Self-adaptive algorithm for changing braking energy recuperation of an electric vehicle based on neuro-fuzzy inference system

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Abstract. This paper describes an expert system prototype that changes the brake energy recuperation coefficient of an electric vehicle. Blackboard is used as the basic architectural pattern, which allowed for working with data obtained from various types of knowledge sources. This approach made it possible to coordinate data from various sources, such as the opinions of drivers, information about the route and the condition of electric vehicles. The expert system is based on the adaptive neuro-fuzzy inference system ANFIS, the rules for which are obtained by mountain clustering data from the training set. Values are averaged using the C-means algorithm.

1. Introduction

There are a number of solutions for integrated monitoring of vehicles. Similar systems are used at various truck and bus depots. However, such systems often handle only the problem of the location determination for the monitored vehicle and in no way provide qualitative adjustment of the operating modes of vehicles.

Modern electric vehicles use braking energy recuperation, which is based on the electric method of kinetic energy recuperation. One of the problems of modern electric vehicles is the inability to “flexibly” adjust the braking energy recuperation. Such a setting will increase the amount of electricity returned to the vehicle power system.

However, there is a point when executing this setting. It depends not only on a specific vehicle, but also on the operating route, as well as on the driving style.

The recovery coefficient is used as one of the parameters describing the intensity of the regenerative braking - the ratio of the maximum generated regenerative braking torque to the maximum possible regenerative braking moment, measured in the range from 0 to 1.

The authors have developed a prototype expert system that, according to available data from various sources (people, vehicles, route information, etc.), adjusts the energy recuperation coefficient of route electric vehicles (hereinafter - electric buses). The work was carried out at BMSTU with the financial support of the Ministry of Education and Science of the Russian Federation under Agreement № 14.574.21.0178 (Unique identifier: RFMEFI57417X0178).
2. Software part design

The difficulty of the problem lies in the need to set the identical energy recuperation coefficients for all electric buses of the same series on the same route, but at the same time individual for each route of operation. It is necessary that the system does not adjust each vehicle for each driver, i.e. there should be an interchangeability of the vehicles. This approach enables to increase the energy efficiency of the vehicle by taking into account the features of the operating route. It is supposed to use 3 types of knowledge:

- information on the state of the electric buses (the number of mechanical brake actuations, the average and maximum speed, total operating time on the route and the time spent at stops);
- information about the route (base route time and energy recuperation coefficient for the route);
- drivers' opinions about the vehicle settings (how hard the vehicle brakes on a scale of 1–10, where 1 is very slow, 5 is normal, 10 is too fast).

Since the system needs to analyze data coming from different types of sources [1], the Blackboard pattern [2, 3] was laid in the basis of the system architecture. The Blackboard pattern is a class interaction shown in figure 1.

![Blackboard pattern](Image)

Figure 1. Blackboard pattern.

It will be shown that the pattern consists of the three main components:

- **Blackboard** – a class that contains all the relevant information from sources of knowledge. In fact, blackboard is the base of knowledge of the system. It should be noted that “knowledge” can be different in information fields, but must have a common structure - a common base class.

- **Knowledge Source** – informing entity of the system. Each entity can update its state at any time, therefore the Blackboard pattern actually implements asynchronous interaction of entities.

- **Control** – the control class – is actually an analogue of the Model MVP pattern. Control processes the data contained on the blackboard, and also generates the command for the knowledge sources to update knowledge on the blackboard. Thus, the expert system is implemented in the control class.

This approach allows us to simplify the processing of data from external sources due to the compactness of the placement of “knowledge”, and also increases the “flexibility” of the system. Knowledge management is carried out in stages.

At the first stage, the calculation of new energy recuperation coefficient for each electric bus is carried out in accordance with the received data on its status and route information. For calculation,
the network-based fuzzy inference system ANFIS is used - an artificial neural network based on the fuzzy inference system Takagi-Sugeno [4, 5].

