric vehicles [3], which is based on an algorithm for amplifying the gradient of the decision tree. The method includes a very large number of factors that cannot be considered by conventional regression methods. The results of using the machine learning method show that the maximum prediction error is 1.58 km, the minimum prediction error is 1.41 km, and the average one is approximately 0.7 km.

It should be noted that there are a large number of applications that also further help to determine the current parameters of SoH, SoC, Road Range and others. For example, for Nissan LEAF electric cars, there is an application called LEAF Spy; for KIA Soul EVs, there is an application called Soul Spy, and a more universal application that is suitable for any car is called Torque [8]. These applications make it possible to receive a wider data range than the car dashboard displays, and that is due to the use of a special OBD2 adapter that receives data directly from the EV's BMS.

A large number of existing studies and tools [3-8], when creating a model for predicting the traveling distance, do not take into account a sufficiently large number of factors, which can lead to poor applicability and accuracy of the prediction model. The methods and tools considered can predict the traveling distance and many factors that affect the prediction of the Road Range, but current research cannot take into account both the accuracy and comprehensiveness of those methods. Additionally, the same vehicle can yield different Road Range results. In the authors' opinion, additional accounting for the individual features of the electric vehicle and its driver is the main thing that will enhance the quality of forecasting the traveling distance of the vehicle and the SoH of its battery. In particular, the style and the nature of driving can be attributed to the parameters that directly influence the short-term determined parameters of SoC and Road Range and the long-term determined parameter of SoH.

The purpose of this research is to develop a concept of a cyber-physical system for intelligent battery health assessment and traveling distance prediction based on the use of Industry 4.0 standards, in particular the IoT. The diagnostic technique established in studies [3, 6, 9] will be the basic method of predicting the Road Range.

In order to achieve that goal, the following tasks were set:

- to develop the structure of a modular predictive device for EV with existing external interfaces for its integration into the overall IoT system of electric vehicles;
- to select the informative input attributes and the structure of the neuro-fuzzy network as a unit of inference and adaptation, which is the core of the predictive device for EVs;
- to build a logical-functional system for the operation of the IoT EV network consisting of EV modular predictive devices, and to determine the basic principles of its functioning;
- to model and analyse the feasibility and rationality of using the proposed concept of a modular cyber-physical system for EVs.

3. The concept of cyber-physical system for intelligent battery health assessment and road range forecast

It should be noted that this article discusses only approaches to the assessment of the SoH and the Road Range based on the data obtained from the BMS and additional sensors. Machine learning techniques require training a model based on extracted input characteristics and measured BMS data to describe battery aging behaviour, as well as the SoH and the Road Range prediction. Other methods considered [3-7] include constructing correlations between the eigenvalues of the EV battery, such as its Coulomb efficiency [10], and its ability to die down. Additionally, before applying to SoH and Road Range forecasting, all battery health and vehicle driving parameters must be effected in a standalone mode based on experimental data after sufficient adjustment and verification to ensure reproducibility and accuracy.

Machine learning is therefore a method of data analysis that automates the construction of an analytical model. It is based on the idea that systems can learn from data, identify patterns and make decisions or predictions with minimal human intervention [11]. Figure 1 shows a general logic-functional diagram of the machine learning process for online assessment and prediction of parameters such as SoH, SoC and Road Range.

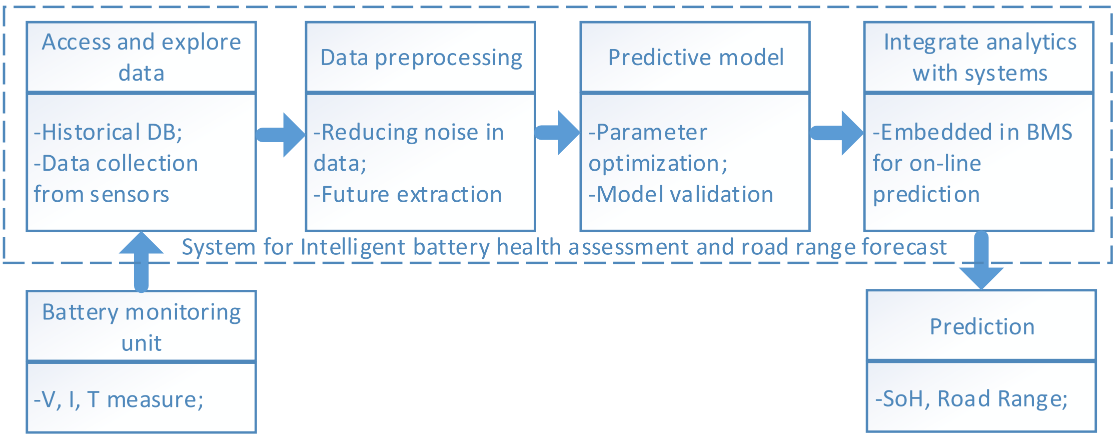

Figure 1: Logic-functional scheme of System for Intelligent battery health assessment and road range forecast

