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SPECIAL SECTION

Stationary supercapacitor energy storage operation algorithm based on neural network learning system

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Abstract. The paper proposes to apply an algorithm for predicting the minimum level of the state of charge (SoC) of stationary supercapacitor energy storage system operating in a DC traction substation, and for changing it over time. This is done to insure maximum energy recovery for trains while braking. The model of a supercapacitor energy storage system, its algorithms of operation and prediction of the minimum state of charge are described in detail; the main formulae, graphs and results of simulation are also provided. It is proposed to divide the SoC curve into equal periods of time during which the minimum states of charge remain constant. To predict the SoC level for the subsequent period, the learning algorithm based on the neural network could be used. Then, the minimum SoC could be based on two basic types of data: the first one is the time profile of the energy storage load during the previous period with the constant minimum SoC retained, while the second one relies on the trains' locations and speed values in the previous period. It is proved that the use of variable minimum SoC ensures an increase of the energy volume recovered by approximately 10%. Optimum architecture and activation function of the neural network are also found.

Key words: stationary energy storage, operation algorithm, machine learning, supervised learning, prediction.

1. Introduction

Growing costs of energy, CO_2 emissions as well as the costs of CO_2 emissions allowances [1] obligate energy suppliers to undertake measures towards decreasing energy consumption and environmental pollution. The last of these issues played a significant role in the development of electric vehicles, which are frequently referred to as zero-emission vehicles [2]. On electrified railways, one of the most commonly used measures to reduce energy consumption significantly is the effective utilization of regenerative braking energy [3, 4]. The energy recovered by the train could be effectively utilized by the DC traction power supply system under the conditions of high or sufficient overhead catenary receptivity, i.e. the ability of the supply system to receive the energy generated by the braking train. The condition has to be achieved if there is at least one train drawing power from the same supply section; otherwise, the control system switches the train into rheostat braking, where the energy recovered is dissipated uselessly. Receptivity of the catenary system could be insured by installing energy storage systems (ESS), which are based on the flywheel, chemical batteries or supercapacitors; the latter solution is by far the most favorable one due to the decreasing prices. Another potential solution is the installation of vanadium-redox flow batteries [5], whose advantages lie inter alia in easy and independent energy and power capacity scalability, long live cycle, or installation of traction inverters for recovering the energy back to the AC grid, for example, to supply the vehicles' charging stations located near the traction substation. The paper describes the supercapacitor (SC) energy storage system, which could be installed in any place along the electrified railway line, however, usually it is installed in the traction substation. The scheme of connection of supercapacitor ESS to the DC traction substation is presented in Fig. 1.

There exist numerous known methods for modelling of supercapacitors [6, 7], sizing and locating of stationary energy storage systems [8–10] as well as the algorithms of energy man-

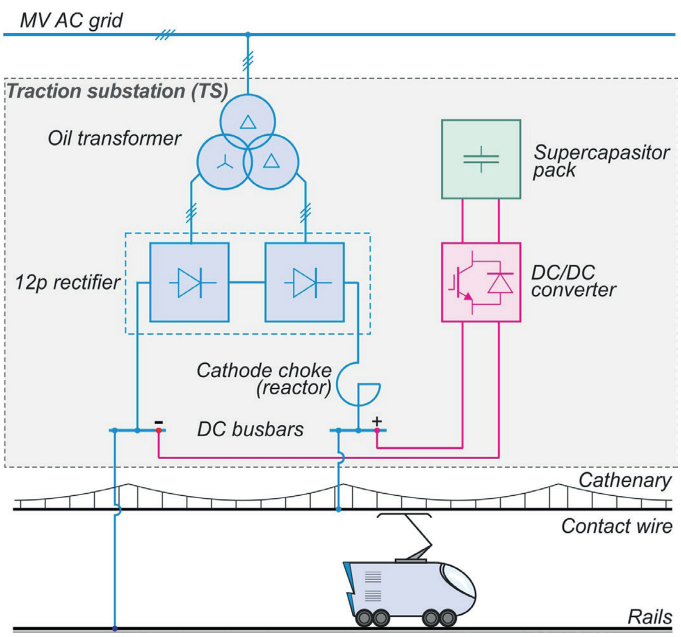

Fig. 1. Generalized scheme of energy storage system connection in a 3 kV DC traction substation

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agement strategy [11, 12]. Among methods used in the algorithms, *the determined rule-based algorithms* have been used as well as AI methods for parameters optimization. They have been applied in the real-time mode.

