Proceedings of the Federated Conference on Computer Science and Information Systems pp. 1149–1155 DOI: 10.15439/2017F389
ISSN 2300-5963 ACSIS, Vol. 11

Prediction of Traffic Intensity for Dynamic Street Lighting

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***Abstract*—In this paper, the problem of short-term prediction of traffic flow in a city traffic network is considered. This prediction is performed in order to provide input data to a dynamic control system for street lighting. The forecasting is done by a multi-layer using artificial neural network. Because of the limited number of sensors, the data is insufficient to describe the relation between the traffic intensity at a given point and the points in which the flow intensity is measured. The proposed approach is tested by using data from the centre of Kraków. The prediction error turned to be low.**

I. Introduction

ENERGY savings due to outdoor lighting optimisation have tremendous impact on a city's economy. This is due to the effect of scale: an average city operates several thousand light points. For security and safety reasons, as well as compliance with standards, these light points are on all night long. Reducing power consumption by even one watt at each luminaire translates into substantial savings. This can be achieved by optimising lighting infrastructure design (through altering lamp placement and parameters [1], [2]) and by introducing intelligent, dynamic control which adjusts lighting levels to the actual needs.

This paper focuses on the latter aspect, i.e. increasing energy savings with use of dynamic control. Dimming is performed using sensor data, with traffic intensity being one of the main factors. However, traffic sensors are not deployed at each intersection. Therefore, other methods must be used to estimate the intensity on streets not equipped with measurement facilities. This way, the control system can cover a wider area which leads to more energy savings [3].

The research described in this paper is part of an innovative lighting infrastructure modernisation project in the city of Kraków, Poland. The project involved replacing almost 4,000 HPS (high-pressure sodium-vapour) lamps with LED ones, equipped with a central management system to provide low-level communications. On top of that, a prototype dynamic control system has been developed to derive and transmit control decisions to each lamp in real time. An outline map of the project is presented in Figure 1.

This work was supported by the AGH University of Science and Technology grant number 11.11.120.859 and by the AGH University of Science and Technology, Faculty of Geology, Geophysics and Environmental Protection, as a part of the statutory project.

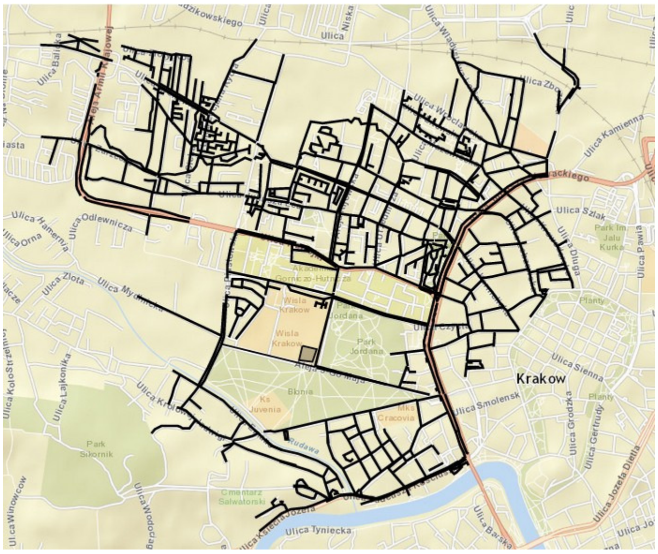

Fig. 1. Outline map of the dynamic lighting project in Kraków.

II. Motivation

The concept of Smart Cities is based on the idea of applying technological solutions, mainly IT-based, to areas such as transport, energy, healthcare, water and waste management, with a projected market of $400 billion by 2020 [4], [5], [6], [7], [8]. It is closely related to the vision of Internet of things (IoT) [9], which involves various systems communicating in a semantic and secure manner to allow interchange of information between devices and systems. According to a report by the International Energy Agency [10], lighting consumes 19% of the electricity produced globally. Therefore, even though lighting affects many areas within the Smart City concept – including safety, comfort and transportation – the main contribution to this paper lies in the field of energy.