3. Algorithm description
ANFIS is one of the first versions of hybrid neuro-fuzzy networks - a feedforward neural network of a special type signal. The architecture of the neuro-fuzzy network is isomorphic to the fuzzy knowledge base. In neuro-fuzzy networks, differentiable implementations of triangular norms (multiplication and serendipitous OR) are used, as well as smooth membership functions. This makes it possible to use fast neural network training algorithms based on the backpropagation for neural-fuzzy networks configuration [7].

ANFIS implements Sugeno's fuzzy inference system as a five-layer feedforward signal propagation neural network.

The layers assignment:
- first layer - terms of input variables;
- second layer - antecedents (premises) of fuzzy rules;
- third layer - normalization of the degree of fulfillment of the rules;
- fourth layer - conclusion of the rules;
- fifth layer - aggregation of the result obtained according to various rules.

At the second stage, the calculation of the “average” selection values is carried out using the C-Means algorithm [6]. Values are calculated for a selection of energy recuperation coefficient and a sample of driver opinions. As a result, this allows us to reduce the selection size to a fixed value, while practically not losing its representativity (a feature of the algorithm is that as a result we obtain points that are the centers of the clusters, i.e. with certain accuracy reflecting the behavior of the entire cluster).

At the third stage, a popular opinion among drivers is selected and the most suitable energy recuperation coefficient is determined taking into account this opinion. After studying the information presented in the articles [8, 9, 10, 11, 12] we designed the update algorithm of the energy recovery coefficient (figure 2).

4. Discussion and results
The prototype of the system was implemented in C#. To conduct the study in accordance with the models describing the motion of LiAZ and PAZ electric buses in Moscow on T36 and T78 routes, a training sample of 1000 records was generated, as well as a test sample of 200 records. As a result of mountain clustering, 493 rules were generated.

When building a neuro-fuzzy network, the choice of membership function (MF) is extremely important. Table 1 shows network learning error obtained for various MF. The study is carried out until the difference between the total network error in the new epoch and the total error of the last epoch is no more than 1E-6.

| №  | MF name                          | Network learning error | Epochs quantity |
|----|----------------------------------|------------------------|-----------------|
| 1. | Triangular membership function (trimf) | 0.076784               | 34              |
| 2. | Trapezium membership function (trampf) | 0.158571               | 84              |
| 3. | General bell membership function (gbellmf) | 0.003864               | 120             |
| 4. | Gaussian symmetric membership function (gaussmf) | 0.006108               | 125             |
| 5. | Product of two sigmoid membership functions (psigmf) | 0.014412               | 290             |
As we can see, the use of a bell-shaped membership function gives the most accurate result. For further research, this function was chosen.

Table 2 presents the result of training a neuro-fuzzy network with a different amount of source data. In each of the tests, the network was trained in such a number of epochs that the total error of the last but one epoch differed from the total error of the last epoch by no more than 1E-5. The training
time was measured when the application was running on the same Intel Core i7-7700 processor with a clock speed of 3.60 GHz.

### Table 2. The result of training the neuro-fuzzy network ANFIS.

| №   | Training set size | Number of rules resulting from mountain clustering | Epochs quantity | Training period (min) | The average value of the error for the test set |
|-----|-------------------|---------------------------------------------------|----------------|-----------------------|-----------------------------------------------|
| 1.  | 100               | 74                                                | 39             | 67                    | 9,3E-1                                        |
| 2.  | 200               | 181                                               | 26             | 69                    | 1,2E-1                                        |
| 3.  | 400               | 318                                               | 12             | 61                    | 3,8E-2                                        |
| 4.  | 700               | 427                                               | 4              | 78                    | 2,3E-2                                        |
| 5.  | 1000              | 609                                               | 3              | 94                    | 8,2E-3                                        |

### 5. Conclusion

As a result of the system’s work, the implementation of the dependence of the energy recuperation coefficient on various types of knowledge sources was obtained. Thus, the implementation of this prototype system allowed us to make an assumption about the possible applicability of systems of this class.

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