The 750 V DC third rail power supply system of the 2nd line of the Warsaw Metro is equipped with supercapacitors ESS installed in a traction cabin between traction substations. Traffic of metro trains is organized regularly, which could increase the usefulness of the method proposed. The results of measurements are currently showing week-day energy savings due to operation of ESS in the range of 2 MWh [13]. Similar results were reported in [14] for high power capacity battery type ESS installed in a metro line in Washington, D.C., with practically double the value of energy saved when this ESS was installed between two traction substations. But both systems are currently based on determined algorithms only and do not have any learning algorithms, even if they have collected vast statistical data and time profiles for all the years of operation. The latter provides huge potential for implementation of neutral networks and energy optimization of the systems.

Not many studies concern the aspect of the minimum state of charge of supercapacitor pack U_{SCmin} of the trackside energy storage system operation. The minimum SoC of supercapacitor ESS in usually assumed on the constant level of 50% or 25% [11]. On the one hand, the lower minimum SoC level allows to get higher usable energy capacity, on the other hand – the power losses in the supercapacitor pack and DC/DC converter are significantly higher during operation under low state of charge, due to the high pack current values. Therefore the middle optimum value of the minimum SoC is highly desirable to recover the maximum value of regenerative energy in an effective manner. This paper proposes the solution of the algorithm adjusting the minimum state of charge value to the changing conditions of ESS operation. The value of the minimum state of charge is determined by the algorithm based on *the artificial neural network* (ANN). Neural networks have been widely used for prediction of the electric load by numerous researchers [15, 16]. A significant contribution to this topic has been made by the recent breakthroughs in the area of deep learning (DL) [17]. U_{SCmin} as a basic parameter of the energy storage system operation could be determined with use of ANN based on the information directly connected to the factors influenced by the ESS operation effectiveness. One of the most significant issues of this paper is founding the appropriate information for teaching, validation, testing and operation of the neural network to ensure accurate prediction of the minimum SoC parameter U_{SCmin}.

2. Model of energy storage system

The model of supercapacitor ESS was developed based on [7, 18, 19]. Special attention was paid to the high accuracy and efficiency of the ESS model. The losses are determined separately for supercapacitor pack and DC/DC converter. The scheme of the energy storage system consisting of a supercapacitor pack and back-bust DC/DC converter is shown in Fig. 2.

