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URBAN DAILY WATER DEMAND FORECASTING

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Abstract. Problem. *The problem of building models and methods of forecasting the daily need for urban water is considered. Much more attention needs to be given to forecasting methods if utilities are to make decisions that reflect the level of uncertainty precisely in future daily demand forecasts. Daily water consumption, unlike annual and monthly water consumption, is much more highly dependent on chance.* ***Goal.*** *The main goal of this paper is to obtain enough accurate forecasts of daily urban water consumption.* ***Method.*** *An algorithm for calculating the urban daily water demand forecast based on the concept of same-type days of water demand for previous years has been suggested.* ***Scientific novelty.*** *The originality of the method lies in the fact that it does not use neural network models, but still makes it possible to obtain enough accurate forecasts of daily urban water needs.* ***Results.*** *The presented algorithm for calculating the urban daily water demand forecast has been implemented in the form of a software package and has been tested for many years in real-life conditions. The average absolute percentage error of the daily forecast of urban water demand for one month does not exceed 5 %.* ***Practical significance.*** *The practical value of this work lies in the fact that the presented software complex for calculating the forecast of the city's daily water demand can be used in the information services of city utility companies to make operational and tactical decisions regarding the provision of water supply services to the population.*

Keywords*: forecasting, forecast, time series, model, artificial neural network, water demand, water supply, statistical analysis.*

Introduction

When making operational, tactical, and strategic decisions by municipal utilities of large cities (municipal water service companies), it is important to have a reliable forecast of the urban daily water demand. For example, municipal utilities need to be aware of the clean water demand several days in advance to ensure this demand with both the sufficient work of pumping stations that pump water and the proper work of treatment plants. Thus, the uncertainty accounting in the forecasts of urban water demand allows the municipal utilities to optimize their operating and investment decisions. Thus, the development of methods and models for urban water demand forecasting, which would adequately describe the process of daily changes in urban water demand and allow to building reliable forecasts of future daily water demand in the city is a crucial task.

Analysis of publications

Currently, the world pays a lot of attention to the issue of urban daily water demand forecasting [1–10], but in Ukraine this issue is almost not considered.

In recent years, a significant number of articles on water demand forecasting have been published in specialized economic, financial and econometric journals around the world.

Thus, publication [1] reviews the literature on urban water demand forecasting, published from 2000 to 2010 in order to identify methods and models useful for solving the problem of water supply of a particular water utility. The results of their research show that, although a wide variety of methods and models are worth noting, the application of these models in practice differs depending on the behavior of the variable (water demand), its periodicity and the forecast horizon. In this paper, it has been concluded that while artificial neural networks are more convenient for short-term forecasting, econometric models combined with modeling and scenario-based forecasting, tend to be more effective when used for long-term strategic decisions.

In article [2], its authors suggest a relatively new method of artificial neural network (ANN) for modeling and forecasting urban water demand. The results of their research have showed that the model of water demand forecasting using an artificial neural network provides an effective way to forecast the domestic water demand in Weinan city in China. The assessment of the model has showed that the correlation coefficients are more than 90 % for both training and test data.

The scientific paper [6] considers the construction of an adaptive model of water demand forecasting, which was put into operation in 1996 and currently forecasts water demand in the Netherlands. Real calculations and graphs are given, the composition of the forecasting model is described in detail and its accuracy and results of its implementation for 2007–2011 have been analyzed, and also it has been revealed that this model allows to cope with rapid changes in demand caused by weather conditions, slow seasonal fluctuations and even social-economic cataclysms.

In article [3], its authors, M. K. Tiwari and J. Adamowski, propose a new hybrid neural network model (WBNN) for urban demand forecasting of water resources in the short term (1, 3 and 5 days, 1 and 2 weeks, as well as 1 and 2 months). The authors tested their method using data from Montreal city of in Canada. As determined in this research, the use of maximum air temperature and total precipitation in wavelet analysis improves the accuracy of water demand forecasts.

