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The concept of intelligent system for street lighting control using artificial neural networks

Abstract. *Street lighting systems which are commonly used today are inefficient in terms of energy consumption, as they don't take into account actual current demand for lighting intensity. This paper presents a concept of an intelligent street lighting control system, whose aim is to improve energy efficiency by matching lighting intensity to weather conditions. In this study, an overview of state-of-the-art solutions of this type is presented, which is a background for the concept of the proposed intelligent system. In the paper selected preliminary experimental results are also shown.*

Streszczenie. *Stosowane powszechnie systemy sterowania oświetleniem ulicznym są wysoce nieefektywne z punktu widzenia zużycia energii, gdyż nie uwzględniają aktualnego zapotrzebowania na natężenie oświetlenia. W artykule zaprezentowano koncepcję inteligentnego systemu wspomagającego sterowanie oświetleniem ulicznym, którego celem jest poprawa efektywności energetycznej poprzez dostosowanie intensywności oświetlenia do aktualnych warunków pogodowych. W pracy przedstawiono także przegląd literaturowy istniejących rozwiązań oraz wstępne wyniki badań symulacyjnych.* ***(Koncepcja inteligentnego systemu wspomagającego sterowanie oświetleniem ulicznym z wykorzystaniem sztucznych sieci neuronowych)***

Keywords: street lighting control, artificial neural networks, optimization of energy consumption
Słowa kluczowe: sterowanie oświetleniem ulicznym, sztuczne sieci neuronowe, optymalizacja zużycia energii

Introduction

In recent time one can observe a new approach to the construction of street lighting control systems. The appearance of new street high-performance LED lamps allows for a full control of lighting of such lamps even in the range of 0 to 100 %. This allows for a development of more advanced control systems also those which are based on artificial intelligence methods that include artificial neural networks, expert systems and genetic algorithms.

Intelligent systems supporting the control process of street lighting compared to the conventional autonomous lighting systems introduce numerous benefits in case of the use of the LED sources. The purpose of such systems is not only a simple lighting of streets, but also ensuring drivers and pedestrians the best possible visibility, depending on the type of the surface, the location of the lamp as well as the weather conditions [1]. Matching the lighting intensity to the needs of the road users and various external conditions allows for a significant reduction of the energy consumption of such systems [2, 3, 4].

Conventional street lighting control systems use simple methods which enable/disable lamp or methods based on regulation of the lighting intensity. In the first case the control units are equipped with timers, astronomical clocks and twilight sensors. These are static systems that switch on and off lighting at fixed hours. Other systems of this type use, for example, light-sensitive photocells to turn on the light at dusk or turn them off at dawn [5]. There are also systems that use street lighting controllers based on GPRS to switch on and off lamps according to the location characteristics like longitude and latitude, sunrise and sunset. More advanced regulated systems are based on LED lamps with possibility of dimming or high-pressure sodium lamps [6] that allow to schedule the moments of the on/off of the light and to control the dimming level of particular lamps or group of lamps. Modern regulating circuits allows for the reduction of the luminous flux almost proportionally to the change of the power consumption [7]. However, all these systems have one common limitation: They do not take into account actual current demand for lighting intensity, which is the source of high inefficiency of such approaches. For example, many benefits would result from taking into account the weather conditions in a given time moment such as fog, rain etc. or traffic intensity [8, 9] during controlling the lighting intensity. In case of the bright moon lighting at night, the lighting intensity of the lamps can be lower, which would decrease the energy consumption and costs.

This topic is a subject of investigations performed in many places of the world. In the literature one can find examples of a successful application of intelligent solutions in overcoming major drawbacks of currently used regulation systems [5, 8, 9]. Investigations in the area of energy management for street lighting, in which the goal is to minimize the energy consumption, became more popular since appearance of first international recommendations concerning the road lighting [10]. Development of such systems is also possible due to continuous improvement of the efficiency of the luminaires and the lamps, especially due to implementation of electronic devices that enable adaptive control of street lighting for both the motorist and pedestrian roads [8]. It is indicated by increase of both the number of publications in this area [5, 8, 9] and practical implementations.