As can be seen from Figure 1, the first stage is data collection (parameters V, I, T). Measured battery parameters, such as temperature, current and voltage data recorded by the BMS during the operation, are registered and used as inputs for training the neural network model. However, not all data is related to battery aging. The second stage is the selection of properties that represent the aging process of the rechargeable battery. The third stage is to prepare the machine learning model and neural network structure for describing the relationship between the SoH, the Road Range, and the extracted functions. Once the model has been trained, the final stage is to implement it in the BMS for online application and forecasting.

The authors propose a new concept of a modular cyber-physical system for predicting the values of SoH and Road Range based on the use of IoT approaches and in accordance with the research presented in papers [9, 12]. It should be noted that the main element of any IoT network is the Smart Box. In terms of design, there can be several variants of Smart Box devices. In particular, in addition to the tasks to be solved, they can differ dramatically in the architecture of the Hardware and Software elements, which may lead to additional costs for their integration into the overall IoT network. This may be due to the use of additional software and hardware, or to the features of their structure. It is therefore advisable to make each SmartBox as a separate module. The model of a modular cyber-physical system using a Smart Box device for predicting the SoH and the Road Range values of an electric vehicle is shown in Fig. 2.

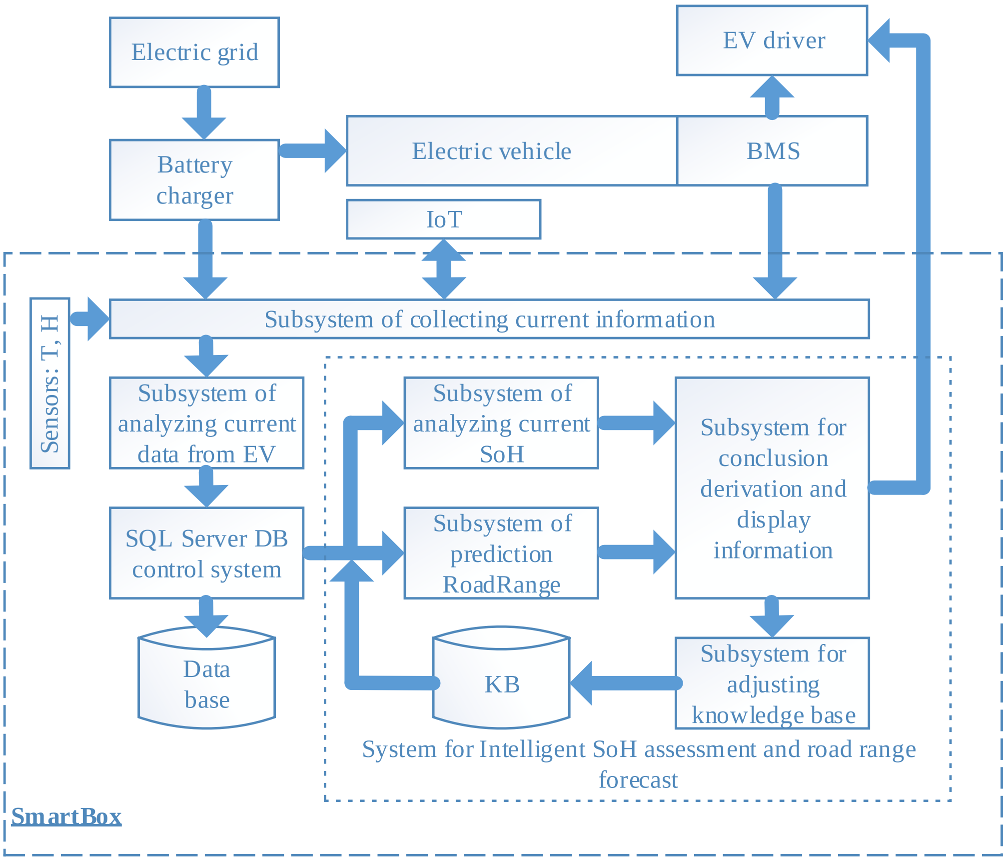

Figure 2: A model of the modular cyber-physical system using a Smart Box device for Intelligent battery health assessment and road range forecast and its information flows