A multi-scale relevance vector regression (MSRVR) approach for daily urban water demand forecasting has been suggested in the scientific publication [4]. The approach uses a stationary wavelet transform to decompose the time series of daily water supplies on different scales. At each level, wavelet coefficients are used for a computer model teaching by the relevance vector regression (RVR) method. The calculated coefficients of the RVR model outputs for all scales are used when restoring the results of forecasting using the inverse wavelet transform. In order to facilitate forecasting in the MSRVR approach, the features of the uncertainty of the daily time series of water demand are analyzed in order to determine the input variables of the RVR model. The MSRVR approach has been assessed using real data collected from two hydraulic structures and compared with traditional methods. The results of the authors' research have shown that the proposed MSRVR method can forecast a daily urban water demand much more accurately than traditional ones in terms of a normalized standard error, a correlation coefficient and a mean absolute percentage error.

Based on the above review of the literature, it can be concluded that most often when forecasting the urban water demand for a short term, the neural network models and combined (hybrid) models are used.

Neural network and hybrid models [5–10], in contrast to classical ones, can modulate nonlinear connections, are scalable, highly adaptive and have many examples of application. Many researchers emphasize the correlation of water demand with weather conditions and other factors, so exactly these models allow to cope with rapid changes in demand that may be caused by seasonal fluctuations, weather conditions, or even socio-economic problems in the society.

Purpose and statement of the problem

A method based on the concept of same-type days in previous years will be considered in this paper. This method does not apply the neural network models but still allows us to obtain enough accurate forecasts of daily urban water demand.

The main goal of this paper is to obtain enough accurate forecasts of daily urban water consumption using a method based on the concept of similar days for previous years.

Presenting the main material

The need to forecast an urban water demand arises for both long-term periods (annual and monthly) and short-term periods (daily and hourly). At the same time, the main problem related to forecasting accuracy arises when forecasting a daily water demand, despite the existence of the main seasonality of seven days, as well as the seasonality per year. This is primarily due to the holidays, both with a fixed date (for example, January 1 or March 8) and holidays fixed to the weekend (for example, Orthodox Easter or Trinity), as well as with transfers of working days to other days. Therefore, to increase the accuracy of the daily forecast, we will apply the idea of same-type days for previous years.

The time series of daily water demand refers to the calendar time series. Calendar time series (not necessarily time series of water demand) occur whenever they contain indicators related to people’s life. Calendar time series of daily indicators are characterized by the fact that their values depend on the following factors:

- which day of the week corresponds to this day;
- whether this day coincides with holidays, pre-holiday, or post-holiday days;
- to which month of the year this day belongs.

The concepts of regular and irregular days have been introduced in order to distinguish the days in the calendar time series. Irregular days mean the days that are festive, pre-holiday, or post-holiday. They are called fixed irregular days if they fall on pre-known fixed dates. Non-fixed irregular days will include days that coincide with religious holidays, or which fall on the transfer of days of the week, etc. All those days that do not belong to irregular days will be called regular days.

It is necessary to have statistics of the values on this series over the past few years in order to analyze a calendar time series.

Let us consider the algorithm for calculating the forecast of daily water demand, which is based on the above concept of regular and irregular days.

The calculation of the daily water demand forecasting is carried out for the whole month and is based on a hierarchical principle: firstly, the forecast of the average daily water demand for the said month is calculated, and then the forecast is calculated by days, i.e. the monthly water demand forecast is distributed by days of the month.

According to the conducted research, the time series of daily water demand can be conveniently replaced by a time series of contribution indices.

The value ***C (n, k, d)*** will be called a contribution index of the *d*-th day, belonging to the *k*-th month of the *n*-th year:

$$C(n,k,d) = Y(n,k,d)/Y_{av}(n,k), \quad (1)$$

where ***Y(n, k, d)*** is a value of daily water demand on the *d*-th day of the *k*-th month of the *n*-th year, $Y_{av}(n, k)$ is a value of the average daily water demand for the *k*-th month of the *n*-th year.

The study of these indices has shown that in different years you can find the same-type days in which the contribution indices are approximately equal.

Now the algorithm for obtaining a daily water demand forecast will be described. Suppose you need to make a forecast $\boldsymbol{Y_{pr}(n,k,d)}$ on the *d*-th day of the *k*-th month of the *n*-th year. This forecast will be calculated by the formula (2), which follows from formula (1):

$$\boldsymbol{Y_{pr}(n,k,d) = Y_{pr}(n,k) * C_{pr}(n,k,d)}, \quad (2)$$

where $Y_{pr}(n, k)$ is a forecast of average daily water demand for the *k*-th month of the *n*-th year, $C_{pr}(n, k, d)$ is a forecast of the contribution index ***C (n, k, d).***

The monthly forecast $Y_{pr}(n, k)$ can be calculated, for example, on the model ARIMA (1, 1, 1) (0, 1, 1) with seasonal lag 12. The structure of the Box-Jenkins model for the monthly water demand forecast was chosen to satisfy the following condition: the average absolute percentage error (for one year) of the forecast with one month's warning does not exceed 1.5 %. Quite a detailed description of the analysis of this model is given in the paper [11]. Therefore, it remains to describe the method of finding the forecast of the contribution index $C_{pr}(n, k, d)$.