Questions may arise as to whether utilisation of renewable energy-powered lighting may be an alternative to the presented

Fig. 2. An off-grid autonomous lamp, equipped with a solar panel and an underground battery. Image courtesy of Wichary Technic, *http://www.wicharytechnic.pl/en/*.

approach. In fact, off-grid, renewable-based luminaires are being produced and used in many places around the World. An example of such luminaire is presented in Figure 2. Such devices are ideal for locations with no power infrastructure or as temporary lighting for events, etc. However, their large-scale utilisation for urban street lighting has two problems:

- The cost. Autonomous, self-sufficient off-grid devices must be equipped with means of generating energy — usually a solar panel and/or a wind turbine – as well as some energy storage devices. That makes the cost of an individual lamp much higher than with traditional, grid-connected hardware.
- Lighting standards (such as CEN/TR 13201-1:2004 [11]) strictly define the parameters of light to be fulfilled to achieve a given so-called lighting class, and conditions when a given lighting class should be applied. Off-grid devices may be inherently unable to provide adequate lighting due to possible insufficient generation and storage capacity. Recent advances in off-grid device operation optimisation mainly focus on replacing a simple, reactive strategy with a more advanced dispatch plan, based on foreseen power generation capabilities and output (lighting) requirements, with methods including simulation [12] and a hybrid neural network/fuzzy logic approach [13]. Therefore, the strategy used to control off-grid lamps is based on providing satisfactory lighting as long as possible, not to always fulfil the requirements of the norm, which is the case in this paper.

In the Smart City context, utilisation of renewable sources is much more efficient with dedicated, more centralised installations of solar panels or wind turbines. Of course, that may cause problems on other levels, such as integration with the existing city power grid or with vehicle charging stations [14]. This paper concerns only grid-connected light points.

Outdoor lighting optimisation can have a significant impact on economy [15]. As mentioned in the introduction, it is due to two factors. First, lights stay on all night, which translates to over 4,000 hours of operation in a year. Second, the number of light points is significant, which gives an effect of scale.

Research indicates that there is a need for intelligent control systems for street lighting. There have been multiple experiments and assessments conducted so far. These include highway lighting [16], tunnels [17] and urban areas [15], [18]. However, there still is much room for improvement.

Technically, so-called Central Management Systems (CMSs) are commonly used to provide communications with the fixtures, support inventory and monitor their operations. They are very efficient in providing insight into the operation of lighting systems and providing basic control of the infrastructure, actually moving it towards the aforementioned concepts of Smart Cities and the Internet of things. Most major manufacturers of lighting equipment now provide CMSs integrated with their products. An example of such a system – Owlet Nightshift by Schréder – has been presented in Figure 3.

CMSs, however, do not support dynamic control: lamps operate according to a predefined schedule rather than sensor readings. However, a schedule must assume a worst-case scenario, and that may lead to a solution far from optimal due to large variations of traffic intensity on different days (see Figure 4). Therefore, an external decision system has been developed to generate control signals and transmit them to the lamps via the CMS's API (Application Programming Interface).

Among available sensor data, traffic intensity has the biggest impact on lighting control. From the economic point of view, deploying traffic sensors solely for the purpose of street lighting might be not feasible. Although most cities already have a sensor infrastructure fit for this purpose as part of their Intelligent Transportation Systems (ITSs), the data produced is used mostly for controlling traffic lights at junctions. Of course, the applications of ITS systems are much broader and mostly concern traffic flow optimisation, with advanced, state-of-the-art systems being able to analyse and simulate traffic at a very high detail level [19]. Usually, a city will already have several intersections at which traffic intensity is already measured. However, there are many "white spots", especially in areas with little or no traffic lights. The main motivation for this paper is therefore is to propose a viable traffic flow prediction algorithms which in turn can be used