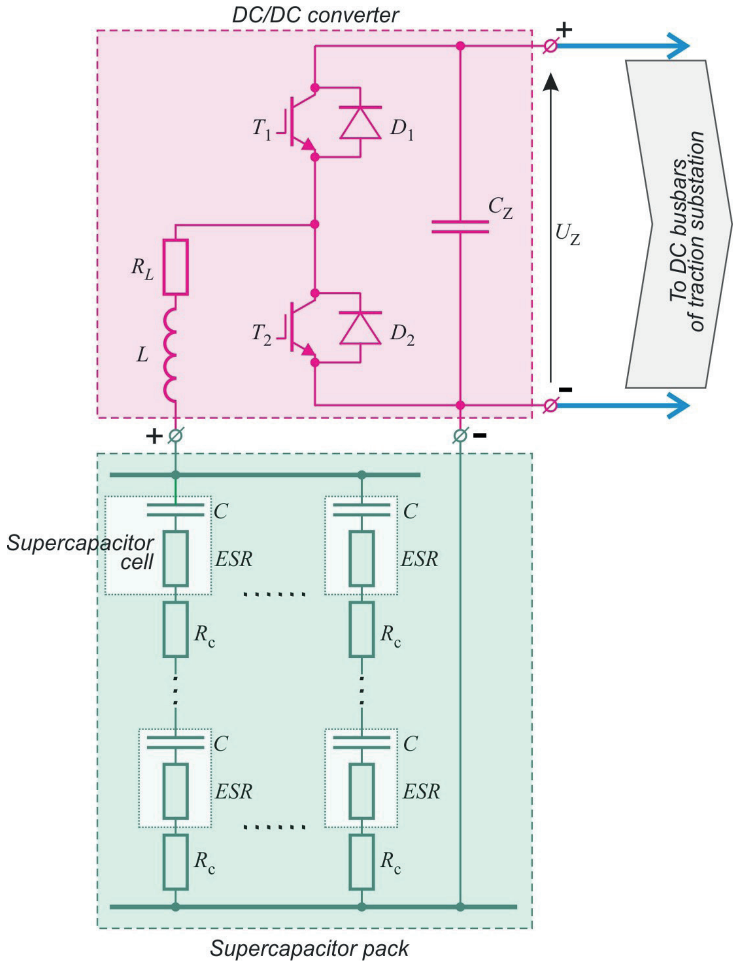

Fig. 2. General scheme of supercapacitor energy storage system consisting of DC/DC converter and supercapacitor pack

2.1. Power losses in supercapacitor pack. The model of the supercapacitor pack is based on the model presented in [7], where the single supercapacitor cell is replaced by capacitance and equivalent series resistance (*ESR*). Additionally, resistance of joint connections R_c between supercapacitors has been considered. The power loss inside the supercapacitor pack is expressed as:

$$\Delta P_{\mathrm{pack}} = I_{\mathrm{pack}}^2 \cdot ESR_{\mathrm{pack}} \tag{1}$$

where ESR_{pack} is the equivalent series resistance of the supercapacitors connected in series (n) and in parallel (m):

$$ESR_{\mathrm{pack}} = \frac{(ESR + R_c) \cdot n}{m}. \tag{2}$$

2.2. Power losses in DC/DC converter. The DC/DC converter of trackside energy storages is usually based on a back-bust scheme, which is shown in Fig. 2. To calculate its efficiency, C. Wang et al. [18] propose to use the model taking into account the power losses on equivalent resistances of the main elements of the back-bust converter, i.e. transistors, inductors and capacitors. Then, the efficiency of the converter in buck mode could be calculated as:

$$\eta = \frac{P_{\mathrm{out}}}{P_{\mathrm{in}}} = \frac{U_2}{A_1 I_L + A_2 + \dfrac{A_3}{I_{\mathrm{L}}}} \tag{3}$$

where:

$$\left\{\begin{aligned} A_1 &= K_{\mathrm{D1}} + R_{\mathrm{on1}} + (1 - K_{\mathrm{D1}}) R_{\mathrm{D2}} + R_{\mathrm{L}} \\ A_2 &= U_2 + \sqrt{(1 - K_{\mathrm{D1}})}\, U_{\mathrm{D2}} \\ A_3 &= \frac{R_{\mathrm{C2}} U_2^2 (1 - K_{\mathrm{D1}})}{12 (f_{\mathrm{s}} L)^2} + \frac{\left(E_{\mathrm{sw(on)}} + E_{\mathrm{sw(off)}}\right) \cdot f_{\mathrm{s}}}{2} \end{aligned}\right\} \tag{4}$$

whereas efficiency of the converter in the boost mode is given in [18] as:

$$\eta = \frac{P_{\mathrm{out}}}{P_{\mathrm{in}}} = \frac{U_1}{B_1 I_L + B_2 + \dfrac{B_3}{I_{\mathrm{L}}}} \tag{5}$$