For regular days, the value $C_{pr}(n, k, d)$ is a moving average of the contribution indices of the same-type days, taken from a given number of *m* years preceding the *n*-th year. To do this, you must first determine the numbers of the same-type days.

In the (*n*-1)-th year, a day identical to the *d*-th day of the *k*-th month of the *n*-th year will also belong to the *k*-th month. Denote the number of this day in the month by $\mathbf{d_s}$ **(1)**. Then, $d_s(i) = d + 2$, if (mon(n, 4) = 0 and k> 2) or (mon(n-1,4) = 0 and k≤2). In other cases $\boldsymbol{d_s(i) = d + 1}$.

Denote by ***Ndm (k,n)*** a number of days in the *k*-th month of the *n*-th year, and by $h_s(1)$ – a difference between $\mathbf{d_s(1)}$ and ***d***. Next, $\mathbf{d_s(i)}$ as a number of the same-type day in the (*n*-i)-th year for $i \geq 2$ will be recursively determined.

Suppose the number $\boldsymbol{d_s}$**(i-1)** has been already found. Let us introduce $\boldsymbol{h_s(i\text{-}1) = d_s(i\text{-}1) - d}$. Then $h_s(i)$ is determined by the following rule:

$$\boldsymbol{h_s(i) = h_s(i) + \Delta h},$$

where $\Delta h = 2$, if (*Ndy(n-i)* = 366 and k>2) or (*Ndy(n-i)* = 366 and k≤2). In other cases $\Delta h = 1$. Here *Ndy(n-i)* is a number of days in the (n-i)-th year. In this case, if $\boldsymbol{h_s(i)>3}$, then $\boldsymbol{h_s(i)= h_s(i) - 7}$ (here "7" is a number of days per week). Finally, we consider:

$$\boldsymbol{d_s(i) = d + h_s(i)}.$$

The suggested method for determining the same- type days provides the maximum proximity of the same-type day $\boldsymbol{d_s(i)}$ to the starting day *d*.

Now let us determine the contribution index $\boldsymbol{C_s(i,k,d)}$ of the same-type day $\boldsymbol{d_s(i)}$ for day ***d***. It will be determined by the following rule:

1. $\boldsymbol{C_s(i,k,d) = C(n-1,k,d_s(i))}$,
   if $1 < d_s(i) \leq Ndm(n-i,k)$;

2. $C_s(i,k,d) = \frac{C(n-1,k,Ndm(n-i,k))\cdot Y(n-1,k,d_s(i)-7)}{Y(n-1,k,Ndm(n-i,k)-7)}$, if $d_s(i) > Ndm(n-i,k)$;

3. $C_s(i,k,d) = \frac{C(n-1,k,1)\cdot Y(n-1,k,d_s(i)+7)}{Y(n-1,k,8)}$, if $d_s(i) < 1$ та $k \notin \{3,10,11\}$;

4. $C_s(i,k,d) = C_s(i-1,k,d)$, if $d_s(i) < 1$ та $k \in \{3,10,11\}$.

Thus, for fixed irregular days, the contribution index forecast is equal to the contribution index of the *d*-th day of the *k*-th month of the next year, which contains the same-type irregular day. For example, the forecast for December 31, 2007 is determined by the value of the contribution index for December 31, 2001, as both of these days fall on Monday.

Finally, for greater accuracy, let us determine for regular days:

$$C_{pred}(n,k,d) = \frac{1+\sum_{i=1}^{m} C_s(i,k,d)}{m+1}, \qquad (3)$$

therefore, for regular days, the value $C_{pred}(n,k,d)$ is the moving average of the contribution indices of the same-type days, taken from a given number of *m* years, which are previous to the *n*-th year.