The presented work is a step in a project that aims at development of a new intelligent system for street lighting control. In this study the author presents a concept of intelligent system supporting the control of street lighting, based on artificial neural networks.

The paper is organized as follows. In next Section the author presents selected publications that focus on various artificial intelligence methods in the control of street lighting. In Section "Artificial neural networks" an idea of supervised neural networks (NNs) is briefly presented. The system supporting the street lighting control is described briefly in following Section, entitled "The proposed concept of the intelligent system for the control of the street lighting". Section "Selected experimental results" includes selected experimental results. Finally, some conclusions are formulated in last Section.

State-of-the art study

Methods which in last several years gain popularity in solving various modelling and control problems are based on artificial intelligence (AI) [11, 12]. Such methods can be classified into several categories that include: artificial neural networks (ANNs), fuzzy systems (FSs) and genetic algorithms (GAs). In case of the problem of control of the street lighting NNs offer several advantages. The lighting systems are rather non-linear which are difficult to be described mathematically and as such require specific algorithms that can generate appropriate control signals. Secondly, NNs can adapt to varying environmental conditions, which in case street lighting is in particular important feature. In addition, NNs can work as classifiers that can indicate some scenarios and thus can make decision about a further course of the control process. In the literature, one can find a growing number of works in which authors use various AI methods in control. For example, the problem of the forecasting of the road traffic has been solved by the application of NNs already in the 90s [9, 13, 14, 15, 16, 17, 18]. In [17] self-organizing fuzzy NN has been used to solve problem of this type. In [18] another approach has been applied which is based on particle swarm optimization (PSO). It is a heuristic hybrid algorithm that combines together wavelet analysis and NNs.

From the point of view of efficient street lighting management, especially in terms of minimizing the energy consumption, important works are [8] and [9], in which ANNs are used to support such process.

In [8] the authors propose a model of the power management of the street lighting for various groups of luminaries [10]. This approach is based on a concept in which luminance take into account various parameters that can affect the value of the luminance. The model includes varying in time parameters such as traffic intensity. The main aim of the authors was to provide a ”power on demand”, which means that energy (the light in this case) is delivered only when it is needed depending on the current traffic intensity. The authors compared several methods in order to choose the most efficient one-hour prediction model of lighting intensity. Te first method was based on statistical modelling, which is one of the simplest and the most widely used methods that rely on constructing the average weekly schedule of hourly sampled traffic intensity. The authors for each day calculated an average daily traffic intensity to obtain its medium distribution consisting of 168 points (24 hours x 7 days). In the second approach a feed-forward supervised ANN has been used, while the third method combine several NNs with an ”ensemble” modeling. In this method each of the NNs worked in parallel on the same task and then the results from particular NNs were combined into one final result. The objective of such an approach is to obtain a better prediction performance than in case in which NNs work separately. Feed-forward multilayer NN with one hidden layer consisting of ten neurons and one neuron in the output layer was used in the model. The NN was trained with backpropagation algorithm. The final conclusion was that the best results were obtained for the third approach. The experiments performed on the public streets of small and medium cities showed that the proposed system allows to save up to 50 % of the energy in the comparison with the system without the adaptation abilities.

In [9] the authors presented a prediction algorithm of traffic flow that can be implemented in the monitoring and control system of street lighting. The aim of the authors was to reduce the energy costs through decreasing the lighting intensity depending on the level of the actual traffic flow. The algorithm makes an analysis and process the information about the traffic flow at different times. The information about the traffic flow are received from the control center. In this algorithm two methods are used. The first of them include supervised ANNs, while the second one is a non-parametric method - k-NN regression algorithm (k-Nearest Neighbors algorithm) which is used for prediction tasks in statistic. The algorithm returns predicted value of the traffic flow which is then used to control the dim percentage of the lamps in the range from 0 to 50 %. The results presented by the authors showed that algorithms based on ANNs provide the best highest performance level (taking into account the value of mean squared error) and can be successfully integrated with the control system of street lighting.