where:

$$\left\{\begin{aligned} B_1 &= (1 - K_{\mathrm{D2}}) R_{\mathrm{on2}} + K_{\mathrm{D2}} R_{\mathrm{D1}} + R_{\mathrm{L}} \\ B_2 &= U_1 + \sqrt{K_{\mathrm{D2}}}\, U_{\mathrm{D1}} \\ B_3 &= \frac{\left(E_{\mathrm{sw(on)}} + E_{\mathrm{sw(off)}}\right) \cdot f_{\mathrm{s}}}{2} \end{aligned}\right\}. \tag{6}$$

Finally, total losses in ESS are the sum of losses generated in the supercapacitor pack and back-bust converter, expressed by the equation below:

$$\Delta P_{\mathrm{ESS}} = \Delta P_{\mathrm{pack}} + \Delta P_{\mathrm{DC/DC}}. \tag{7}$$

3. Algorithm of ESS operation

3.1. General information. The basic algorithm of the supercapacitor ESS operation is shown in Fig. 3 [10]. The algorithm belongs to the group of *rule-based determined strategies*, which are commonly used in practice because of their simplicity; it is also applied in the study. The manner of ESS operation is determined by the value and sign of the power of traction substation P_{TS} and by the voltage on the supercapacitor pack terminals. The power of traction substation P_{TS} is calculated using the instantaneous values of busbar voltage and current. The maximum value of the supercapacitor voltage U_{SCmax} could be

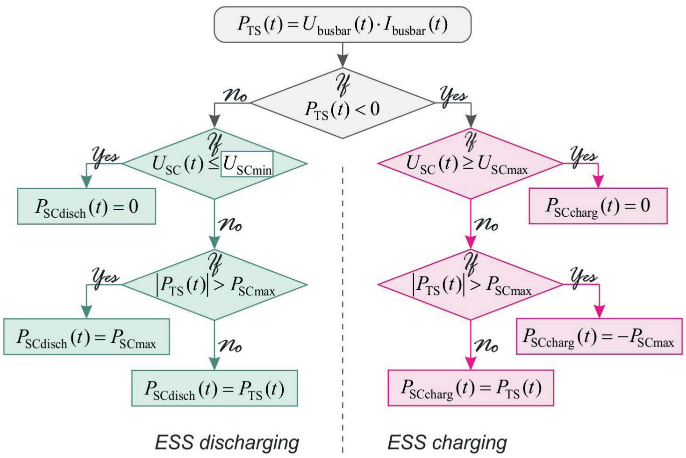

Fig. 3. Basic algorithm of supercapacitor ESS operation (the minimum SoC, being under consideration in this paper, is highlighted with white background)

defined by the nominal voltage of a single SC cell and by the number of cells connected in series (n). As it was mentioned above, the main criterion in the center of attention of this paper is U_{SCmin}, highlighted in Fig. 3. The influence of U_{SCmin} on ESS operation is described in the next subsection.

3.2. Minimum state of charge. As it is known, the minimum state of charge U_{SCmin} determines the usable energy capacity of the supercapacitor ESS. On the one hand, the lower the U_{SCmin} is, the higher its usable energy capacity, but on the other hand, the operation of ESS in low state of charge is associated with high values of supercapacitor current I_{SC}. The supercapacitor pack current could be determined as:

$$I_{\mathrm{SC}} = \frac{U_{\mathrm{Cat}}}{U_{\mathrm{SC}} \cdot \eta_{\mathrm{DC/DC}}} \tag{8}$$

where U_{Cat} is voltage between the catenary and rails, $\eta_{\mathrm{DC/DC}}$ is efficiency of the DC/DC converter, and U_{SC} is voltage of the supercapacitor pack expressed as:

$$U_{\mathrm{SC}} = U_{\mathrm{SoC}} - I_{\mathrm{SC}} \cdot ESR_{\mathrm{pack}}. \tag{9}$$