The forecast $C_{pred}(n,k,d)$ for fixed irregular days will be found according to the rule:

$$C_{pred}(n,k,d) = C(n(s),k,d), \qquad (4)$$

where *n(s)* is a number of the year comprising the same-type irregular *d*-th day of the *k*-th month for the *n*-th year, so that the contribution index forecast coincides with the index of the same-type irregular day.

In general, the value of ***n(s)*** is found from Table 1.

Table 1– Table for determining a number of the year comprising the same-type irregular day

	mod(n,4)= =0	mod(n,4)= =1	mod(n,4)= =2	mod(n,4)= =3
k≤2	n(s)=n-6	n(s)=n-5	n(s)=n-11	n(s)=n-6
k>2	n(s)=n-5	n(s)=n-11	n(s)=n-6	n(s)=n-6

For example, for n = 2008, k = 1, d = 1, n(s) = 2002, because January 1, 2008 and January 1, 2002 fall on Tuesday.

For the case when it is necessary to obtain a forecast for irregular non-fixed days, the forecast for these days is firstly calculated on the assumption that these days are regular. Then they are adjusted using correction factors, which are calculated from the analysis of similar irregular days in previous years.

Since the daily forecast is calculated on the basis of the projected average daily value for a month, the errors of the daily forecast, calculated for the month ahead, increase by the error of the forecast of the average daily value for a month. To reduce the errors of the daily forecast, it was advisable to apply the adjustment of daily forecasts by obtained actual values of daily water demand during a month.

The method of calculating the daily water demand forecast, given above, is implemented in software and included in the software package "Forecast".

Here is a brief description of the software package "Forecast" designed to forecast urban water demand, both long-term (annual, monthly) and short-term (daily, hourly).

The calculation of the current forecast of urban water demand is carried out sequentially, starting with an annual one and then descending. At the same time, the annual forecast is a basis for a monthly one, the monthly one – for a daily one, and the daily one – for an hour one. The algorithm for calculating the forecast of hourly water demand is described in [12].

The daily forecast includes the following modes: a forecast for the current month, a forecast for the next month and a retrospective forecast. The retrospective forecast is a forecast for a period of time for which the actual data is already available, but they are not used when setting up the forecast model. The peculiarity of the daily forecast (in the software package "Forecast") is that it is calculated immediately for all days of a given month. It means that during the month the previously calculated forecast of the average daily water demand for a month should be adjusted according to the obtained actual data. To increase the accuracy of the daily forecast, it is necessary to take into account the impact of irregular days, i.e. days when the demand is quite different from neighboring days. The list of irregular days should be prepared in advance.

Fig. 1 and fig. 2 show graphs of the retrospective forecast of daily water demand in some large city in Eastern Europe for December 2008 and January 2009 in order to illustrate the effectiveness of the suggested method of forecasting. Fig. 1 shows the case when the days of December 31 and January 1 are considered as regular days, and Fig. 2 shows the case when these days are already marked as irregular ones.

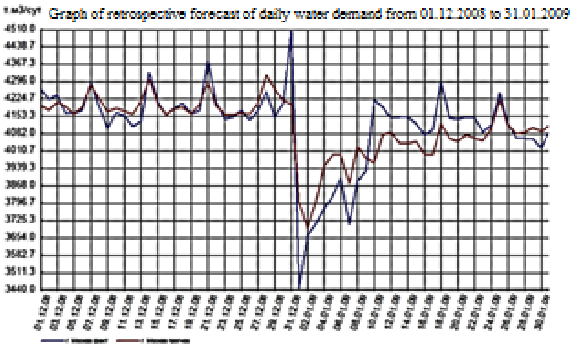

Fig. 1. Graph of the retrospective forecast of daily water demand for the case when the days of December 31 and January 1 are considered regular days

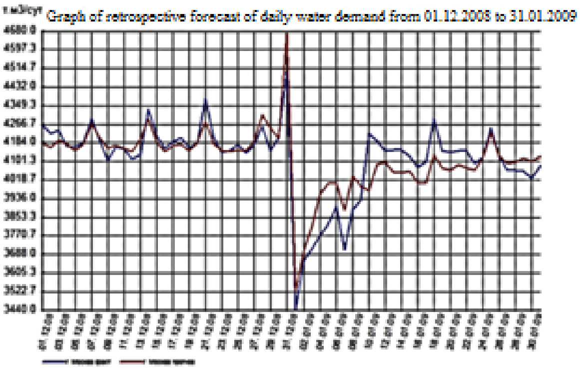

Fig. 2. Graph of the retrospective forecast of daily water demand for the case when the days of December 31 and January 1 are considered irregular days