According to Figure 2, at the time of its charging, the electric vehicle is connected to the power grid by means of a special charger. Accordingly, in addition to the data available in the BMS, the amount of power received (battery charger) and environmental indicators (temperature and humidity) are also analysed. In order to analyse further the data obtained, the current information collection subsystem therefore analyses the data received from the BMS, the Battery Charger and the external sensors. It should be noted that data from BMS is obtained based on the use of an OBDII adapter and from the battery charger based on the use of Wi-Fi Watt meter, as well as humidity and ambient temperature sensors directly connected to the SmartBox device. This subsystem can be represented as a regular data logger with a Wi-Fi interface. The task of the database management subsystem (DBMS) is to store and manage all the necessary data for the correct and efficient operation of the modular SmartBox device. In particular, such data can include the following: data that is responsible for preserving the previous and forecasting the next SoH and RangeRoad values; data that is responsible for the current values of the operation parameters of the EV under investigation. The subsystem for making inferences and outputting information is an expert system. It should be noted that the final decision on the current parameters is made by the BMS. All data obtained is for informational purposes only, and does not affect the management of the system. This is due to the peculiarities of the interaction between the BMS and the mechanical part of the EV and the probability of error occurring as a result of calculations, which in turn can lead to a certain error when making inferences regarding the SoH and the Road Range indicators.

It should also be noted that the above model (Figure 2) makes it possible to use one Smart Box device for a group of similar electric vehicles. In order to distinguish each electric vehicle as a separate object of the research, indicators such as SoH, SoC and Road Range are used that make it possible to determine the individual characteristics of the EV and identify it from a group of similar ones. It should be noted that object identification is one of the main provisions of the IoT concept [13].

The proposed approach makes it possible to monitor and predict the current state of the EV based on the use of a fewer number of SmartBox devices, e.g. when using a single SmartBox for several EVs. It should be noted that their number is determined by the type and quantity of equipment used, the features of the technical condition of the EV, and their geographical distance from each other. The general logic-functional diagram of using Smart Box for forecasting the SoH and the Road Range indicators on the basis of the modular principle can be presented as follows (Figure 3):

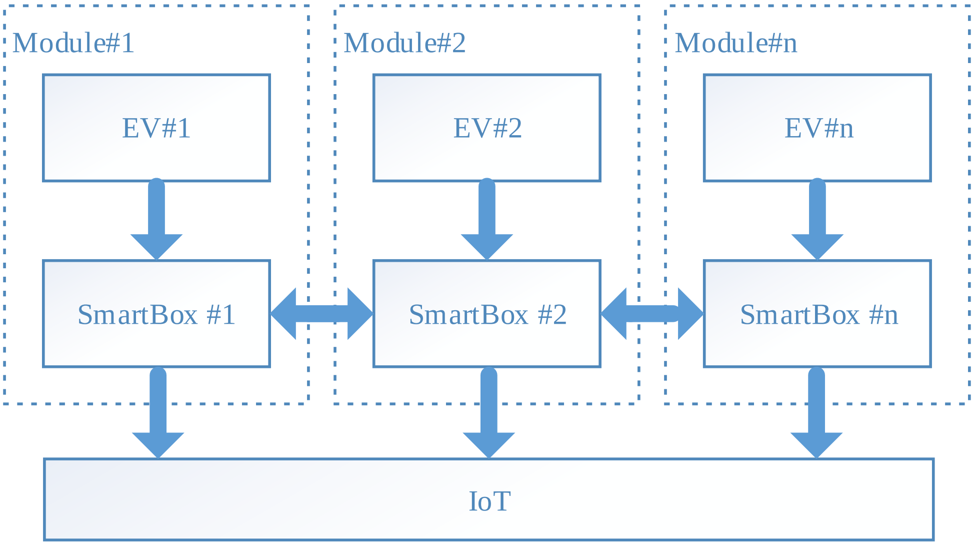

Figure 3: Modular network of Smart Box devices for EV

It should be noted that only one SmartBox device and one electric vehicle could be located within one module. In general, all modules form an information computing cluster. A distinctive feature of organizing objects in a cluster is an increase in their productivity and reliability. For example, arranging cluster of such a type is a fairly good solution for organizations such as car sharing [14], car rental and car service stations.