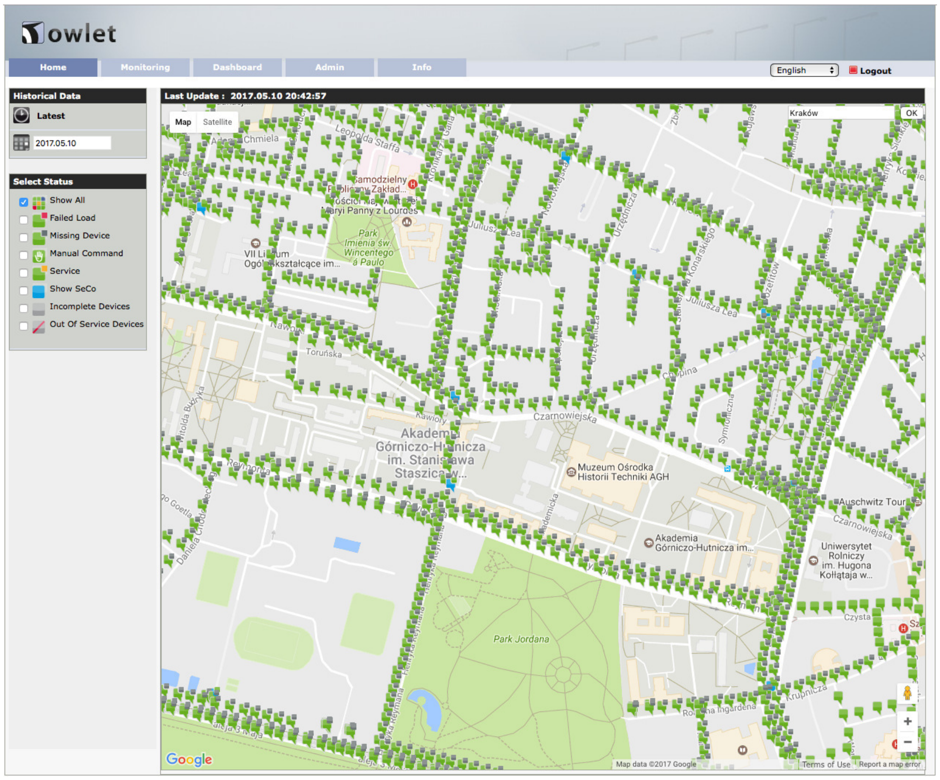

Fig. 3. Owlet Nightshift as an example of an operational lighting Central Management System. Image courtesy of Schréder Polska Sp. z o.o., *http://www.schreder.com/pl-pl*.

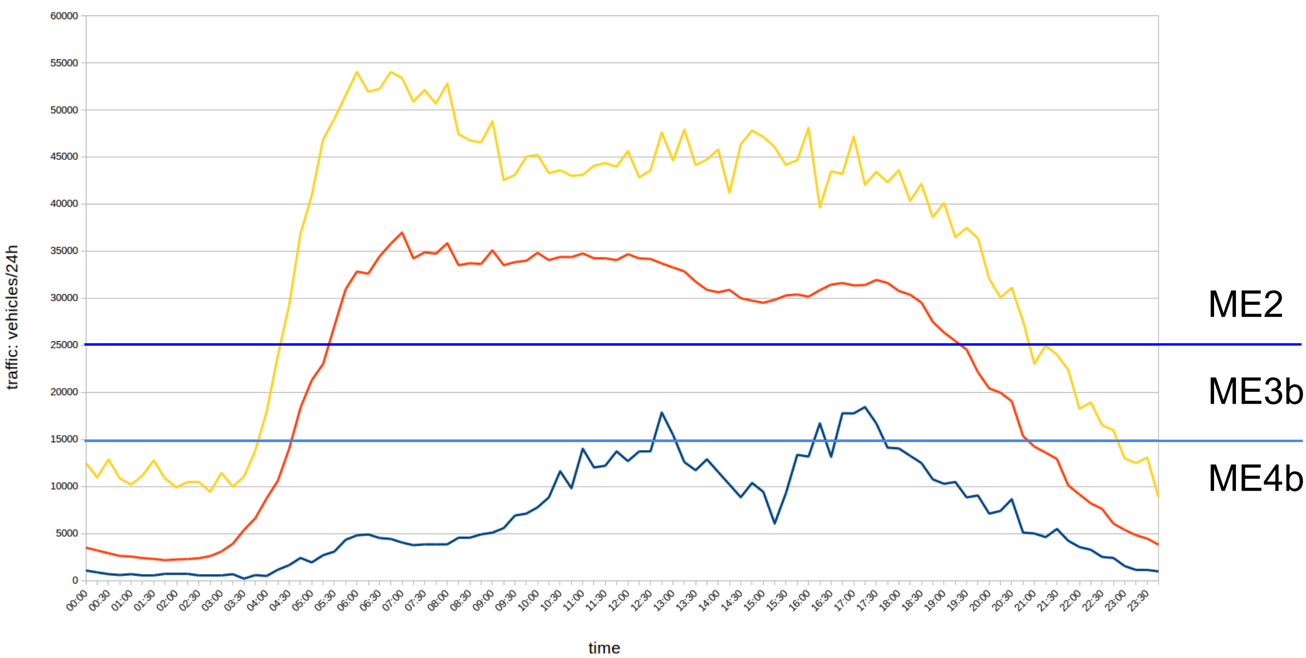

Fig. 4. Traffic intensity registered on different days in one of the streets within the Kraków project area. Horizontal lines denote the traffic level thresholds which allow switching from the main lighting class (ME2) to a lower one (ME3b or ME4b). Lighting classes as defined by the CEN/TR 13201-1:2004 standard [11].

by an intelligent street lighting control system to minimise energy consumption.

