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COMPARISON OF QUALITY OF UTC(PL) AND UTC(NPL) SCALES PREDICTION BY MEANS OF GMDH NEURAL NETWORK

The article presents research results on predicting the deviations for two different timescales, UTC(PL) and UTC(NPL) by means of GMDH type Neural Network. UTC(PL) timescale was realized by commercial caesium atomic clock. The UTC(NPL) timescale, on the other hand, is based on an active hydrogen maser, additionally supervised by the primary frequency standard in the form of a caesium fountain. Input data has been prepared in the form of two time series. Better quality of prediction has been obtained for UTC(NPL) timescale. Obtained values of predictions differ from the deviations published by the BIPM at the same day of prediction by max ±3.6 ns for two time series.

PORÓWNANIE JAKOŚCI PROGNOZOWANIA SKAL UTC(PL) I UTC(NPL) Z ZASTOSOWANIEM SIECI NEURONOWEJ GMDH

W pracy przedstawiono wyniki badań prognozowania wartości odchyleń dla dwóch różnych skali UTC(PL) oraz UTC(NPL) z zastosowaniem sieci neuronowej typu GMDH. Skala UTC(PL) realizowana jest w oparciu o komercyjny cezowy zegar atomowy. Natomiast skala UTC(NPL) realizowana jest w oparciu o aktywny maser wodorowy, nadzorowany dodatkowo przez pierwotny wzorzec częstotliwości w postaci fontanny cezowej. Dane wejściowe zostały przygotowane w postaci dwóch szeregów czasowych. Lepszą jakość prognozowania otrzymano dla skali czasu UTC(NPL). Otrzymane wartości prognoz różnią się od odchyleń publikowanych przez BIPM na ten sam dzień prognozy o maksymalnie ±3,6 ns dla obydwu szeregów czasowych.

1. INTRODUCTION

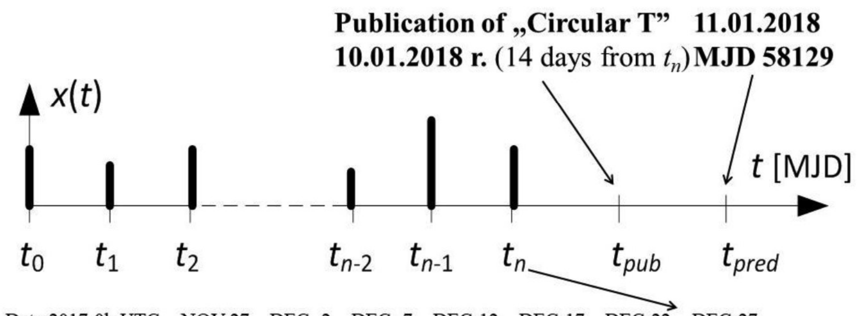
The UTC(k) national time scales are physical realizations of Universal Coordinated Time (UTC) and are supervised by the International Bureau of Weights and Measures BIPM (French for Bureau International des Poids et

Measures). The National Metrology Institutes (NMI) are responsible for the implementation of the national UTC(k) time scales. The process of calculating the UTC scale is a very complex and time-consuming process [1]. Pre-collection and appropriate preparation of measurement data from local and remote comparisons of over 400 atomic clocks, sent to BIPM via the NMI, is required.

In each month, for individual UTC(k), the deviations are determined by BIPM with a five-day interval, determined according to the relationship

$$xb(t) = UTC(t) - UTC_k(t), \tag{1}$$

determining the divergence of national time scales in relation to UTC [1]. These deviations are published in the "Circular T" bulletin, between the 8th and 12th day of the following month (t_{pub}) (Fig. 1). Deviations are determined as single values per day for MJD days (Modified Julian Date), ending with digits 4 and 9.



Date 2017 0h UTC	NOV 27	DEC 2	DEC 7	DEC 12	DEC 17	DEC 22	DEC 27
MJD	58084	58089	58094	58099	58104	58109	58114
NPL (Teddington)	**-2.7**	**-2.6**	**-2.7**	**-2.4**	**-2.3**	**-3.1**	**-3.7**
PL (Warszawa)	**-5.2**	**-7.7**	**-0.8**	**4.8**	**-5.6**	**-18.2**	**-36.5**

Fig. 1. Illustration of $xb(t)$ deviation publication.
Rys. 1. Ilustracja publikacji odchyleń $xb(t)$.