It should also be taken into account that the Smart Box cannot make correct forecasts based only on experimental (current) data. This is due to the impossibility to take into account all varied situations of the system that may arise, for example, as a result of sensor measurement errors (those of Watt meters, temperature and humidity sensors), the lack of accurate mathematical models of the SoH, SoC, RoadRange patterns, sensor failures, etc. When operating a Smart Box, there may therefore occur inconsistencies in the classification of situations. One of the possible solutions to this problem is therefore the use of fuzzy logic, neural network structures, classification trees, etc.

Based on the analysed varieties of intelligent systems [9, 15] and for the implementation of the SmartBox expert system (subsystem "Logical inference and control information generation"), it was proposed to use a multilevel hybrid fuzzy-neural network system that would consist of subnetworks of various architectures (neural network and fuzzy logic ones). It should be noted that modelling of control processes was performed in the MatLab environment with the Fuzzy Logic Toolbox extension package [13].

The "Logical inference and the control information generation" subsystem generates the result of forecasting the SoH and the RoadRange indicators (displaying the relevant information on the driver's dashboard screen). Additionally, this subsystem can perform a control action for the BMS of the EV. For example, in the event of critical values of the SoH and the RoadRange indicators, switching over to the economy mode and turning on of special sensors is performed, which signals the need to check the technical condition of the battery. In addition, the control action is formed on the basis of information about the inconsistency of data between the predicted and current value of the SoH of the electric vehicle.

The "Logical inference and the control information generation" subsystem contains two fuzzy output systems, viz. systems for outputting information on the SoH and the RoadRange, whose values can be used to create a control action for the BMS. Both systems are represented as neuro-fuzzy five-layer direct error propagation networks (Figure 4). The network implements a zero-order Sugeno type fuzzy output system, and has four input variables (both systems have sets of identical input data):

1. IVG – actual power consumption (amount of kW consumed per battery charge);
2. IT – current SoH value (value obtained from the BMS of the EV);
3. ICO – meteorological data (ambient temperature);
4. ICZ – current RoadRange value (value obtained from the BMS of the EV).

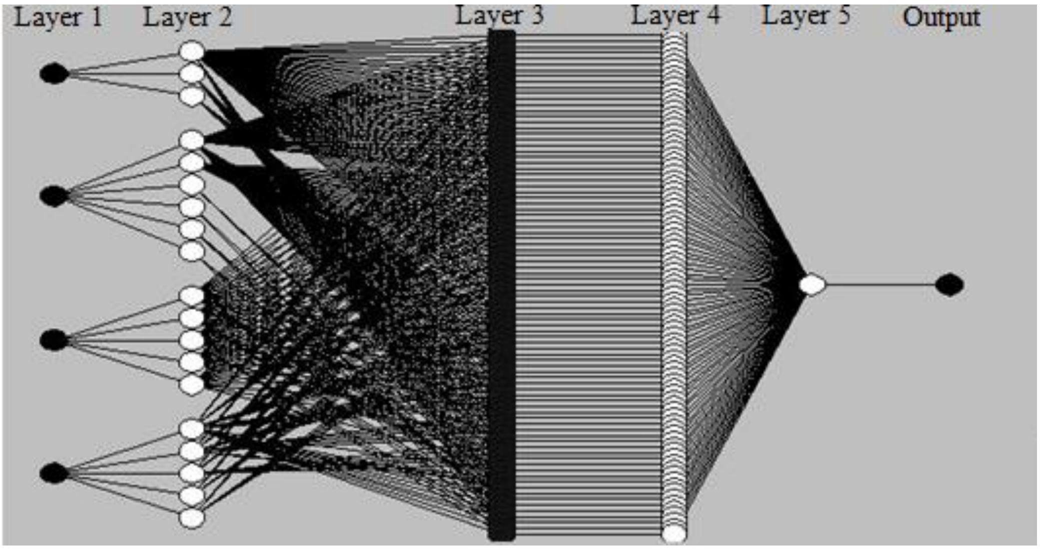

Figure 4: The structure of the neuro-fuzzy system and the fuzzy visualization

The output of the first network is the linguistic variable OUS that, depending on the values of the input variables, generates the predicted value of the SoH and control information for the BMS. Similarly, the output of the second network is the linguistic variable OUR that, depending on the values of the input variables, generates the predicted value of the RoadRange.