III. State of the Art

Traffic flow prediction is a problem which has been intensively studied for a long time [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33]. Both the traffic on highways and the traffic in city networks is considered. Usually, the traffic intensity is predicted by using historical data. In this approach, however, a few problems appear. First of all, there number of traffic sensors in roads and streets is still insufficient. Furthermore, random events, both on-road and off-road, can impact the flow intensity [21]. Therefore, the method which turned to be effective in traffic flow prediction in a given place can be useless in other locations. For these reasons, intensive studies are being carried out, concerning new methods of prediction as well as application of known methods in new places and contexts. Statistical tools as well as artificial intelligence can be used to solve these problems.

In San Francissco [21], an autoregressive model was used to predict traffic load in San Francisco in two time horizons: five minutes and thirty minutes. The method was tested by using a traffic flow simulator. The errors varied from 2% for five-minute prediction to about 12% for thirty-minute prediction.

A support vector machine (SVM) regression algorithm was used for traffic flow prediction under both typical and untypical traffic conditions, where the term *untypical* denotes holidays or traffic accidents [22]. The approach was tested by using data from California state, USA.

A support vector regression model was also applied for short-term traffic flow prediction in combination with the ant colony optimisation algorithm [25]. The approach has been tested on data from Taiwan.

Many authors reported the application of artificial neural networks for traffic flow prediction [23], [27], [28], [32]. A standard multi-layer perceptron trained by using the Levenberg-Marquardt algorithm with input data preprocessed using the hybrid exponential smoothing method was applied to predict short-term traffic conditions on the Mitchell freeway in Australia [23]. The error varied from 6% to 12% and was significantly smaller than for the reference methods: a wavelet neural network and a Bayesian neural network.

In the paper [32], an interesting idea of application a genetic algorithm is presented. It is used for optimal selection of both the representation and the characteristics of the traffic flow data. Furthermore, the genetic algorithm is also applied to choose the optimal structure and training parameters of the multi-layer neural network used for prediction.

A hybrid fuzzy-neural approach to traffic flow prediction in a city network is described in [33]. The system consists of two modules. The fuzzy module is responsible for clustering of the traffic patterns into sets of similar characteristics. The neural module finds relationships inside the clusters. The effectiveness was tested using real data from Hong Kong. The maximal prediction error was equal to four vehicles per minute.

In the paper [26], deep learning methods for big data were used for sixty-minutes traffic flow prediction at the roads. The used method allowed the authors to detect nonlinear both the spatial as well as the temporal correlations in the traffic data.

IV. Problem Statement and Methodology

In this paper, the following general problem is considered. The traffic flow at point A should be predicted provided that the traffic flows at other points at the preceding time points are given. The data is insufficient to create an analytical formula which describes traffic flow intensity at point A as a function of flows at the points for which data is given. This means that junctions with other roads are situated between A and other points. The problem is solved by using a multi-layer neural network.

This general problem is considered for a small fragment of Kraków city traffic network. The geometry of the studied fragment is shown in Fig.5. The flow is predicted at the point A. Two following tasks have been put forward.

1) The workday is divided into 48 half-hour time intervals. The traffic flow is predicted at point B using data from sensors at points F and G – see Figure 5. Two versions of the input vector have been tested. The first one had the following form: $[t, F_{t-1}, ..., F_{t-n}, G_{t-1}, ..., G_{t-n}]$, where $t \in \{1, ..., 48\}$ denotes the time interval in which the flow is predicted, F_k and G_k, denote the traffic flow intensity at the points B and C respectively, at the time intervals $k \in \{t-1, ..., t-n.\}$. In the second version, the number of the day d was given as an additional component of the input vector.
2) Each day of the week is divided into ninety-second time intervals. The traffic flow is predicted at the point B by using data from the sensor at point A or F – see Figure 5. The input vector had the following form: $[d_c, t, A_{t-1}, ..., A_{t-m}]$, where d_c encoded the type of a day: Sunday, Saturday or ordinary day and this data was optional; $t \in \{1, ..., 960\}$ denotes the time interval of the day in which the flow is predicted and was optional as well, A_l, F_l denote the traffic flow intensity at the point A or F at the time interval $l \in \{t-1, ..., t-m\}$.

