Acta Technica 62 (2017), No. 6B, 1373–1384

A Smart City Construction Scheme based on Large Data Analysis Services

Jingya Yue[1]

Abstract. To improve the accuracy of smart city development potential evaluation , a method for smart city development potential evaluation based on convolutional neural network of adaptive moment estimation is proposed. Firstly, the index system for city development potential evaluation including such five aspects as economic development potential, social development potential, public service potential, scientific and technological innovation potential and information infrastructure is constructed; secondly, to improve the performance of convolutional neural network algorithm, the first moment estimation and secondary moment estimation of the gradient are used for the dynamic adjustment of the learning rate of each parameter; after offset correction, each time of iteration learning rate has a definite scope to make the parameters relatively stable, so as to improve the performance of convolutional neural network algorithm. Finally, the effectiveness of the algorithm is verified through simulation experiment.

Key words. Adaptive moment estimation, Convolutional neural network, Smart city, Development potential.

1. Introduction

Smart city is a kind of new concept and new model for the promotion of the city planning, construction, management and service smartness through such new generation of information technology as cloud computing, big data, Internet of Things, mobile Internet and spatial geographic information integration. The construction of smart city can help further promote the deep integration of industrialization, informatization, informatization and agricultural modernization and accelerate the construction of "two-oriented" society; intelligently push forward the progress of new-type urbanization and realize the scientific management of society, having importance significance for solving the difficulty in city development, transforming lifestyle, enhancing the soft power of the city, promoting the sustainable development of city and improving the city competitiveness. Globally, the smart city development is still at the pilot stage and there are about 100 smart cities under construction. The

[1]Zhengzhou University of Aeronautics, Zhengzhou Henan, 450046, China

domestic smart city construction makes its first appearance: there were 90 pilot cities in 2012 and 103 cities in 2013. According to the survey, more than 95% sub-provincial cities, 76% cities at prefecture level and above, about 230 cities in total throughout the country are constructing or have proposed to construct smart city and the investment scale exceeds RMB 500 million yuan.

The construction of smart city is growing vigorously and the construction modes are mutually emulated. As the orientation of many cities is initially determined and the foundation required for the construction is initially complete and the construction opportunity is initially mature and driven by such factors as government performance examination, the phenomenon of "one side thousand cities" occurs. Meanwhile, as the recognition for the city elements required for the construction of the smart city and the existing development potential of the city is fuzzy, the construction of smart city is faced with many challenges and many new city problems occur in succession and even the phenomena of "shelling" and "lonely city" of the city, thus, making the city lack the required vitality and vigor. The smart city development potential refers the comprehensive ability of various development elements formed under the support of information infrastructure of smart city, which can measure the strength of smart city construction and promote the smart city development with the objective of promoting economic growth, social management, public service and making residents live a good life. The smart city development potential reflects the development ability and innovation ability the city shall be equipped with; it is the important evaluation dimension for the smart city construction and it is very important for the earlier stage demonstration and current situation identification of the city and it is closely linked with the selection of construction opportunity, construction mode innovation, normalization of construction standard as well as management operation. Therefore, the evaluation of smart city development potential is imperative. George proposes the conceptual model of the smart city planning and construction and evaluates the the implementation effect of the smart city construction planning by building the evaluation model. Liu Xiaoyin et.al evaluate the smart city through principal component analysis. It is found through comprehensive analysis of the existing research results that although many scholars propose the smart city evaluation index system, there are few researches on the evaluation of the construction ability and development potential of smart city and there is no systematic evaluation of the smart city development potential.

Therefore, according to the current situation of the development of domestic smart city and the practice and development foundation of pilot smart city construction, it is planned to design a set of development potential evaluation system of the smart city and build the evaluation methods to evaluate the development potential of the smart city in the Thesis. At the same time, to improve the performance of convolutional neural network algorithm, the first moment evaluation and second moment evaluation of gradient are used for the dynamic adjustment of the learning rate of each parameter; after offset correction, the iteration learning rate each time has a definite scope to make the parameters stable, so as to improve the performance of the convolutional neural network algorithm. Finally, entropy weight method, TOPSIS method and gray correlation analysis method are adopted for the evaluation an comparison is made for the results to further prove the scientificity and reasonability of the evaluation method of the smart city development potential. Through the evaluation of smart city development potential, people can better understand the foundation required for the smart city construction and master the development potential and construction ability of smart city to provide basis for overcoming the unicity of the construction mode of smart city, so as to provide necessary decision-making reference and practice guidance for the smart city development planning.