3 terms are used for the linguistic evaluation of the input IVG variable, 6 terms are used for the IT variable, 5 terms are used for the ICO variable, and 5 terms are used for the ICZ variable. Set TIVG = {"33% of the battery capacity", "66% of the battery capacity", "100% of the battery capacity"}is used as a term set of the first linguistic variable IVG, which is written symbolically as TIVG = {IVGZ1, IVGL, IVGL2}. Set TIT = {"Very low SoH", "20% SoH", "40% SoH", "60% SoH", "80% SoH", "100% SoH"} is used as a term set of the second linguistic variable IT, which is written symbolically as TIT = {ITR, ITU, ITP, ITV, ITPV, ITN}. Set TICO = {"cold", "cool", "comfortable", "hot", "very hot"} is used as a term set of the third linguistic variable ICO, which is written symbolically as TICO = {ICOH, ICOP, ICOK , ICOJ, ICON}. Set TICZ = {"Very low RR", "20% RR", "40% RR", "60% RR", "80% RR", "100% RR"} is used as a term set of the fourth linguistic variable ICZ , which is written symbolically as TICZ = {ICZH, ICZP, ICZK, ICZJ, ICZN}. The term set of the input linguistic variables OUS and OUR constitutes the set of values TOU = {Uj}, j = 1, .. 10.

Depending on the values obtained, the following modes of system operation can be distinguished for the linguistic variable OUS:

- Us1 – «Lower than 10%» - alarm signal to the BMS;
- Us2 - «Lower than 20%» - alarm signal to the BMS;

- Us3 - «Lower than 30%» - alarm signal to the BMS;
- Us4 - «Lower than 40%» - alarm signal to the BMS;
- Us5 - «Lower than 50%» - displaying the predicted SoH value on the screen;
- Us6 - «Lower than 60%» - displaying the predicted SoH value on the screen;
- Us7 - «Lower than 70%» - displaying the predicted SoH value on the screen;
- Us8 - «Lower than 80%» - displaying the predicted SoH value on the screen;
- Us9 - «Lower than 90%» - displaying the predicted SoH value on the screen;
- Us10 - «Lower than 100%» - displaying the predicted SoH value on the screen.

Similarly, the following modes of system operation can be distinguished for the linguistic variable OUR:

- Ur1 – «Lower than 10%» - alarm signal to the BMS;
- Ur2 - «Lower than 20%» - alarm signal to the BMS;
- Ur3 - «Lower than 30%» - displaying the predicted RoadRange value on the screen;
- Ur4 - «Lower than 40%» - displaying the predicted RoadRange value on the screen;
- Ur5 - «Lower than 50%» - displaying the predicted RoadRange value on the screen;
- Ur6 - «Lower than 60%» - displaying the predicted RoadRange value on the screen;
- Ur7 - «Lower than 70%» - displaying the predicted RoadRange value on the screen;
- Ur8 - «Lower than 80%» - displaying the predicted RoadRange value on the screen;
- Ur9 - «Lower than 90%» - displaying the predicted RoadRange value on the screen;
- Ur10 - «Lower than 100%» - displaying the predicted RoadRange value on the screen.

The layers of the fuzzy network have the following purpose:

Layer 1. It defines fuzzy terms of input parameters. The outputs of this layer represent the values of the membership function for specific values. Each node of the layer is adaptive with the membership function μAi (χ), where χ is the value of the i-th node, i = 1,…, n; Ai is a linguistically fuzzy variable associated with this node. Trapezoidal membership functions were chosen for the terms of input variables.

Layer 2. It defines premises of fuzzy rules. This layer is non-adaptive. Each node is connected to those nodes of the first layer that form the prerequisites for the respective rule. This layer performs a fuzzy logical "AND" operation according to the parameters of the rule's premises. The neurons' outputs of this layer are the truth measures of the premises of each j-th rule of the knowledge base of the system calculated according to the following formula:

$$w_j = \min|\mu_{IVGj}(IVG), \mu_{ITj}(IT), \mu_{ICOj}(ICO), \mu_{ICZj}(ICZ)|, \tag{1}$$

where j=1,..300 – determines the total number of rules for the fuzzy output system.

Layer 3. It effects the normalization of the degree of compliance with the rules. The non-adaptive nodes of this layer calculate the relative degree (weight) of the fuzzy rule according to the following formula:

$$\overline{W_j} = w_j / \sum_{j=1}^{200} w_j, \tag{2}$$

Layer 4. The clear number Uj that defines the result of each j-th rule is considered a fuzzy set with a singleton membership function. The adaptive nodes of the fourth layer calculate the contribution of each fuzzy rule to the network output according to the following formula:

$$y_j = \overline{W_j} U_j, i = 1,..,300, \tag{3}$$

Layer 5. The non-adaptive node of this layer summarizes the contributions of all the rules:

$$y = \sum_{j=1}^{300} y_j, \tag{4}$$

The software implementation of the neuro-fuzzy network was obtained in the Matlab Fuzzy Logic mathematical package using the ANFIS program m-function. The fuzzy output system was configured automatically. The parameters of the network nodes were configured during training in such a manner so that to minimize the root mean standard error (RMSE) using the following formula:

$$E = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[v_P(i) - OU_{s/r}(i)]^2} \longrightarrow \min, \quad (5)$$

where vP – discrepancy between the predicted and current SoH and RoadRange values, N – number of observations in the vP learning data sample.