Figure 4 shows the comparison of power losses in energy storage between two variants of minimum SoC – 40% and 60% of the nominal voltage of the supercapacitor pack for the same energy storage power profile. Figure 4a and Fig. 4b are shown in the same scale for better comparability of the values. It is seen that in the case of the 40% SoC the maximum losses are approximately two times higher than in the case of the 60% SoC. The analysis presented in this paper is based on the case study described in [10]. The supercapacitor pack consists of 1167 cells connected in series and 3 branches connected in parallel. The parameters of each cell are $C = 3000$ F and $U_{\mathrm{n}} = 2.8$ V. The power of the DC/DC converter is 0.8 MW. Simulation of the traction load has been carried out for the elec-

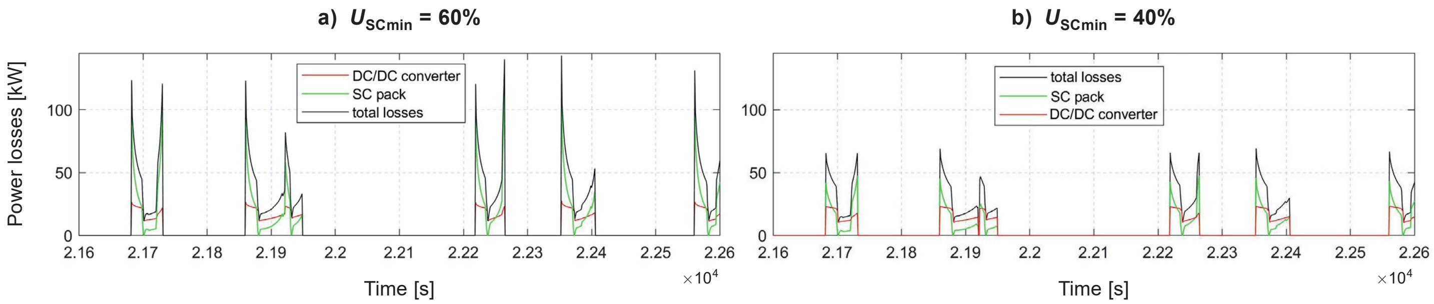

Fig. 4. Power losses in supercapacitor ESS for different minimum SoC

trified railway line with five types of trains operating – multiple electric units and carriage passenger trains.

To investigate the influence of minimum SoC on regenerative braking energy recovery, the following analysis has been carried out. Based on the traction power profile obtained in the previous stage, operation of the energy storage has been simulated for different variants of minimum SoC to get the relationship between the daily input and output energy of ESS and the minimum SoC; the results are shown in Fig. 5. The difference between input (black line) and output energy (green line) is equal to the daily energy losses inside ESS, which include both types of losses – those in the DC/DC converter and supercapacitor pack. The minimum state of charge corresponding to the maximum value of output energy could be assumed as the optimum value of U_{SCmin} for the given time profile of the traction load during a 24-h cycle.

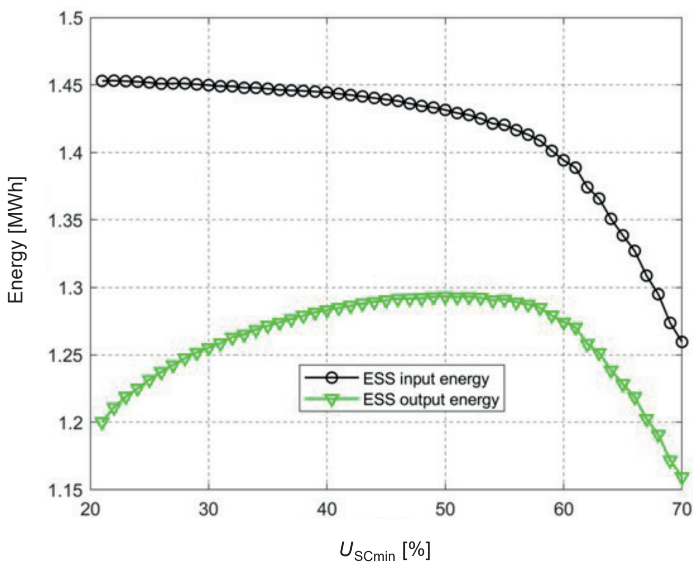

Fig. 5. Relationship between minimum SoC and input and output energy of ESS over 24 hours