Let us remark that according to the geometry of the street connections, the traffic flow at point B in which the flow intensity is predicted does not depend directly on the flows at the point in which sensors A, F and G are situated.

V. Results

Each experiment was done by using a multi-layer neural network with one hidden layer and one output neuron. In the hidden layer the neurons had sigmoidal activation function whereas the output neuron was linear. In the description of experiments the components of the input vector are specified as well as the mean error i.e. $e := \frac{|y-z|}{N}$, where y is the measured number of vehicles at the point B, z is the predicted number at the point B and N denotes number of events. Furthermore, the correlation coefficient r_{y-z} between z and y is specified as well. The input vector is denoted as $\mathbf{x}$. In each

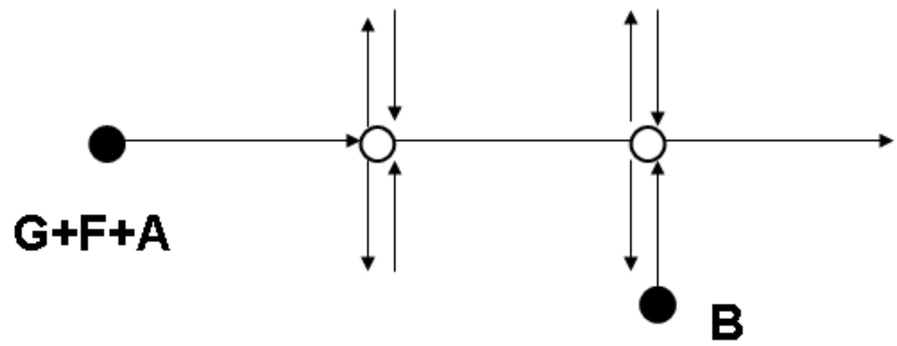

Fig. 5. Geometry of the studied fragment of the city traffic network. The points in which sensors are situated are marked by filled circles whereas crossings are marked by empty circles. Sensors G, F and A are situated at the three-lane fragment of a one-way road, each at the separate traffic lane. Sensors G and F are at the lanes from which cars can go only straight ahead whereas sensor G is at the lane from which buses ant taxi cars can go straight ahead whereas other cars have to turn right. Sensor B is situated at the one-way road which has two traffic lanes. It is at the lane from which all vehicles have to turn right.

experiment several trials with neural networks having various number of neurons in hidden layer have been performed. The results are described for the most effective neural network. In each experiment the intensity of the traffic flow at the point B at the time t is predicted.

In the frame of the task 1 – see section IV (a workday is divided into 48 half-hour time intervals) – the following experiments have been performed with input vectors ($\mathbf{x}$) as stated.

1) $\mathbf{x} = [t, F_{t-1}, F_{t-2}, F_{t-3}, G_{t-1}, G_{t-2}, G_{t-3}]$, $t \in \{1, ..., 48\}$.
   The number on neurons in the hidden layer was equal to 10.
   Mean error $e = 6.7$, $r_{y-z} = 97\%$.
2) $\mathbf{x} = [d, t, F_{t-1}, G_{t-1}]$, $t \in \{1, ..., 48\}$, $d \in \{1, 2, 3, 4, 5\}$.
   The number on neurons in the hidden layer was equal to 10.
   Mean error $e = 5.2$, $r_{y-z} = 98\%$.
3) $\mathbf{x} = [d, t, F_{t-1}, F_{t-2}, G_{t-1}, G_{t-2}]$, $t \in \{1, ..., 48\}$, $d \in \{1, 2, 3, 4, 5\}$.
   The number on neurons in the hidden layer was equal to 10.
   Mean error $e = 4.3$, $r_{y-z} = 99\%$.

In the frame of the task 2 – see section IV (a workday is divided into 960 ninety-seconds time intervals) – the following experiments have been done performed input vectors ($\mathbf{x}$) as stated.