The reverse error propagation method based on the gradient method of the fastest descent was chosen as the ANFIS network training algorithm for determining the parameters of the membership function [14].

The proposed neural network system, as a logic output device for the SmartBox, can therefore make it possible to solve problems of current control and prediction of the EV parameters in a real-time mode [14, 15].

4. Results of modelling the operation of a cyber-physical system for intelligent battery health assessment and road range forecast

For the purpose of analysing the feasibility and rationality of using the proposed concept of a modular cyber-physical system for the intelligent assessment of battery status and the traveling distance prediction, experimental studies were conducted using the Monte Carlo simulation method. The learning sample was obtained using the Monte Carlo method. The initial value of the learning step in the direction of the anti-gradient of criterion E when changing the parameters of the membership function was set at $\alpha = 10^{-4}$. The permissible change in the step value during one iteration was 15%. For the network learning, the value of the learning criterion averaged E = 2.125, after 500 iterations it was E = 0.144. The response of the learning error value to the amount of the learning sample data is shown in Figure 5.

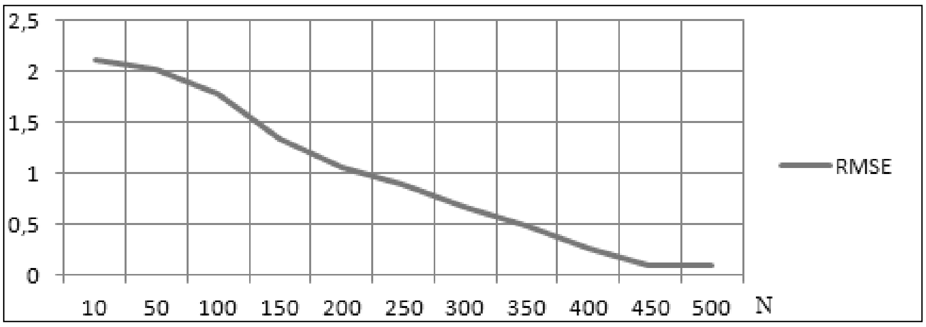

Figure 5: The structure of the neuro-fuzzy system and the fuzzy visualization

When modelling the operation of the expert system, it was assumed that rechargeable batteries with existing heating and cooling systems were used. The driver's driving style was assumed to be moderate and meeting the driving standards for the relevant car brand. In the research in question, experimental data were selected for a KIA Soul EV + (the maximum speed in the eco-mode was 70 km/h with an average power consumption of 12 kWh /100 km, SoH = 91.1%).

The results of modelling the expert system operation (the SoH and the Road Range forecasting) are shown in Figure 6 and Figure 7, respectively.