The delay in the publication of $xb(t)$ deviations by BIPM adversely affects the compliance of UTC(k) with UTC. Therefore, in order to speed up the transmission of information about the divergence of UTC(k) in relation to UTC, BIPM in 2012 has launched a Rapid UTC project [2]. On the basis of the UTCr scale, every Wednesday on the BIPM ftp server, deviations determined according to the relationship

$$xbr(t) = UTCr(t) - UTC_k(t) \tag{2}$$

for the previous week for individual clocks using UTC(k) scales are published.

Taking into account the publication date of the $xb(t)$ and $xbr(t)$ deviations, ensuring the highest compliance of UTC(k) with UTC is possible by correcting the UTC(k) time scale by NMI institutes. Atomic timescales are determined and realized physically by intentionally steering signals taken from atomic clocks, whereas frequency and phase drift of atomic clocks are predicted. The process of steering UTC(k) timescales and analysing clocks behaviour can be very complex, including usage of statistical methods based on predicting. The literature for predicting national time scales UTC(k) presents statistical methods based on: Allan's deviations [3], linear regression method [4], Kalman filter [5], stochastic differential equations [6] or based on artificial intelligence [7, 8]. In the few NMI laboratories, the results of which have been presented, for example, in [9, 10], the correction of the UTC(k) scale is carried out on the basis of data from atomic fountains. The determined prediction value may be the basis for the correction of the UTC(k) scale.

Research in the area of applying neural networks to predict UTC(k) national time scales have been started in 2008 at the Institute of Metrology, Electronics and Computer Science of the University of Zielona Góra in cooperation with the Central Office of Measures. At that time, it has been an innovative approach, previously unknown in world literature. The proposal of applying neural networks resulted from their properties. Neural networks can be used where there is a partial or complete lack of knowledge of the rules describing objects or processes, i.e. there is a high complexity of problems [11, 12]. The behavioural models created by the neural network have an internal structure and principle of operation that correspond to the behaviour of the modelled objects or processes. A unique property of neural networks is the possibility of building models using a method based solely on the analysis of specific examples, i.e. the inductive method. Neural networks are a very good mathematical tool used to solve problems of a non-linear nature [11, 12, 13, 14].

Timescale predicting enables the most accurate realization of the local UTC(k) time scale, which allows to obtain a reliable source of measurement traceability in the time and frequency domain, the possibility of precise synchronization, independence from less reliable external sources, and also increases the possibilities of conducting research, also in the field of basic sciences. The purpose of the work is to compare the quality of predicting the UTC(PL) time scale, based on a single commercial caesium clock, with the UTC(NPL) scale, based on an active hydrogen maser with autotuning cavity, additionally supervised by the primary frequency standard in the form of a caesium fountain. The paper presents the results of the research on predicting the deviation values for UTC(PL) and UTC(NPL) by means of the developed procedure based on data prepared in the form of two time series, built on the basis of deviations determined according to the UTC and UTCr scales.

2. SELECTION OF A TYPE OF NEURAL NETWORK

The obtained results of research on the application of MLP, RBF, GRNN and GMDH neural networks, presented for example in works [7, 15, 16, 17], for predicting deviations for the UTC(k) national time scales have shown that the most favourable predicting results of the deviations are shown by GMDH (Group Method of Data Handling) neural networks [18, 19]. The conclusions from the research have been the basis for the development of the deviation predicting procedure for the UTC(k) national time scales based on the GMDH neural network [20, 21]. The results of the research has shown that the developed procedure enables the achievement of very good quality of predicting UTC(k) national time scales.

GMDH neural networks, using the group method of data handling, belong to the group of self-organizing networks. The group method of data handling is used in many areas, mainly related to data acquisition, prediction, system modelling or optimization [18].

Fig. 2 shows an example of the structure of a GMDH neural network, which in the training process is optimized in terms of the number of hidden layers and the number of neurons in these layers [18]. The activation functions of neurons are in the form of polynomials.