1) $\mathbf{x} = [A_{t-1}, A_{t-2}, A_{t-3}, A_{t-4}, A_{t-5}]$, $t \in \{1, ..., 960\}$.
   The number on neurons in the hidden layer was equal to 12.
   Mean error $e = 1.12$, $r_{y-z} = 68\%$.
2) $\mathbf{x} = [d_c, A_{t-1}, A_{t-2}, A_{t-3}, A_{t-4}, A_{t-5}, A_{t-6}, A_{t-7}, A_{t-8}, A_{t-9}]$, $t \in \{1, ..., 960\}$.
   The number on neurons in the hidden layer was equal to 18.
   Mean error $e = 1.10$, $r_{y-z} = 70\%$.
3) $\mathbf{x} = [d_c, t, A_{t-1}, A_{t-2}, A_{t-3}, A_{t-4}, A_{t-5}, A_{t-6}, A_{t-7}]$, $t \in \{1, ..., 960\}$.
   The number on neurons in the hidden layer was equal to 20.
   Mean error $e = 1.04$, $r_{y-z} = 72\%$.
4) $\mathbf{x} = [d_c, t, A_{t-1}, A_{t-2}, A_{t-3}, A_{t-4}, A_{t-5}, A_{t-6}, A_{t-7}, A_{t-8}, A_{t-9}]$, $t \in \{1, ..., 960\}$.
   The number on neurons in the hidden layer was equal to 18.
   Mean error $e = 1.02$, $r_{y-z} = 74\%$.
5) $\mathbf{x} = [d_c, t, A_{t-1}, A_{t-2}, A_{t-3}, A_{t-4}, A_{t-5}, A_{t-6}, A_{t-7}, A_{t-8}, A_{t-9}, A_{t-10}]$, $t \in \{1, ..., 960\}$.
   The number on neurons in the hidden layer was equal to 30.
   Mean error $e = 0.95$, $r_{y-z} = 78\%$.
6) $\mathbf{x} = [d_c, t, A_{t-1}, A_{t-2}, A_{t-3}, A_{t-4}, A_{t-5}, A_{t-6}, A_{t-7}, A_{t-8}, A_{t-9}, A_{t-10}, A_{t-11}]$, $t \in \{1, ..., 960\}$.
   The number on neurons in the hidden layer was equal to 30.
   Mean error $e = 0.99$, $r_{y-z} = 77\%$.
7) $\mathbf{x} = [d_c, t, F_{t-1}, F_{t-2}, F_{t-3}, F_{t-4}, F_{t-5}, F_{t-6}]$, $t \in \{1, ..., 960\}$.
   The number on neurons in the hidden layer was equal to 10.
   Mean error $e = 1.70$, $r_{y-z} = 95\%$.
8) $\mathbf{x} = [d_c, t, F_{t-1}, F_{t-2}, F_{t-3}, F_{t-4}, F_{t-5}, F_{t-6}, F_{t-7}, F_{t-8}, F_{t-9}, F_{t-10}, F_{t-11}, F_{t-12}, F_{t-13}]$, $t \in \{1, ..., 960\}$.
   The number on neurons in the hidden layer was equal to 25.
   Mean error $e = 1.90$, $r_{y-z} = 92\%$.

VI. Concluding Remarks

The experiments have shown that the proposed method yields very good results even with little reference data.

Moreover, the algorithms are quickly saturated with regard to the length of the history provided. For task 1, the optimal number of time units provided is 2; for task 2, no significant improvement is noticeable beyond 10 historical time units.

It must be noted that the presented research is performed with a well-defined application in mind, which is dynamic control of street lighting. In particular, the algorithms are used to provide accurate estimates of traffic intensity in streets not equipped with sensor devices. The presented work does not try to compete with Intelligent Transportation Systems, as they have a different purpose. In particular, the algorithms do not attempt to optimise urban traffic; they are only used to try to reflect the actual situation. However, the proposed methods can find broad application to predict flows in any graph-like structures.

Since deployment of traffic intensity sensors is a costly operation, such methods play a crucial role in lowering the energy consumptions of lighting infrastructure. They allow for a vast increase of the scope of dynamic control, thus leveraging the effect of scale. As most energy used in Poland (as well as many other countries) originates from fossil fuel-based power plants, any reduction of its consumption leads to significant reduction of carbon dioxide emission. Furthermore, saving energy also has obvious economic benefits. It should also be noted that the estimated traffic intensity data can also be used for other types of Smart City solutions.

References

[1] A. Sędziwy and L. Kotulski, "A new approach to power consumption reduction of street lighting," in *2015 International Conference on Smart Cities and Green ICT Systems (SMARTGREENS)*, May 2015, pp. 1–5.