2. Establishment of the evaluation system of smart city development potential

The establishment of the scientific and reasonable evaluation index system if the important precondition for the evaluation of the smart city development potential. In 2009, the regional science center of Vienna University of Technology firstly proposed 6 dimensions reflecting the smartness of city: economic growth, convenient movement, comfortable environment, popular wisdom, living safety and management fairness. Liu Xiaoyin et.al evaluate the smart city development with such 4 Level-I indexes and 19 Level-II indexes as information infrastructure, public support platform, city competitiveness and value realization. Tu Zhenyuan et.al establishes the evaluation system for smart city development through the analytic hierarchy process, including 4 Level-I indexes, 13 Level-II indexes and 40 Level-II indexes. In 2014, the State Council issued the index system for the pilot declaration of smart city, including 4 Level-I indexes and H Level-II indexes: the security and infrastructure, construction and livability, management and service as well as industry and economy. During the research of the smart city evaluation index, there are more evaluation index systems for smart city construction and development and fewer evaluation index systems for smart city development potential.

The evaluation index system of smart city development potential is established based on the existing research results in accordance with the characteristic of the smart city development: ①economic development potential. The economic development potential reflects the economic development strength of a region or city and it is not only the important driving force for smart city development, but also the capital resource for the smart city construction. It is measured mainly by such 4 indexes as per capita gross domestic product, the proportion of fixed asset investment in the regional GDP, per capita disposable income of urban resident and per capital annual expenditure on consumption of urban resident; ②social development potential. Social development potential is the important ability for the normal running and smooth implementation of smart city construction and it reflects the vitality and vigour of the city. It is evaluated mainly through such 3 indexes as year-end population, operational highway tonnage mileage and passenger turnover; ③public service potential. Public service potential is not only the foundation of smart city construction, but also the purpose of smart city construction with the promotion of public service ability and service level of the city being the standing point. It is mainly evaluated through such 4 indexes as per capita living space, actual number of hospital beds per thousand people, per capita park greenbelt area and per capita library collection; ④scientific and technological innovation potential. Scientific and technological innovation potential reflects the scientific and technological development level and such new information technologies as Internet of Things and mobile Internet required for smart city construction as well as the dependence of the construction mode innovation on the scientific and technological development of the city. It is mainly measured through such 5 indexes as the proportion of local financial allocation for sci-tech in the local financial expenditure, the proportion of research and development (R & D) expenditure in GDP, number of patents applied, number of general institutes of higher education and number of students in colleges and universities; ⑤information infrastructure. The information infrastructure is not only the carrier of construction, but also the means for the operation and management of smart city, laying a material basis and precondition for the smart city construction. It is mainly evaluated through 5 Level-II indexes as the proportion of city infrastructure investment in the all-region gross regional domestic product, cable TV transmission length per thousand, the number of fixed telephone subscribers per hundred households, the number of mobile telephone per hundred and the number of broadband internet subscribers per hundred households.

Table 1. Evaluation index system of smart city development potential

Level-I index	Level-II index
Economic development potential (A)	All-region per capita GDP (yuan)
	Proportion of social-fixed-asset investment in regional GDP (%)
	Per capita disposable income of city resident (yuan)
	Per capital annual expenditure on consumption of city resident (yuan)
Social development potential (B)	Year-end gross population (ten thousand people)
	Operational highway tonnage mileage (ten thousand people)
	Operational highway passenger turnover (ten thousand people)
Public service potential (C)	Per capita living space (m^2)
	Actual number of hospital beds per thousand (No.)
	Per capita park greenbelt area (m^2)
	Per capita public library collection (volume)
Scientific and technological innovation potential (D)	Proportion of local financial allocation for sci-tech in the local financial expenditure (%)
	Proportion of research and development (R & D) expenditure in GDP (%)
	Number of patents applied (piece)

Level-I index	Level-II index
Information infrastructure (E)	Number of general institutes of higher education (No.)
	Number of students in general institutes of higher education (ten thousand people)
	Proportion of city infrastructure investment in the all-region gross regional domestic product (%)
	trunk network length of cable Radio & TV transmission per thousand (thousand people/m)
	Number of fixed telephone subscribers per hundred households (No./hundred households)
	Number of mobile telephone per hundred (No./hundred people)
	Number of broadband internet subscribers per hundred households (No./hundred households)

3. Model analysis of convolutional neural network

3.1. Basic topological structure of the network

The biggest difference between convolutional neural network and other neural networks is that the convolutional neural network connects to the convolutional layer before the input layer, so that the convolutional layer becomes the data input of the convolutional neural network. LeNet-5 is the classical convolutional neural network model developed for handwritten character recognition by Yan Lecun and Fig.1 is the structure chart of it.