One can also find the works, in which FSs are used to support the system of street lighting control [1, 19].

The authors of [1] demonstrate how to design the lighting control system using fuzzy logic. The proposed system allows to adjust the light intensity depending on the illumination present in the environment. The system can be used in many different areas such as street lighting control and car headlights lighting level which allow to reduce the energy consumption through proper dimming of the lamp.

The authors of [19] proposed a new concept of a scalable and flexible architecture for street lighting control in cities. The aim was to reduce the energy consumption while ensuring the proper safety for the road users. The authors proposed a two-step control strategy based on qualitative processing of the inputs. The authors of [19] motivate the importance of their investigations by the imprecision of the sensors used to measure the environmental parameters. The lower-level ”Zone Lighting Coordination Unit” (ZLCU) adjusts the lighting intensity of each lamp post through fuzzy logic. The parameters of the fuzzy controller are set at a higher level by the so-called ”Lighting Coordination Unit” (LCU) depending on the situation prevailing in the city. LCU implements a knowledge based mechanism to adjust on-line the parameters of the individual fuzzy controllers. The system ensures the real-time responses for various unexpected events which appear periodically or unexpectedly. Each subsystem (lighting equipment) has its own fuzzy controller which operates to satisfy the local lighting objectives and constraints (required lighting intensity, weather conditions etc.). This driver uses aggregated measurement values in order to overcome the imprecision of the sensors (luxmeters and traffic sensors). The lighting intensity depends on the traffic in the observed area and is controlled automatically based on several dusk indicators covering the area, and a variable number of lighting points [19]. Lighting intensity increases or decreases depending on the inputs of LCU. The second-level controller (LCU) determines the action of the local ZLCUs to compensate for the interaction of the various subsystems. It also maintains connectivity with all other systems within the city adjusting the appropriate lighting intensity for various unplanned events (traffic jams, street works etc.). Furthermore, LCU adjusts the ZLCU parameters in respect to the planned events like concerts, fairs etc.

In the literature one can also find attempts to use GA for the optimization of the control of the street lighting, in which the lighting intensity is adjusted depending on the traffic [20]. Simulation results presented by the authors show that it is possible to reduce the energy consumption by 12,9 % per year.

The results presented in [1, 5, 8, 9, 13, 14, 15, 16, 17, 18, 19, 20] indicate that further investigations in which AI methods are used to support the process of the control of street lighting systems are worth to be continued. Such algorithms lead to substantial energy saving and thus high financial benefits.

Artificial neural networks

Artificial neural networks (ANNs) can be seen as universal expert systems, that are more and more frequently used in various areas including engineering [8, 9]. An ANN can be seen as a mathematical model that is inspired by the structure and functional aspects of biological neural network. They can learn themselves, basing on properly arranged training patterns, and generalize as well as utilize the acquired knowledge in prognostic assessments of new cases.

Various types of NNs and various ways of their realizations have been reported. Although the most popular are software implementations, the area of hardware and mixed hardware-software realizations of the ANNs increases rapidly [21, 22]. Under some circumstances, the hardware implemented ANNs can operate faster and consume lower power compared to the software ones. As a result, they create new possibilities in the field of portable signal processing devices and instruments [21, 22]. The author considers such realization of the presented system in the future.

The ANN usually consists of an interconnected group of artificial neurons that are basic elements of such systems. The neuron is an element that has many inputs and one output. The outputs of particular neurons are connected to the inputs of other neurons forming the overall NN. The structure of ANN is determined by the way how the neurons are connected with each other. The neurons can be grouped into layers. The input signals are provided to the neurons through connections with established weights.