[2] A. Sędziwy, "A new approach to street lighting design," *LEUKOS*, vol. 12, no. 3, pp. 151–162, 2016. doi: 10.1080/15502724.2015.1080122. [Online]. Available: http://dx.doi.org/10.1080/15502724.2015.1080122

[3] I. Wojnicki and L. Kotulski, "Street lighting control, energy consumption optimization," in *Artificial Intelligence and Soft Computing - 16th International Conference, ICAISC 2017, Zakopane, Poland, June 11-15, 2017, Proceedings, Part II*, ser. Lecture Notes in Computer Science, L. Rutkowski, M. Korytkowski, R. Scherer, R. Tadeusiewicz, L. A. Zadeh, and J. M. Zurada, Eds., vol. 10246. Springer, 2017. doi: 10.1007/978-3-319-59060-8_32. ISBN 978-3-319-59059-2 pp. 357–364. [Online]. Available: https://doi.org/10.1007/978-3-319-59060-8_32

[4] "Smart cities: background paper," UK Department for Business, Innovation & Skills, Tech. Rep., 2013.

[5] S. Brodowski, A. Bielecki, and M. Filocha, "A hybrid system for forecasting 24-hour power load profile for polish electric grid," *Applied Soft Computing*, vol. 58, 05 2017.

[6] A. Bielecki and M. Wójcik, "Hybrid system of art and rbf neural networks for online clustering," *Applied Soft Computing*, vol. 58, 04 2017.

[7] A. Bielecki, M. Bielecka, and S. Ernst, "Proposal of an intelligent, predictive fuzzy controller for off-grid devices," *IFAC-PapersOnLine*, vol. 49, no. 25, pp. 523 – 528, 2016. doi: http://dx.doi.org/10.1016/j.ifacol.2016.12.077 14th IFAC Conference on Programmable Devices and Embedded Systems PDES 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S240589631632715X

[8] A. Bielecki and M. Lenart, *Neural System for Power Load Prediction in a Week Time Horizon*. Cham: Springer International Publishing, 2016, pp. 25–34. ISBN 978-3-319-39378-0. [Online]. Available: https://doi.org/10.1007/978-3-319-39378-0_3

[9] A. Bahga and V. Madisetti, *Internet of Things: A Hands-On Approach*. Vijay Madisetti, 2014. ISBN 9780996025522. [Online]. Available: https://books.google.pl/books?id=mYmzoQEACAAJ

[10] "Light's labour's lost," International Energy Agency, Tech. Rep., 2006.

[11] CEN, "CEN/TR 13201-1:2004, Road lighting. Selection of lighting classes," European Commitee for Standardization, Brussels, Tech. Rep., 2004.

[12] Ernst, Sebastian, "Optimization of renewable energy-based autonomous device operation using simulation," *E3S Web Conf.*, vol. 10, p. 00020, 2016. doi: 10.1051/e3sconf/20161000020. [Online]. Available: https://doi.org/10.1051/e3sconf/20161000020

[13] A. Bielecki, M. Bielecka, and S. Ernst, "Proposal of an intelligent, predictive fuzzy controller for off-grid devices," *IFAC-PapersOnLine*, vol. 49, no. 25, pp. 523 – 528, 2016. doi: http://dx.doi.org/10.1016/j.ifacol.2016.12.077. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S240589631632715X

[14] F. Mwasilu, J. J. Justo, E.-K. Kim, T. D. Do, and J.-W. Jung, "Electric vehicles and smart grid interaction: A review on vehicle to grid and renewable energy sources integration," *Renewable and Sustainable Energy Reviews*, vol. 34, pp. 501 – 516, 2014. doi: https://doi.org/10.1016/j.rser.2014.03.031. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1364032114001920

[15] I. Wojnicki, S. Ernst, and L. Kotulski, "Economic impact of intelligent dynamic control in urban outdoor lighting," *Energies*, vol. 9, no. 5, p. 314, 2016. doi: 10.3390/en9050314. [Online]. Available: http://www.mdpi.com/1996-1073/9/5/314

[16] L. Guo, M. Eloholma, and L. Halonen, "Intelligent road lighting control systems," Helsinki University of Technology, Department of Electronics, Lighting Unit, Tech. Rep., 2008. [Online]. Available: http://lib.tkk.fi/Diss/2008/isbn9789512296200/article2.pdf

[17] S. Fan, C. Yang, and Z. Wang, "Automatic Control System for Highway Tunnel Lighting," in *Computer and Computing Technologies in Agriculture IV*, ser. IFIP Advances in Information and Communication Technology, D. Li, Y. Liu, and Y. Chen, Eds. Springer Boston, 2011, vol. 347, pp. 116–123. ISBN 978-3-642-18368-3. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-18369-0_14http://www.springerlink.com/index/N1520PT884727374.pdf

[18] I. Wojnicki, S. Ernst, L. Kotulski, and A. Sędziwy, "Advanced street lighting control," *Expert Systems with Applications*, 2013.