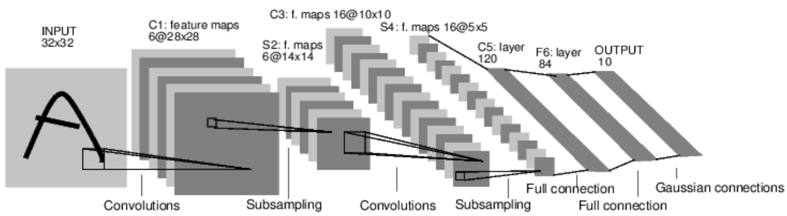

Fig. 1. Structure chart of LeNet-5

The architecture of LeNet-5 has 7 layers in which 3 layers are convolutional layers. As convolutional layer 1 is composed of 6 Feature Maps (FM), C1 contains 156 trainable parameters (seven 5×5 kernels plus 6) to create 122304 (156× (28×28) -122, 304) connections. The size of FM in Layer C1 is 28 × 28. Because of the boundary conditions, convolutional layer 2-C3 contains 1500 weight and 16 offset and Layer C3 has 1516 trainable parameters and 151600 connections. Lecun designs these features with connection maximization and the number extracted by layer C3 and reduce the number of weight. The convolutional layer C5 in the end contains 120 Feature Maps and the output size is 1×1.

The architecture of LeNet-5 also contains two sub-sampling layers: S2 and S4 in which S2 contains 6 Feature Maps and S4 contains 16 Feature Maps. Layer S2 has 12 trainable parameters and 5880 connections which Layer S4 has 32 trainable parameters and 156000 connections

3.2. Activation function

Activation functions often used in the neural network include Sigmoid function, Tanh function and Relu function. The first two activation functions are more often used in the traditional BP neural network while Relu function is more often used in deep learning.

Relu (rectified finear unit) function is the rectified finear unit (Relu) proposed by Hinton. After training with Relu function for several times, CNNs is obviously faster than the traditional sigmoid and tanh function.

It is assumed that the activation function of a neural unit is $h^{(i)}$, where, i represents the number of hidden units and $w^{(i)}$ represents the weight of hidden unit; then the expression of Relu function is as follows:

$$h^{(i)} = \max((w^{(i)})^T x, 0) = \begin{cases} (w^{(i)})^T x & (w^{(i)})^T x > 0 \\ 0 & else \end{cases} \tag{1}$$

Its graph of function is as shown in Fig.2:

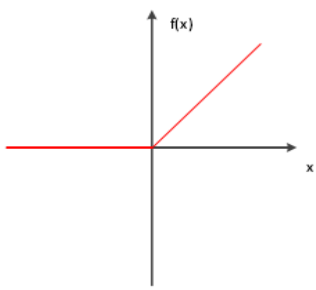

Fig. 2. Graph of function of relu

As the Relu function has linear and unsaturated form, unilateral inhibition, relatively wide excitement boundary and sparse activation, using effect in convolutional neural network it better than that sigmoid and tanh function.

3.3. Learning algorithm

During the learning of neural network, we mainly use the back propagation algorithm for gradient calculation and use the gradient to carry out parameter updating and main methods include Stochastic Gradient Descent (SDG) and Adaptive Moment Estimation (Adam). Under normal conditions, as our training data set is large and how to loan all training samples for training one time often involves memory overflow, we often adopt a mini-batch (the quantity is N<< |D|) of the data set and the cost function at that time is as follows:

$$J(\theta) = \frac{1}{|N|}\sum_{i}^{|N|} f_\theta(x^{(i)}) + \lambda r(\theta)\,. \tag{2}$$