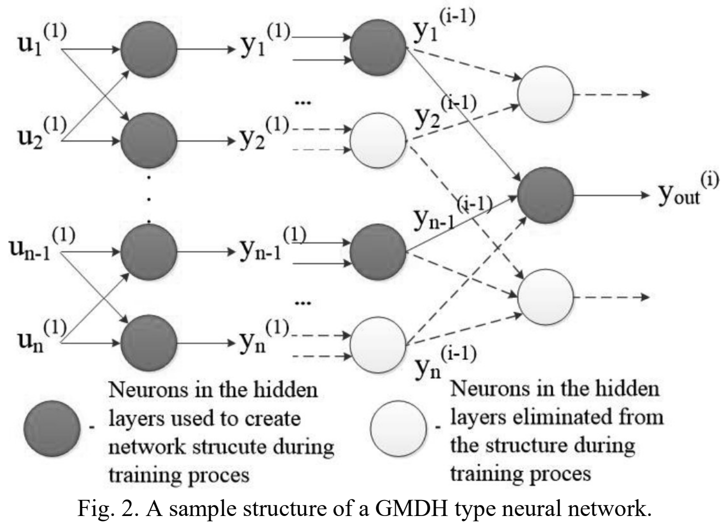


Fig. 2. A sample structure of a GMDH type neural network.
Rys. 2. Przykładowa struktura sieci neuronowej typu GMDH.

The structure of the GMDH network is created automatically on the basis of prepared training and testing data sets. During the training process, the network grows and evolves, as long as it leads to an improvement in its effectiveness [19]. Before the next layer of neurons is attached to the current network structure, the components of the new layer are selected for processing accuracy. Neurons that do not satisfy the imposed evaluation criterion, i.e. the processing error associated with these neurons is too great, are eliminated from the network structure.

3. INPUT DATA PREPARATION FOR GMDH TYPE NEURAL NETWORK

Predicting the deviations for UTC(k) based on GMDH neural networks requires a training process, the quality of which depends on the number of training data and the method of their preparation [22]. Neural networks require an appropriate number of input data to properly conduct the training and predicting process [12, 13, 16]. The research has been carried out for two different time scales implemented by completely different atomic clocks. The active hydrogen maser has different properties compared to commercial caesium clocks. It has better short-term stability compared to caesium clocks, which are characterized by better long-term stability. Therefore, it required the preparation of an appropriate number of input data for both the studied time scales, UTC(PL) and UTC(NPL). In order to extend the number of data, the set of $xb(t)$ values has been interpolated with the PCHIP function (Hermite interpolation available in the MATLAB program), which gives better results than other interpolation methods. Thanks to this, it has been possible to determine the value of $xb(t)$ deviations for each day.

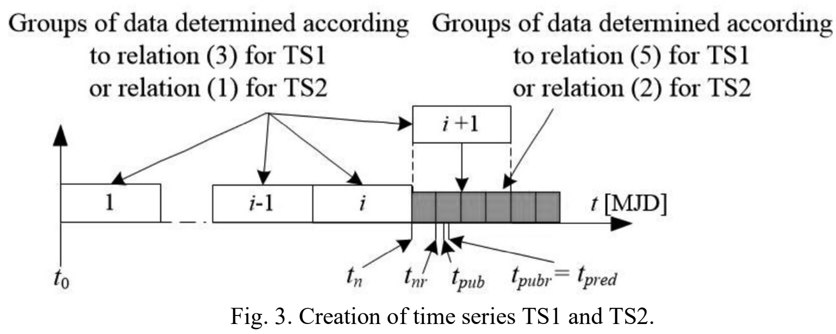


Fig. 3. Creation of time series TS1 and TS2.
Rys. 3. Tworzenie szeregów czasowych TS1 oraz TS2.

The input data for the GMDH neural network have been prepared in the form of two time series TS1 and TS2. The difference in the prepared time series is fundamental. The time series TS1 enables the prediction of the behaviour of the atomic clock realizing the given UTC(k) time scale, while in the case of the time series TS2 the UTC(k) time scale is directly predicted. Based on the obtained predictions, both time series enable the operator to make a frequency correction for a given time scale.