[19] D. Leihs and A. Adamski, "Situational analysis in real-time traffic systems," *Procedia - Social and Behavioral Sciences*, vol. 20, pp. 506 – 513, 2011. doi: http://dx.doi.org/10.1016/j.sbspro.2011.08.057. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1877042811014376

[20] A. Adamski, "Intelligent traffic control in ITS systems," *Global Journal of Engineering Science and Research Management*, vol. 2, no. 7, pp. 75–86, 2015.

[21] A. Abadi, T. Rajabioun, and P. A. Ioannou, "Traffic flow prediction for road transportation networks with limited traffic data," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 2, pp. 653–662, April 2015. doi: 10.1109/TITS.2014.2337238

[22] M. Castro-Neto, Y. Jeong, M. K. Jeong, and L. D. Han, "Online-svr for short-term traffic flow prediction under typical and atypical traffic conditions." *Expert Syst. Appl.*, vol. 36, no. 3, pp. 6164–6173, 2009. [Online]. Available: http://dblp.uni-trier.de/db/journals/eswa/eswa36.html#Castro-NetoJJH09a

[23] K. Y. Chan, T. S. Dillon, J. Singh, and E. Chang, "Neural-network-based models for short-term traffic flow forecasting using a hybrid exponential smoothing and levenberg-marquardt algorithm," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 2, pp. 644–654, June 2012. doi: 10.1109/TITS.2011.2174051

[24] J.-M. Chiou, "Dynamical functional prediction and classification, with application to traffic flow prediction," *Ann. Appl. Stat.*, vol. 6, no. 4, pp. 1588–1614, 12 2012. doi: 10.1214/12-AOAS595. [Online]. Available: http://dx.doi.org/10.1214/12-AOAS595

[25] W.-C. Hong, Y. Dong, F. Zheng, and C.-Y. Lai, "Forecasting urban traffic flow by svr with continuous aco," *Applied Mathematical Modelling*, vol. 35, no. 3, pp. 1282–1291, 2011. doi: 10.1016/j.apm.2010.09.005

[26] Y. Lv, Y. Duan, W. Kang, Z. Li, and F. Y. Wang, "Traffic flow prediction with big data: A deep learning approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 2, pp. 865–873, April 2015. doi: 10.1109/TITS.2014.2345663

[27] B. L. Smith and M. J. Demetsky, "Short-term traffic flow prediction models-a comparison of neural network and nonparametric regression

approaches," in *Proceedings of IEEE International Conference on Systems, Man and Cybernetics*, vol. 2, Oct 1994. doi: 10.1109/ICSMC.1994.400094 pp. 1706–1709 vol.2.

[28] ——, "Short-term traffic flow prediction: neural network approach," *Transportation Research Record*, vol. 1453, pp. 98–104, 1994.

[29] ——, "Traffic flow forecasting: Comparison of modeling approaches," *Journal of Transportation Engineering*, vol. 123, no. 4, pp. 261–266, Issue: object: doi:10.1061/jtpedi.1997.123.issue-4, revision: rev:1479465310792-29747:doi:10.1061/jtpedi.1997.123.issue-4, . doi: 10.1061/(ASCE)0733-947X(1997)123:4(261)

[30] A. Stathopoulos and M. Karlaftis, "A multivariate state space approach for urban traffic flow modeling and prediction," *Transportation Research Part C*, vol. 11, no. 2, pp. 121–135, April 2003. doi: 10.1016/S0968-090X(03)00004-4

[31] S. Sun and X. Xu, "Variational inference for infinite mixtures of gaussian processes with applications to traffic flow prediction," *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 2, pp. 466–475, June 2011. doi: 10.1109/TITS.2010.2093575

[32] E. I. Vlahogianni, M. G. Karlaftis, and J. C. Golias, "Optimized and meta-optimized neural networks for short-term traffic flow prediction: A genetic approach," *Transportation Research Part C: Emerging Technologies*, vol. 13, no. 3, pp. 211 – 234, 2005. doi: https://doi.org/10.1016/j.trc.2005.04.007. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0968090X05000276

[33] H. Yin, S. Wong, J. Xu, and C. Wong, "Urban traffic flow prediction using a fuzzy-neural approach," *Transportation Research Part C: Emerging Technologies*, vol. 10, no. 2, pp. 85 – 98, 2002. doi: https://doi.org/10.1016/S0968-090X(01)00004-3. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0968090X01000043