Adam (Adaptive Moment Estimation) is RMSprop with momentum in essence which used first moment estimation and second moment estimation of gradient for the dynamic adjustment of the learning rate of each parameter. The main advantage of Adam is that each iteration learning rate has a definite scope after offset correction to make the parameter stable and the iteration equation is as follows:

$$m_t = \mu m_{t-1} + (1-\mu)\nabla J(\theta_t)\,. \tag{3}$$

$$n_t = v n_{t-1} + (1-v)\nabla^2 J(\theta_t)\,. \tag{4}$$

$$\hat{m}_t = \frac{m_t}{1-\mu^t}\,. \tag{5}$$

$$\hat{n}_t = \frac{n_t}{1-v^t}\,. \tag{6}$$

$$\Delta\theta_t = -\frac{\hat{m}_t}{\sqrt{\hat{n}_t}+\varepsilon}\eta\,. \tag{7}$$

Where, m_t and n_t represent the first moment estimation and second moment estimation of gradient respectively and they can be considered as the estimation of $E|\nabla J(\theta_t)|$ and $E|\nabla^2 J(\theta_t)|$; $\hat{m}_t$ and $\hat{n}_t$ are corrections of m_t and n_t and they can be approximate to the unbiased estimation of expectation. It can be seen that the direct moment estimation of gradient has no additional requirement for memory and it can be adjusted dynamically in accordance with the gradient while $-\frac{\hat{m}_t}{\sqrt{\hat{n}_t}+\varepsilon}$ forms a dynamic constraint on learning rate and has definite scope.

4. Experimental analysis

4.1. Sample selection

Data in the Thesis are mainly from the development and construction statistics data of such 15 smart cities as *2013 Bulletin of National Economic and Social Development Statistics*, *2013 Bulletin of Scientific and Technological Progress Statistics and Monitoring Result and Scientific and Technological Statistics*, *2013 Comparison of Financial Inputs to Science and Technology of Nineteen Cities*, *2013 Bulletin of National Economic and Social Development Statistics of Hefei*, *2013 Bulletin of National Economic and Social Development Statistics of Guangzhou*, *2013 Bulletin of National Economic and Social Development Statistics of Nanjing*, *2013 Bulletin of National Economic and Social Development Statistics of Wuhan*, *2013 Bulletin* *of National Economic and Social Development Statistics of Chengdu*, *2013 Bulletin of National Economic and Social Development Statistics of Kunming* and *2013 Bulletin of National Economic and Social Development Statistics of Wuxi* and individual data come from Internet search. For the convenience of calculation, smart city is expressed with English abbreviation and samples of 15 smart cities are successively expressed with SC1, SC2, SC3, SC4, SC5, SC6, SC7, SC8, SC9, SC10, SC11, SC12, SC13, SC14 and SC15.

4.2. Result analysis

Parameter setting of the training process: as the input sample is 20-dimension input vector, there are 20 nerve cells in the input layer and the node in input is 1. The number of neuron in hidden layer will be determined in accordance with the empirical equation $M = \sqrt{n+m} + a$, where, M is the number of neuron in hidden layer, $m$is the number of neuron in output layer, n is the number of neuron in input layer and a is constant between [0, 10]. In accordance with the object of neural network training and scale of training, attempt and comparison one by one will be adopted to build BP neural network, so as to design the neural network with the best training and simulation performance.

The blue solid line represents training curve, red solid line represents inspection curve and green dotted line represents the optimal intersection point of network training curve. When the number of node in the hidden layer of BP neural network is 5, the optimum performance of neural network training is 0. 016259 and the number of iterations is 21; when the number of iterations of training reaches 15, the curve converges, as shown in Fig.3

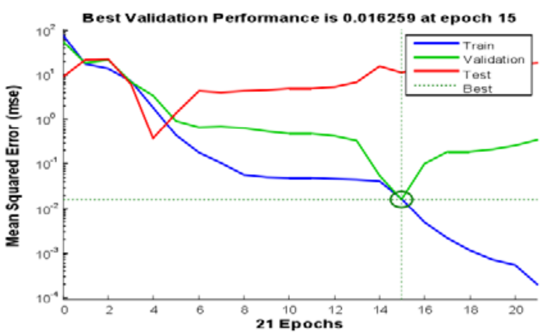

Fig. 3. Training result when the number of node in hidden layer is 5

Table 2 is the results of evaluation of smart city development potential by four different methods. In accordance with the pre-classification of the training result, the evaluation of different cities is classified based on gray correlation and evaluation method of neural network. The results show that the error between the expected output value and actual output value is very small and basically meets the prediction objective of users and meets the conformance requirements of user evaluation. In addition, before the neural network training, the pre-classification of training results is conducted. After distinguishment of different classification results of various cities, it is found from the output results that there is little difference in the levels of smart city development potential and it is basically in a controllable section.