Feed-forward NNs are the most popular. In such networks the connections between inputs and outputs are not uniformly distributed. In such NNs, the information is transmitted in a single direction, forward, from the input neurons, through the hidden neurons (if any exist) to the output neurons [9]. The output values of particular layers of neurons are entered as the inputs to the next layers. Signals from the output layer are treated as a response of the overall NN. The number of layers depends on the complexity of the analyzed problem and has to be determined experimentally. The most popular feed-forward NNs are those with the back-propagation (BP) algorithm, with radial basic functions as well as various self-organizing NNs. One can also finds many other types of NNs like, for example, recursive NNs. In the proposed paper the author uses a feed-forward supervised NN with the back-propagation algorithm (BPNN), and therefore further description will be concern such type of networks.

In the NN the learning process rely on the rule that the output values of the NN are compared with the correct answer given by the teacher (supervised learning) in order to measure the error. The error is fed back to the network and the algorithm adjusts the weights of each connection in order to diminish the error as much as possible. After repeating this process for a sufficiently large number of training cycles, the network will usually converge towards a certain error [9]. The general structure of such NN is presented in Figure 1.

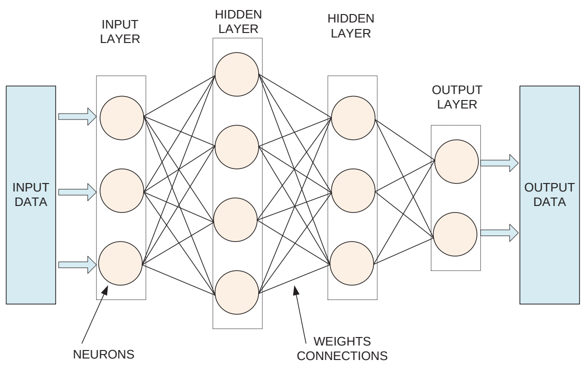

Fig. 1. A general structure of the feed-forward (FF) NN.

ANNs can be trained to be able to solve given problems by the use of a teaching method and sample data (training set). Identically constructed NN can be used to perform different tasks, depending on the prepared training set. ANN allows for a generalization, which is the ability to recognize similarities among different input patterns, in particular such patterns that have been corrupted by the noise.

Three different training algorithm can be applied in BPNN:
- the method with cumulative updating network weights,
- the method with incremental updating network weights without changes in the order of training patterns provided to the NN,
- the method with incremental updating network weights with changes in the order of the input training patterns.

In the proposed paper the third method has been implemented. In this case the weights of the neurons are updated immediately after obtaining a new training vector. The prediction error was evaluated using the mean squared error described by the following expression:

$$Q_{\mathrm{err}} = \sqrt{\frac{1}{nLP}\sum_{j=1}^{nLP}\sum_{i=1}^{NO}(y_{i,j}-d_{i,j})^2} \quad (1)$$

where nLP is the number of the training patterns, NO is the number of the output layer neurons.
- X - training vector defined as: X = [x_1,..., x_M],
- Y - output vector defined as: Y = [y_1,..., y_{NO}],
- D - expected answer vector defined as: D = [d_1,..., d_{NO}],
- W - weight vector of a given neuron W = [w_1,..., w_R].

The proposed concept of the intelligent system for the control of the street lighting

As has been presented in previous sections various AI methods and algorithms are used to provide intelligent supporting of the lighting process like expert systems, ANNs, GAs and FSs. While assessing the intelligent systems proposed so far one can notice that the most commonly used methods are ANNs. The main advantages of such solutions include: the possibility of a flexible reconfiguration of the structure of the NN depending on the needs, the ability to introduce various types of input data, for example environmental conditions in presented problem, and generating the output signals that control the lighting level for a single luminary or a group of luminaires. Another advantage of using ANNs is also the ability to coaching created NN and on-line modifying its parameters.