The basic elements of these time series are $xb(t)$ and $xbr(t)$ deviations. Fig. 3 shows the method of creating both time series.

The first created time series TS1 consists of two subsets (Fig. 3). The first subset contains data groups (from 1 to i), determined according to the relationship:

$$x_1(t) = xa(t) + xb(t) = UTC(t) - clock_k(t), \tag{3}$$

from day t_0 to day t_n for which the last value of the time series is known before each publication date (t_{pub}). The values of $xa(t)$ are the historical results of the measurements of the phase time between the 1 pps signals from $UTC_k(t)$ and the atomic clock using this scale ($clock_k$), determined for each day according to the relationship:

$$xa(t) = UTC_k(t) - clock_k(t). \tag{4}$$

The second subset complements the TS1 time series with a group of data between days t_n and t_{nr}, with values being determined on the basis of the relationship:

$$x_2(t) = xa(t) + xbr(t) = UTCr(t) - clock_k(t). \tag{5}$$

The $xbr(t)$ deviation values are published by the BIPM on t_{pubr} day (Fig. 3). The publication day of the $xbr(t)$ deviations can also be the day (t_{pred}), on which the deviation value of $xb(t)$, hereinafter referred to as $xb_p(t_{pred})$ is predicted. Each week, the TS1 time series data is supplemented with new data groups calculated on the basis of (5). Therefore, it is possible to determine the next values of $xb_p(t_{pred})$ predictions in the following weeks. When the new "Circular T" bulletin containing the $xb(t)$ deviation values is published, a new data group i + 1 is created on the basis of (3) (Fig. 3), which for the relevant days replaces the previous data designated on the basis of (5). Of course, new $xb(t)$ data is extended using PCHIP function.

The TS2 time series is based only on the $xb(t)$ and $xbr(t)$ deviation values published by BIPM and consists of two subsets prepared according to the principle described in Fig. 3.

4. RESEARCH RESULTS

Predicting of deviations for the studied UTC(PL) and UTC(NPL) time scales has been carried out for the period of 6 months, from MJD 58124 to MJD

58279, for MJD days ending with digits 4 and 9. At the input of the GMDH neural network data in form of TS1 or TS2 time series have been provided. In the case of using time series TS1, the prediction of this time series ($x_{1p}(t_{pred})$) has been obtained at the output of the GMDH neural network. After taking into account the value of $xa(t_{pred})$ measured on the day of predicting, the prediction of $xb_p(t_{pred})$ has been calculated from the relationship:

$$xb_p(t_{pred}) = x_{1p}(t_{pred}) - xa(t_{pred}). \tag{6}$$

For the time series TS2, the determined prediction value is simultaneously the value of the predicted deviation $xb_p(t_{pred})$.

Figure 4 presents values of $xb(t)$ deviations determined by the BIPM for UTC(PL) and UTC(NPL) scales for analysed period of time.