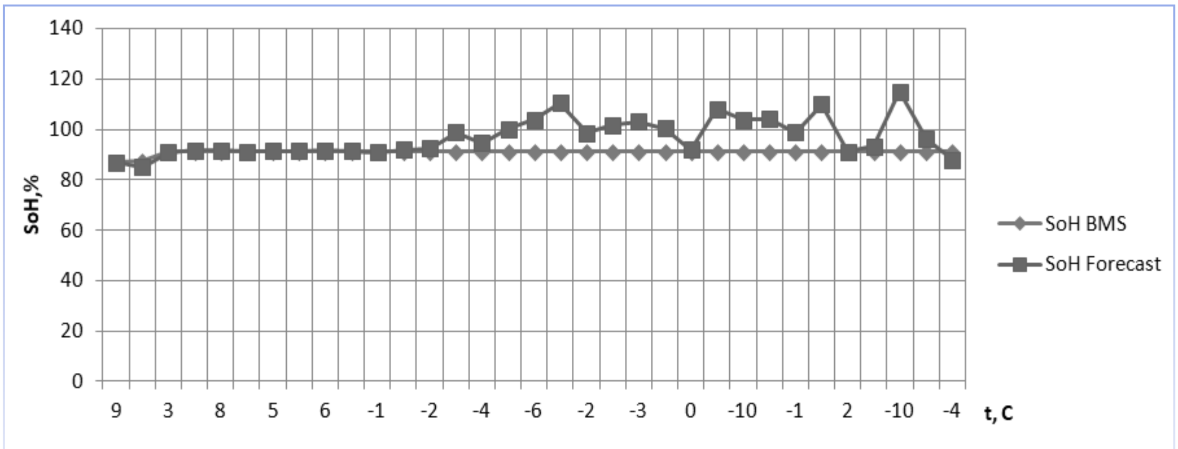

Figure 6: The results of modelling the SoH forecast

As can be seen from the graph (Figure 6), there are areas where the SoH calculated by the BMS system and the predicted one either coincide (the deviation is within 0.58%) or sharply deviate (the deviation is up to 6%). This is primarily due to the different nature of the SoH BMS and the SoH Forecast calculations. In particular, SoH BMS was calculated as follows [8]:

$$SoH_{BMS} = \frac{110-(MaxDet-MinDet)}{2}110, \tag{6}$$

where MaxDet – value of the maximum degradation of the battery cell, MinDet – value of the minimum degradation of the battery cell. In turn, the predicted value of the SoH was determined based on the amount of power consumed to charge the battery. It should be remembered that during cold and hot seasons, during the battery charging process, a certain part of the power is spent on preheating or precooling.

As can be seen from the simulation results (Figure 7) of the Road Range indicator, the discrepancy between the Real Road Range and the Forecast Road Range is up to 1.3%, while the discrepancy between the Real Road Range and the BMS Road Range is up to 6%. It should be noted that the ambient temperature value has a strong effect on the BMS Road Range. Most likely, this is due to the forced downward bias of the Road Range values in order to prevent the occurrence of a situation of the full discharge of the car battery and the impossibility of further movement. In addition to weather conditions, the value of the Road Range is influenced by the driver's driving style, features of implementing the eco-driving mode and other factors used by a particular manufacturer for its vehicle brand.

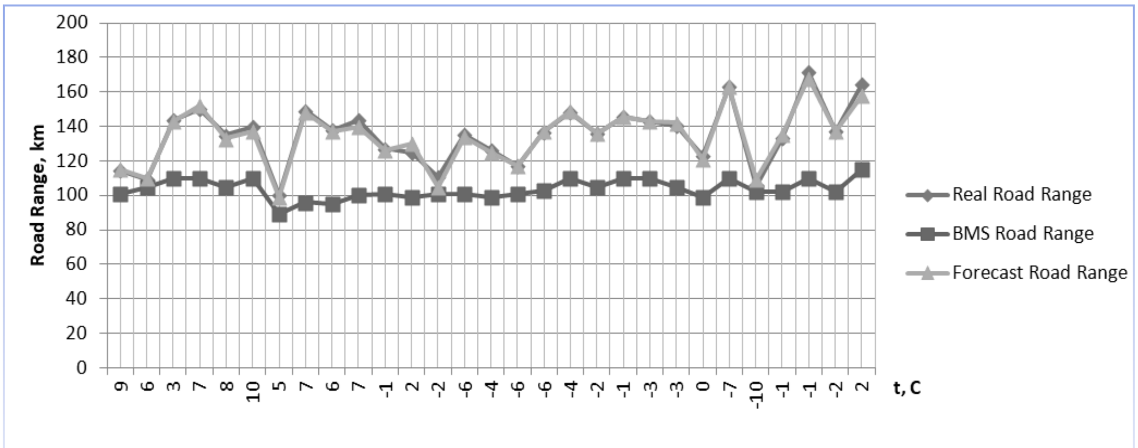

Figure 7: The results of modelling the Road Range forecast

It should be noted that when training the neuro-fuzzy network, to achieve a lower root mean square learning error, it is necessary to use a learning sample with a high value of input data or a higher value of the number of learning epochs. However, as the number of learning epochs increases, the total learning time of the neuro-fuzzy network increases as well, which in turn impacts the overall response of the system. The response of the learning time to the number of epochs is presented in Figure 8. The value of N was selected to be equal to 300, $E = 10^{-3}$, while a computer with the Intel Xeon L5420 2.5 GHz processor and RAM = 6 GB was selected as hardware support.

5. Conclusions

A structure was proposed of the cyber-physical system for the intelligent assessment of the battery status and forecasting the traveling distance based on the use of the IoT principles, in particular, modular Smart Box devices that, drawing on the empirical data and the BMS data of the electric vehicle, are capable of predicting the SoH and the Road Range. Using this approach makes it possible to combine all IoT devices for additional data accumulation and enhancement of the reliability of the data being obtained.