Establishing the architecture of the ANN is not the basic problem while developing the system supporting the control of the lighting. The main problem relies on providing appropriate training data to the NN. Based on the training data the NN predicts the level of lighting for the lamp or the groups of lamps, which is its main task here. In contrast to other works in this area, in the presented concept it is assumed that the input data provided to such system should contain the information about cloudy, rain, haze, atmospheric pressure, temperature and others. Such data are mostly forecasted for a certain area like region of the country, the city, less frequently for small villages. The forecasts are prepared on the basis of meteorological measurements that are registered only in a selected geographic locations. Therefore, it is really difficult to create a well-functioning intelligent system for some intended narrow region, based only on such data. It is why such systems should be equipped with many number of meteorological stations allowing for a measurement of selected parameters. This situation means that the cost of such system is increasing. A compromise solution is in this case a

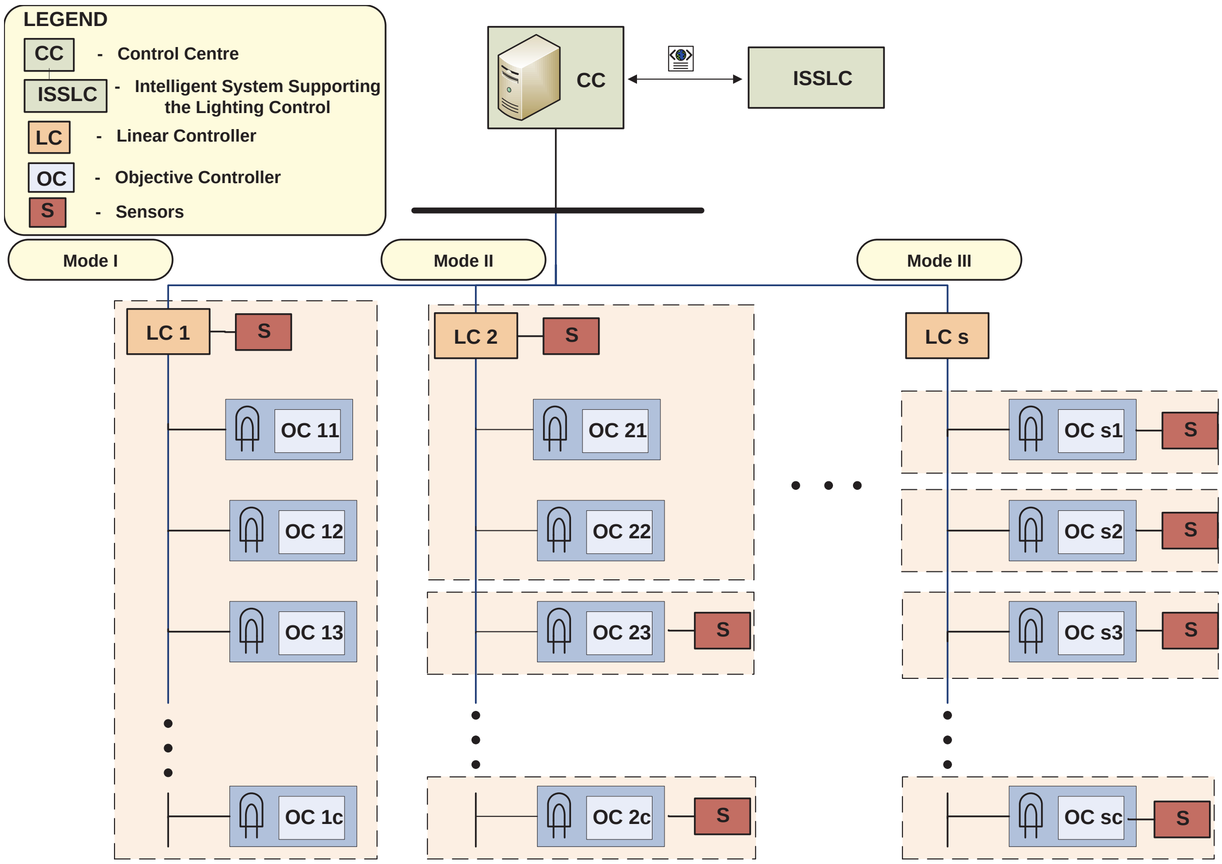

Fig. 2. The general idea of the city lighting control system

hybrid system in which some data like rain, temperature can be read from the meteorological services, while some data like fog, wind speed, wind direction, environmental lighting intensity at selected points can be measured in a real time.

The intelligent system supporting the lighting control, proposed in this paper, can provide a dual functionality. The first one, the so called prognostic functionality, is related with the preparation of the control plan for the luminaires in order to obtain the suitable level of the illumination for the next 24 hours. In this case the necessary data are available at, for example, many national and foreign meteorological services. By the assumption, it is a supporting system in which the values determining the lighting intensity are compared with the values of the classical control system. The operator determines which system takes the priority - either the classical or the intelligent one, while the results obtained in this case are transmitted to the control units of the luminaires.

The second functionality is the ongoing correction of the level of lighting intensity for particular luminaires depending on the current weather conditions. In this case it is necessary to install in the selected luminaires, lighting strings or control cabinets set of sensors from which the values can be read to the input of the NN. These values are used to correct the previously prepared plan.