The time profile of the traction load should include both positive and negative values of the power. The positive values denote the power drawn by the trains and the negative ones – the regenerative power available in the point of ESS connection to the catenary due to the limitation of receptivity of the catenary system. The time profile of power on traction substation busbars has been obtained by means of the simulation model of the electrified railway line with the limitation of receptivity to the level of real conditions [10, 20].

Apart from regenerative braking energy recovery, the criteria of supercapacitors degradation should also be taken into account. The main factor influencing the supercapacitor aging process is the temperature of its operation. The model of supercapacitor aging is described in [21] and [22]. The aging factor should be considered by means of a dynamic thermal model of the supercapacitor pack. The danger of exceeding temperature limits occurs during the low minimum state of charge.

As it was mentioned above, Fig. 5 shows the situation in which minimum SoC is constant. For comparison's sake, the application of different values of minimum SoC during operation was performed, where the minimum SoC changed its value every 20 min. For each 20-min. period of ESS operation, the optimum state of charge was found to obtain maximum output energy. The results of this simulation, allowing to get maximum output energy in each 20-min. period, are presented in Fig. 6. The results were obtained for the same case study and ESS parameters shown in Fig. 5. The total 24 hour energy recovered

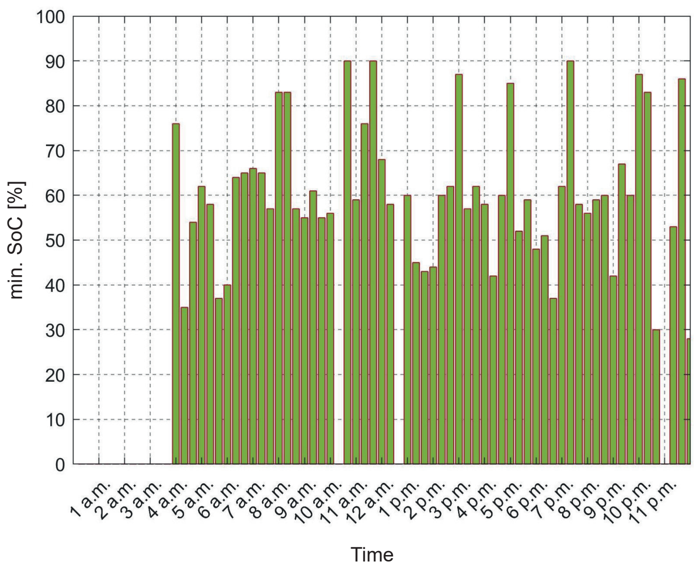

Fig. 6. Minimum SoC corresponding to maximum energy recovery

by usage of the variable minimum states of charge is around 10% higher than for the case where the minimum SoC value was constant.

3.3. Prediction of minimum state of charge. Minimum SoC values shown in Fig. 6 have been obtained based on the known power time profiles for the corresponding 20-min. periods. In the process of real operation, the exact time profile of traction power is not known, hence it depends on the future chain of events on the railway track, which are stochastic in their character. To predict the optimum value of the minimum state of charge U_{SCmin}, it is proposed to use the artificial neural network. In the learning processes the 20-min. traction load profile for the previous period of operation was discretized with the step of 1 s, which gave a total of 1200 samples, i.e. 1200 input neurons of input layer of the neutral network. To analyze these data, the neural network with a single hidden layer was used. The input and hidden layers of the neural network have been activated by the ReLU function. Determination of U_{SCmin} was performed by means of regression and classification functions for the comparison of effectiveness of algorithm operation. For the regression problem, a single output neuron without the activation function has been used. Then the classification problem included the 61 output neurons with sigmoid activation function, determining the probability of the particular U_{SCmin} value with the accuracy of 1% in the range of (21÷80% and 0%). Application of the presented multi-class classification approach showed more efficient results than the regression approach. The neutral network described above for the classification approach is shown in Fig. 7.