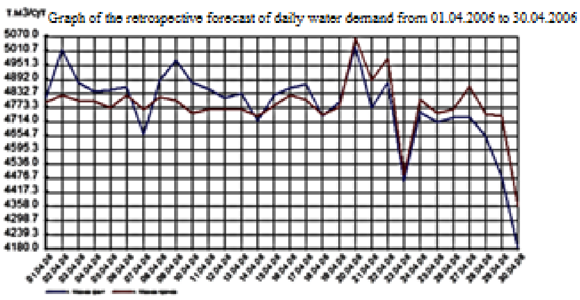

Fig. 3. Graph of the retrospective forecast of daily water demand for April 2006

As it is clear from Fig. 1 and Fig. 2 the forecast for December 31 and January 1, when they are considered as irregular days, is much better.

Fig. 3 shows the graph of the retrospective forecast of daily water demand for April 2006. That year, the Orthodox Easter fell on April 23, so when forecasting this date was defined as a non-fixed irregular day. Also, when calculating the daily forecast for April, the date of April 30 was considered an irregular (but fixed) pre-holiday.

In general, the mechanism of using the concept of irregular days in the daily forecast allows getting a forecast with a relative error not exceeding 5 %.

It should be noted that a sharp change in air temperature also affects the accuracy of the daily water demand forecast. This is noted by other researchers as well, for example [1, 2]. With decreasing air temperature, the water demand increases, and with increasing temperature, on the contrary, it decreases.

Conclusions

Daily forecasting of the water demand is an effective measure for planning the operation of urban water supply facilities. Uncertainty assessment in urban water demand forecasts enables the public utilities to optimize their operating and investment decisions.

A review of the literature on forecasting the demand for water resources that has been published recently is presented.

A method allowing to obtain sufficiently accurate forecasts of daily urban water demand, but does not use neural network models, is suggested. The method is based on the concept of the same-type days for previous years. The algorithm of the method is implemented in software and included in the software package "Forecast". The suggested method has passed many years of testing in real conditions of application, which confirmed its effectiveness. The average absolute percentage error of the daily forecast of urban water demand for one month does not exceed 5 %.

References

1. Urban Water Demand Forecasting: Review of Methods and Models / Donkor E., Mazzuchi T., Soyer R., Roberson A. Journal of Water Resources Planning and Management. 2014. № 140 (2). P. 146–159.
2. Junguo L., Savenije H, Xu J. Forecast of Water Demand in Weinan City in China using WDF-ANN model. Physics and Chemistry of the Earth. 2003. № 28. P. 219–224.
3. Tiwari M. K., Adamowski J. Urban water demand forecasting and uncertainty assessment using ensemble wavelet-bootstrap-neural network models. Water Resources Research. 2013. Vol. 49. P. 6486–6507.

4. A multi-scale relevance vector regression approach for daily urban water demand forecasting / Yun Bai, Pu Wang, Chuan Li, Jingjing Xie, Yin Wang. Journal of Hydrology. 2014. Vol. 517. P. 236–245.
5. Research on the Prediction of the Water Demand of Construction Engineering Based on the BP Neural Network / Hao Peng, Han Wu, Junwu Wang [Electronic resource]. Access mode: https://doi.org/10.1155/2020/8868817.
6. Water demand forecasting: review of soft computing methods / Ghalehkhondabi I., Ardjmand E., Young W. A. et al. Environmental Monitoring and Assessment. 2017. Vol. 189, 313.
7. Regional annual water consumption forecast model / Zhang X., Yue M., Yao Y., and Li H. Desalination and Water Treatment. 2018. Vol. 114. P. 51–60.
8. Piasecki A., Jurasz J., Kazmierczak B. Forecasting daily water consumption: a case study in town. Periodica Polytechnica-Civil Engineering. 2018. Vol. 62. № 3. P. 818–824.
9. Zhao Z., Xu Q., Jia M. Improved shuffled frog leaping algorithm-based BP neural network and its application in bearing early fault diagnosis. Neural Computing and Applications. 2016. Vol. 27. № 2. P. 375–385.
10. Huang S. M. Production capacity prediction based on neural network technology in an efficient economic and management environment of oil field. Fresenius Environmental Bulletin. 2020. Vol. 29. № 4. P. 2442–2449.
11. Horielova K. A., Zadachyn V. M. Long-term and medium-term forecasting of water consumption of large cities. Information processing systems. Ivan Kozhedub Kharkiv National Air Force University. 2016. Vol. 1 (138). P. 76–80.
12. Zadachyn V. M. Forecasting of urban hourly water consumption. Information processing systems. Ivan Kozhedub Kharkiv National Air Force University. 2018. Vol. 2 (153). P. 36–42.