Using the proposed structure of the expert system as part of a cyber-physical system for the intelligent assessment of the battery status and prediction of the traveling distance will make it possible to enhance the quality of the Road Range forecast to 98.7% (the maximum forecast error is 2.06 km, the minimum forecast error is 0.68 km) and that of the SoH to 99.42%.

It should be noted that in the course of the research, it was found that the discrepancy between the predicted value of the SoH BMS and the SoH Forecast, depending on the weather conditions, can constitute 6%. This feature can be used in the feature to determine the amount of power that will be spent on heating or cooling the rechargeable battery of the electric vehicle, and to take it into account in the MicroGrid and SmartGrid systems.

6. References

[1] X. Yuan, L. Li, H. Gou, T. Dong, “Energy and environmental impact of battery electric vehicle range in China,” Applied Energy, vol. 157, (2015), pp. 75–84.

[2] A. Shekhar, V. Prasanth, P. Bauer, and M. Bolech, “Generic methodology for driving range estimation of electric vehicle with on-road charging,” in Proceedings of the IEEE Transportation Electrification Conference and Expo, (2015), ITEC '15.

[3] Shuai Sun, Jun Zhang, Jun Bi, Yongxing Wang, "A Machine Learning Method for Predicting Driving Range of Battery Electric Vehicles", Journal of Advanced Transportation, (2019), Article ID 4109148, 14 pages, (2019). https://doi.org/10.1155/2019/4109148

[4] I. Cunningham and K. Burnham, “Online use of the fuzzy transform in the estimation of electric vehicle range,” Measurement and Control, vol. 46, no. 9, (2013), pp., 277–282.

[5] W. Vaz, A. K. R. Nandi, R. G. Landers, and U. O. Koylu, “Electric vehicle range prediction for constant speed trip using multi-objective optimization,” Journal of Power Sources, vol. 275, , (2015), pp. 435–446.

[6] A. Bolovinou, I. Bakas, A. Amditis, F. Mastrandrea, and W. Vinciotti, “Online prediction of an electric vehicle remaining range based on regression analysis,” in Proceedings of the 2014 IEEE International Electric Vehicle Conference, IEVC '14, December 2014.

[7] X. Yuan, C. Zhang, G. Hong, X. Huang, and L. Li, “Method for evaluating the real-world driving energy consumptions of electric vehicles,” Energy, vol. 141, (2017), pp. 1955–1968.

[8] MyKiaSoulEV, Setting up Torque to show BMS data (2020), Available at: https://www.mykiasoulev.com/forum/viewtopic.php?t=471

[9] A. Kupin, D. Kuznetsov, I. Muzyka, D. Paraniuk, O. Serdiuk, O. Suvorov, V. Dvornikov. The concept of a modular cyberphysical system for the early diagnosis of energy equipment. Eastern European Journal of Enterprise Technologies. 4, (2018), pp. 71-79. doi:10.15587/1729-4061.2018.139644.

[10] M. Murnane, A. Ghazel, A Closer Look at State of Charge (SOC) and State of Health (SOH) Estimation Techniques for Batteries, 2017.

[11] Li, Yi Liu, Kailong Foley, Aoife Aragon Zulke, Alana Berecibar, Maitane Nanini-Maury, Elise Van Mierlo, Joeri Hoster, Harry. Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review. Renewable and Sustainable Energy Reviews. Vol 11, (2017). 10.1016/j.rser.2019.109254.

[12] Z. Mohammed, , E. Ahmed, Internet of Things Applications, Challenges and Related Future Technologies, World Scientific News, №67(2), (2017), pp.126-148.
[13] I. Semanjski, S. Gautama, Forecasting the State of Health of Electric Vehicle Batteries to Evaluate the Viability of Car Sharing Practices. Energies. 9. 1025. (2016). 10.3390/en9121025.
[14] A. Kupin, I. Vdovichenko, I. Muzyka, D. Kuznetsov, Development of an intelligent system for the prognostication of energy produced by photovoltaic cells in smart GRID systems, Eastern-European Journal of Enterprise Technologies, № 5/8 (89), , (2017), pp.4-9. doi:10.15587/1729-4061.2017.112278.
[15] O. Drozd, K. Zashcholkin, R. Shaporin, J. Drozd, Y. Sulima, "Development of ICT Models in Area of Safety Education," Proc. of the 18th IEEE East-West Design & Test Symposium, Varna, Bulgaria, 2020, pp. 115 –119. DOI: 10.1109/EWDTS50664.2020.9224861