Table 2. Classification of evaluation results and evaluation results of four different methods

City No.	Algorithm in the Thesis	Simulation category	Entropy weight method	TOPSIS method	Gray correlation
SC1	0.755	Good	0.828	0.364	0.804
SC2	0.764	Good	0.795	0.125	0.790
SC3	0.708	Good	0.519	0.072	0.724
SC4	0.635	Good	0.638	0.191	0.742
SC5	0.700	Good	0.781	0.123	0.775
SC6	0.630	Good	0.326	0.413	0.663
SC7	0.624	Good	0.461	0.072	0.692
SC8	0.693	Good	0.522	0.017	0.703
SC9	0.688	Good	0.448	0.026	0.715
SC10	0.691	Good	0.535	0.073	0.703
SC11	0.534	Fine	0.375	0.010	0.669
SC12	0.715	Good	0.508	0.048	0.717
SC13	0.667	Good	0.388	0.054	0.691
SC14	0.663	Good	0.525	0.053	0.715
SC15	0.711	Good	0.603	0.031	0.753

Fig.4 shows the evaluation of 15 smart cities through four different methods. The evaluation results have different degrees of difference. Green dotted line represents the result of gray correlation analysis; yellow dotted line represents the evaluation result of TOPSIS evaluation method; blue solid line represents the evaluation result of entropy weight method while the brown solid line represents the evaluation of GRA-BPNN model. The evaluation result of the gray correlation and BP neural network used in the Thesis is the fourth brown curve and its stability and smoothness of the solid line are better than that of the other three methods and the evaluation result reflected is more reasonable than that of the other three methods, better proving the feasibility and scientificity of evaluation of smart city development potential by the evaluation method in the Thesis.

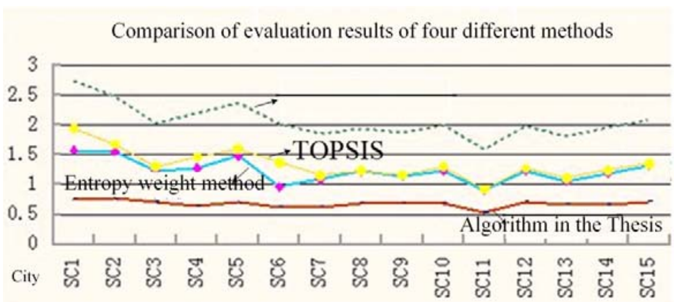

Fig. 4. Comparison of algorithm evaluation results

5. Conclusion

In accordance with the evaluation result of smart city development potential, as such cities as Beijing, Shanghai and Guangzhou have relatively complete information infrastructure, higher social management ability and public service level, leading scientific and technological development and innovation ability throughout the country and great potential of smart city development, their level and quality of smart city construction are higher. However, the economic development speed of such inland cities as Lanzhou, Guiyang and Kunming is relatively slow; the urban infrastructure is under construction and improvement; science & technology and education level lags behind relatively and the informationization level is relatively slow. Therefore, their smart city development potential and construction ability are not high and the pace of smart city construction is slow. On the whole, the differences of smart city development potential can be roughly classified into three categories: Category I smart cities refer to eastern coastal smart cities with great development potential, such as Beijing, Shanghai, Guangzhou and Shenzhen, being not only closely linked with the economic development degree, but also the support of national policy and they are almost the political centers, cultural centers or economic centers of the whole country. Category II smart cities refer to central smart cities which many refer to central developmental cities, such as Wuhan and Hefei. The smart city development potential of these cities is lower that that of the eastern coastal smart cities but higher than that of the western smart cities. In addition, they have fast economic development speed, good natural geographical environment and high city livability level and the majority of them belong to provincial capitals of large central provinces and serve as the political centers, cultural centers or economic centers of the whole province. They can often centralize powers of the whole province for construction and their comprehensive smart city development potential is relatively high with a trend of rapid of good development. Category III smart cities refer to western smart cities, such as Chengdu, Kunming and Guiyang which basically belong to provincial capitals with relatively fast economic development speed, relatively abundant city resources. However, as their economic development quality and level have a certain difference compared with central smart cities or eastern coastal smart cities and the geographical conditions of these cities have significant influence on the city development, the transportation convenience degree of these cities is falls far below the development level of central or eastern cities and the development potential of these smart cities is relatively low, influencing the later construction and development of smart city to a certain extent. Therefore, the development condition and environment of smart city are relatively vulnerable and the gap with central and eastern smart cities is obvious.