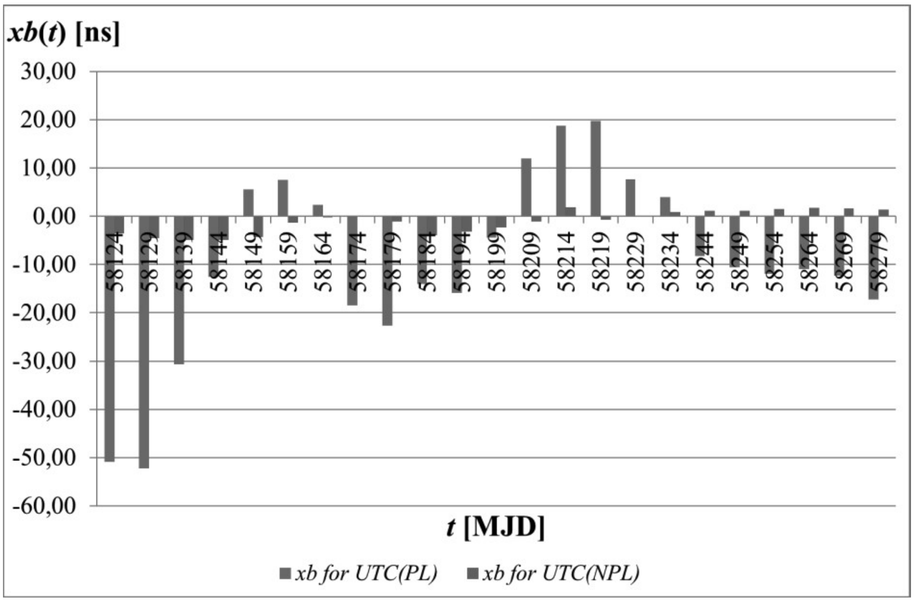


Fig. 4. Determined by the BIPM values of $xb(t)$ deviations for UTC(PL) and UTC(NPL).
Rys. 4. Wyznaczone przez BIPM wartości odchyleń $xb(t)$ dla UTC(PL) i UTC(NPL).

Figures 5 and 6 show the values of the residuals (r), i.e. the differences between the predicted deviation value and the $xb(t)$ deviation published by BIPM for the same prediction day, calculated from the relation:

$$r(t_{pred}) = xb(t_{pred}) - xb_p(t_{pred}). \tag{7}$$

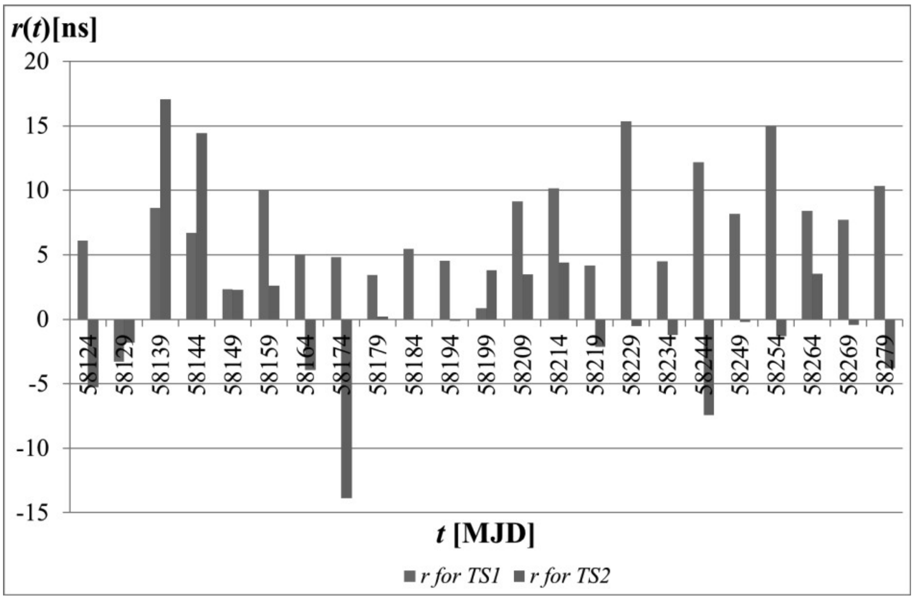


Fig. 5. Determined values of *r* residuals based for UTC(PL).
Rys. 5. Otrzymane wartości residuów *r* dla UTC(PL).