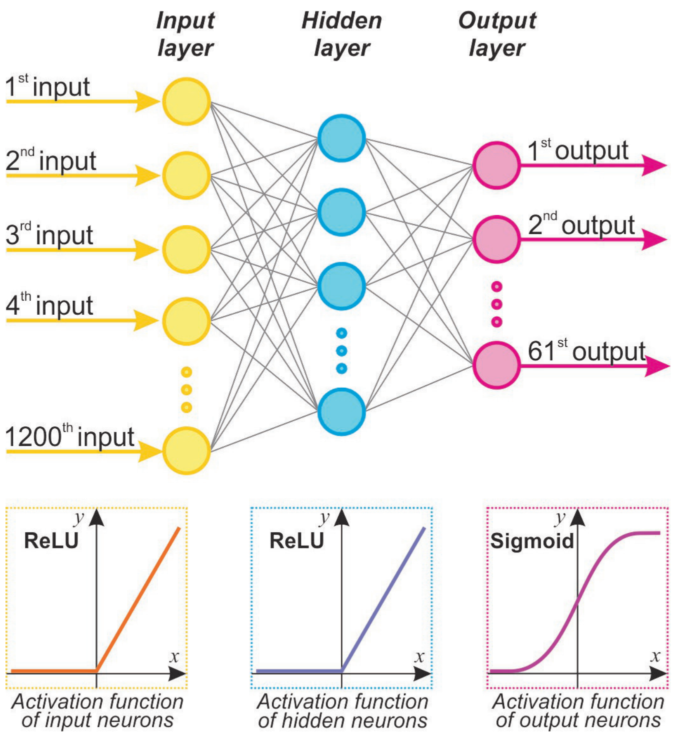

Fig. 7. Architecture of the neural network applied for multi-class classification approach

Finally, the training, validation and test data have been prepared based on 7 different 24-h time profiles of ESS. The different 1200 s traction power profiles have been obtained by shifting the 1200 s length window. For each period, the train labels have been found by determining the optimum minimum state of charge.

The results showed that the neural network for the model with 128 neurons in a hidden layer could achieve the accuracy of 23% of the classification. The result is satisfactory, taking into account that in the particular multi-class classification problem the results of energy recovery are comparable in the wide range of values of minimum state of charge, which is shown in Fig. 5.

4. Conclusions and future work

This paper presents the possibility of control of stationary ESS using the variable minimum state of charge. The simulation results show that this solution could increase the use of regenerative energy by even 10%, considering the equal duration periods in which the minimum state of charge is constant – 20 min. The main problem of the algorithm is prediction of the U_{SCmin} value for the subsequent time period. Yet an appropriately trained neural network could classify the optimum minimum state of charge based on the given traction load profile. This method could be used under the condition of the periods of constant U_{SCmin} becoming much shorter than the periods with the power profiles of similar character. This condition is met if railway traffic is regular. Otherwise the minimum state of charge could not be accurately determined using the traction power profile. For that situation other quantities should be selected for prediction of the minimum state of charge. Parameters of railway traffic – trains location and speed values – appear most promising for this purpose. In practice, they could be obtained by the GPS system. For better operation of ESS, the variable duration of the periods with constant U_{SCmin} could be used. Comparative analysis should be carried out in the future to investigate the influence of applying variable duration of the periods on energy recovery as compared to the constant minimum state of charge. Moreover, the power losses influence on supercapacitor temperature and the aging effect should also be taken into account.

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