The intelligent system supporting the lighting control (ISSLC) communicates with the control centre (CC). The CC has many different functions like, for example, the transmission of the control signals to the lighting strings (LS), receiving the information about errors from many devices etc. The CC is responsible for reading the information about the forecast weather conditions. Also the current weather measurement from particular sensors are provides to the CC. The ISSLC reads this data from the CC and sends the information about the level of lighting intensity for each lumianairy to the CC. It was assumed that ANN supports one lighting string (LS) composed of for example 10 luminaires, which is managed by the higher-level linear controller (LC). For each luminairy it is responsible a lower-level controller called objective controller (OC), which through the communication with the LS enables a proper setting of the luminaires. The OC is also responsible for reading the values from the sensors placed directly in the luminaires. The general idea of the city lighting control system is presented in Figure 2.

The proposed ISSLC can work in three modes. In the first one (called ”Mode I”) all sensors are placed in the LC. This solution allows to control the overall LS. The NN in this case has only one output indicating the percentage level of lighting for all luminaires in the LS. The second mode (denoted as ”Mode II”) is used when there is a need to control individual luminaires or a group of luminaires in a given LS, which for some conditions should be controlled in other way than the remaining ones (like in place of intersections, residential streets etc.). In this case the LC as well as selected OC have their own sensors, which allow for better individualization of the control process in a given area. In this case the designer decides which luminaires are connected together into a sections that are controlled in a given way. In this case the NN has as many outputs as the number of sections in the LS. However, due to the increased number of sensors the number of the NN inputs also increases. As a result, the architecture of the NN has to be more complex which makes the learning process to be longer. The third mode (denoted as ”Mode III”) is the most complex, as in this case each OC has its own set of sensors. This solution is least economic due to the large number of sensors, but the advantage is the ability to control each luminaires separately.

In this case, each LS should be equipped with a dedicated NN. All LSs operating in a given mode can use the same NN working sequentially or one can implement individual NN for each LS in the control centre. To create a universal solution, working with all three modes, one has to do some generalizations. One has to assume that the NN will have as many outputs as the number of luminaires in the LS and the number of inputs equal to the number of signals possible to be read from the forecast data and from the sensors in each OC. If a given OC does not contain a sensors, then the input data are received from the neighboring OC that belong to a given section or to the LS. If the input data to the NN are provided only from the LS, the data are duplicated c times, where c is the number of luminaires (and also OC) in a given LS.