Література

1. Urban Water Demand Forecasting: Review of Methods and Models / Donkor E., Mazzuchi T., Soyer R., Roberson A. Journal of Water Resources Planning and Management. 2014. № 140 (2). P. 146–159.
2. Junguo L., Savenije H, Xu J. Forecast of Water Demand in Weinan City in China using WDF-ANN model. Physics and Chemistry of the Earth. 2003. № 28. P. 219–224.
3. Tiwari M. K., Adamowski J. Urban water demand forecasting and uncertainty assessment using ensemble wavelet-bootstrap-neural network models. Water Resources Research. 2013. Vol. 49. P. 6486–6507.
4. A multi-scale relevance vector regression approach for daily urban water demand forecasting / Yun Bai, Pu Wang, Chuan Li, Jingjing Xie, Yin Wang. Journal of Hydrology. 2014. Vol. 517. P. 236–245.
5. Research on the Prediction of the Water Demand of Construction Engineering Based on the BP Neural Network / Hao Peng, Han Wu, Junwu Wang [Electronic resource]. Access mode: https://doi.org/10.1155/2020/8868817.
6. Water demand forecasting: review of soft computing methods / Ghalehkhondabi I., Ardjmand E., Young W. A. et al. Environmental Monitoring and Assessment. 2017. Vol. 189, 313.
7. Regional annual water consumption forecast model / Zhang X., Yue M., Yao Y., and Li H. Desalination and Water Treatment. 2018. Vol. 114. P. 51–60.
8. Piasecki A., Jurasz J., Kazmierczak B. Forecasting daily water consumption: a case study in town. Periodica Polytechnica-Civil Engineering. 2018. Vol. 62. № 3. P. 818–824.
9. Zhao Z., Xu Q., Jia M. Improved shuffled frog leaping algorithm-based BP neural network and its application in bearing early fault diagnosis. Neural Computing and Applications. 2016. Vol. 27. № 2. P. 375–385.
10. Huang S. M. Production capacity prediction based on neural network technology in an efficient economic and management environment of oil field. Fresenius Environmental Bulletin. 2020. Vol. 29. № 4. P. 2442–2449.
11. Horielova K. A., Zadachyn V. M. Long-term and medium-term forecasting of water consumption of large cities. Information processing systems. Ivan Kozhedub Kharkiv National Air Force University, 2016. Vol. 1 (138). P. 76–80.
12. Задачин Віктор. Прогнозування міського погодинного водоспоживання. Системи обробки інформації. 2018. № 2(153). С. 36–42. https://doi.org/10.30748/soi.2018.153.04.

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Прогнозування міського добового водоспоживання

Анотація. *Розглянуто моделі та методи прогнозування міської потреби у воді. Набагато більше уваги необхідно приділяти методам прогнозування, якщо комунальні підприємства мають приймати рішення, які відображатимуть* *рівень невизначеності саме в щоденних прогнозах попиту. Добове споживання води, на відміну від річного та місячного споживання води, залежить від різноманітних випадків. Основною метою цієї роботи є отримання достатньо точних прогнозів добового водоспоживання міста. Запропоновано алгоритм розрахування прогнозу міської добової потреби води на основі концепції однотипних днів водоспоживання за попередні роки. Цей метод не використовує моделі нейронних мереж, але все ж дозволяє отримати досить точні прогнози щодо щоденної міської потреби у воді. Поданий алгоритм розрахування прогнозу міської добової потреби у воді реалізований як програмний комплекс, застосований у реальних умовах. Середня абсолютна відсоткова похибка добового прогнозу водоспоживання на один місяць не перевищує 5 %. Розроблений програмний комплекс для розрахування прогнозу міської добової потреби у воді може бути використаний в інформаційних службах міських комунальних підприємств для прийняття оперативних, тактичних і стратегічних рішень щодо надання послуг водопостачання населенню.*

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