Acknowledgement

The Key research projects of Henan higher education institutions.

References

[1] Mahapatra C, Sheng Z, Leung V C M, et al.: (2015) *A reliable and energy efficient IoT data transmission scheme for smart cities based on redundant residue based error correction coding*[C]// IEEE International Conference on Sensing, Communication, and NETWORKING-Workshops. IEEE, 2015:1-6.

[2] Pahlavan K, Krishnamurthy P and Geng Y: (2015) *Localization challenges for the emergence of the smart workd.* IEEE Access, 3(1), pp. 3058-3067

[3] Chaturvedi A, Mishra D, Mukhopadhyay S: (2013) *Improved Biometric-Based Three-factor Remote User Authentication Scheme with Key Agreement Using Smart Card*[M]// Information Systems Security. Springer Berlin Heidelberg, 2013:63-77.

[4] Wei J, Liu W, Hu X: (2016) *Secure and efficient smart card based remote user password authentication scheme*[J]. International Journal of Network Security, 18(4):782-792.

[5] Lv, Z., Tek, A., Da Silva, F., Empereur-Mot, C., Chavent, M., & Baaden, M.: (2013). *Game on, science-how video game technology may help biologists tackle visualization challenges.* PloS one, 8(3), e57990.

[6] Lv, Z., Halawani, A., Feng, S., Li, H., & Réhman, S. U.: (2014). *Multimodal hand and foot gesture interaction for handheld devices.* ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 11(1s), 10.

[7] Gnanaraj J W K, Ezra K, Rajsingh E B: (2013) *Smart card based time efficient authentication scheme for global grid computing*[J]. Human-centric Computing and Information Sciences, 3(1):16.

[8] Xu Y, Chen X, Liu A, et al.: (2017) *A Latency and Coverage Optimized Data Collection Scheme for Smart Cities Based on Vehicular Ad-Hoc Networks*[J]. Sensors, 17(4):888.

[9] Weisen Pan, Shizhan Chen, Zhiyong Feng: (2013) *Automatic Clustering of Social Tag using Community Detection.* Applied Mathematics & Information Sciences, 7(2): 675-681.

[10] Chaturvedi A, Mishra D, Mukhopadhyay S: (2013) *Improved Biometric-Based Three-factor Remote User Authentication Scheme with Key Agreement Using Smart Card*[C]// International Conference on Information Systems Security. Springer Berlin Heidelberg, 2013:63-77.

[11] Yingyue Zhang, Jennifer W. Chan, Alysha Moretti, and Kathryn E. Uhrich: (2015) *Designing Polymers with Sugar-based Advantages for Bioactive Delivery Applications*, Journal of Controlled Release, 219, 355-368.

[12] Lu R, Lin X, Zhu H, et al.: (2009) SPARK: A New VANET-Based Smart Parking Scheme for Large Parking Lots[C]// INFOCOM. IEEE, 2009:1413-1421.

[13] Yingyue Zhang, Qi Li, William J. Welsh, Prabhas V. Moghe, and Kathryn E. Uhrich: (2016) *Micellar and Structural Stability of Nanoscale Amphiphilic Polymers: Implications for Anti-atherosclerotic Bioactivity*, Biomaterials, 84, 230-240.

[14] Wang D, Ma C G, Wu P: (2012) *Secure Password-Based Remote User Authentication Scheme with Non-tamper Resistant Smart Cards*[C]// Ifip Conference on Data and Applications Security and Privacy. Springer Berlin Heidelberg, 2012:114-121.

[15] Xie S, Yang J, Xie K, et al.: (2017) *Low-Sparsity Unobservable Attacks Against Smart Grid: Attack Exposure Analysis and a Data-Driven Attack Scheme*[J]. IEEE Access, PP(99):1-1.

[16] Jennifer W. Chan, Yingyue Zhang, and Kathryn E. Uhrich: (2015) *Amphiphilic Macromolecule Self-Assembled Monolayers Suppress Smooth Muscle Cell Proliferation*, Bioconjugate Chemistry, 26(7), 1359-1369.

Received May 7, 2017