Selected experimental results

In this paper the case denoted as the mode I has been selected for the preliminary research. This means that the NN predicts the lighting level of all luminaires in a given linear string in a similar way. Selection of this solution results from the fact that the public meteorological data provided by the weather stations which are used to perform the learning process of the NN and its later work does not feature a sufficient resolution. Usually there is one weather station for a city. Therefore, in the initial stage of the presented investigations research greater detailing for working of the ISSLC was not expedient. Implementation of the proposed solution on a selected area of a city, in which the sensors will be installed directly in the individual lamps, will allow for extending the system and for introducing the modes II and III.

In the ISSLC it has been used a feed-forward multilayer NN with the back-propagation algorithm with a momentum factor. The NN is composed of three layers: the input, the hidden and the output ones. The number of neurons in particular layers can be selected by the user, depending on the needs. In this work the size of the input vector, which is related to the number of neurons in the input layer, was equal to 9. The informations about date, time and several weather factors were provided to the NN. The number of neurons in the hidden layer was the subject of an optimization. It is important since the effective training process strongly depends on the number of neurons in this layer. The following numbers of neurons in this layer have been used during the experiments: 8, 12, 16, 20 and 26. In each experiment, 10 learning cycles were performed, while the number of iterations in each cycle varied between 100 and 35000. Initial values of the weights of particular neurons were selected randomly and were close to zero. It is important to carry out at least a dozen number of the learning processes (simulations) for a given number of neurons in this layer to avoid stopping the function of error in a local minimum. Finally, for testing the purposes the NN architecture the hidden layer was composed of 16 neurons, while the output layer contained one neuron. The neuron in the output layer provides an information about the lighting level of the luminaires in a given LS according to current weather conditions. However, selection of the most effective NN architecture and the values of its parameters requires extensive time-consuming simulations. Such studies are planned in the nearest future.

Training dataset was composed of 8758 patterns obtained from three weather stations in Bydgoszcz city. These data consist of meteorological measurements for the whole year 2014. Data have been divided into three subsets, i.e. training, validating and testing sets. The learning rate, η, and the momentum coefficient in the training process have been selected to be equal to 0.1 and 0.8, respectively. Both values have been determined experimentally to achieve the final prediction error to be minimal. During the learning process, these values were kept constant.

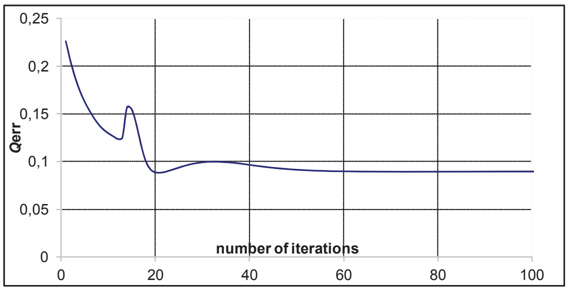

Fig. 3. An example training process of the NN

The training process was stopped when the mean-square error, described by 1, reached a minimum for a given validation data set. An example training process for 100 training epochs is presented in Figure 3. In this case, for 100 training epochs, the mean square error of the NN is equal to 0,08984.

Preliminary studies have shown that the NN can effectively facilitate the process of the street lighting significantly minimizing the energy consumed by the whole system. At this moment it is not possible to give a precise numerical data, as they require to carry out long-term simulations in terms of actual operation of the system.

Conclusion

This paper presents development of an intelligent street lighting control prediction system based on artificial neural networks. The system can be integrated with the overall street lighting monitoring and control system which is the subject of the larger project. The role of the system is to improve the energy efficiency by decreasing the lighting intensity, depending on the actual weather conditions. Such solution enables the reduction of the energy costs.

This work is one of stages of a larger project and, therefore, the presented studies should be considered as preliminary. The results obtained so far will have to be verified in terms of actual operation of the system. Such experiments are planned in Toruń city in the near future. The presented methodology will be also further optimized by including other variables to the training vector.

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