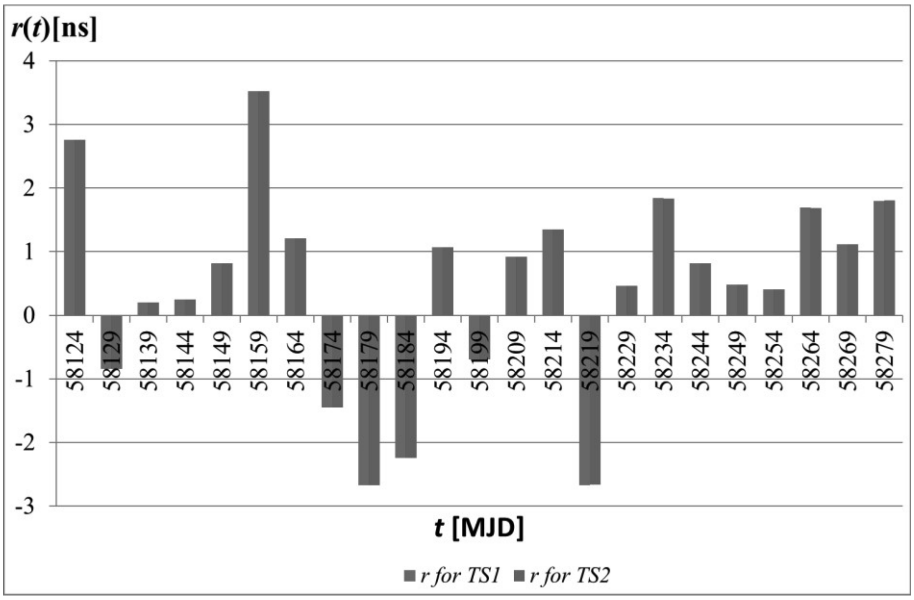


Fig. 6. Determined values of *r* residuals based for UTC(NPL).
Rys. 6. Otrzymane wartości residuów *r* dla UTC(NPL).

On the basis of the calculated residuals (*r*), the values of selected prediction quality measures have been determined [24]: mean error (*ME*), absolute mean error (MAE), mean square error (MSE), with its components (MSE_1, MSE_2, MSE_3) and the root of the mean square error ($RMSE$) as shown in Table 1. The MSE_1 term determines the inaccuracy of the prediction estimation of the average value of the prediction variable, that is, it represents the bias of the prediction. The MSE_2 component is associated with insufficient prediction flexibility, that is, lack of accuracy in predicting fluctuations in the predicted variable. On the other hand, the MSE_3 component informs about an error related to insufficient compliance of the direction of changes in the prediction as compared to the direction of changes in the prediction value. The quality of $xb_p(t_{pred})$ predictions has been assessed on the basis of the following criteria: residuals, selected prediction quality measures [23, 24] and the modified Allan deviation (MDEV) [25].

Figures 7 and 8 show a logarithmic comparison of the dependence of the Modified Allan Deviation (MDEV) from the averaging time (τ) for the determined prediction by means of the GMDH neural network for the analysed TS1 and TS2 time series, respectively for the UTC(PL) scale and the UTC(NPL) scale.

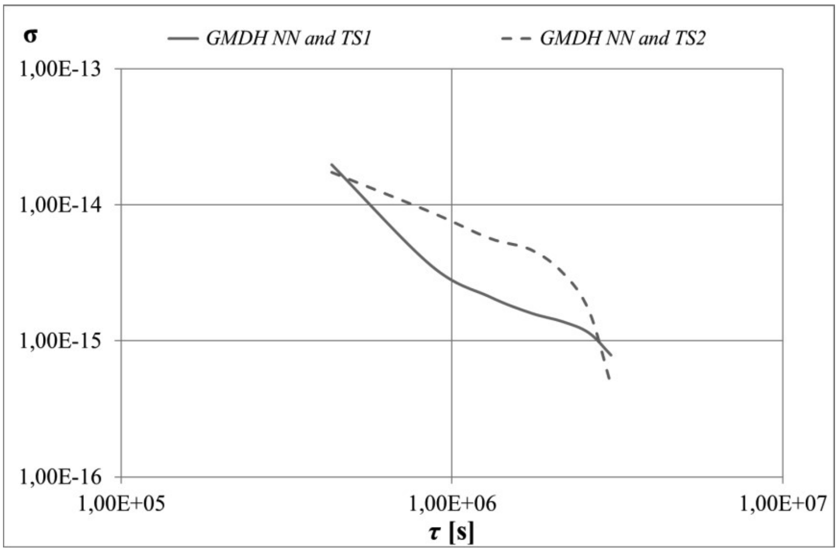


Fig. 7. The relationship MDEV of averaging time (τ) for GMDH neural network with time series TS1 and TS2 for UTC(PL).

Rys. 7. Zależność MDEV od czasu uśredniania (τ) dla sieci neuronowej GMDH dla szeregów czasowych TS1 oraz TS2 dla UTC(PL).

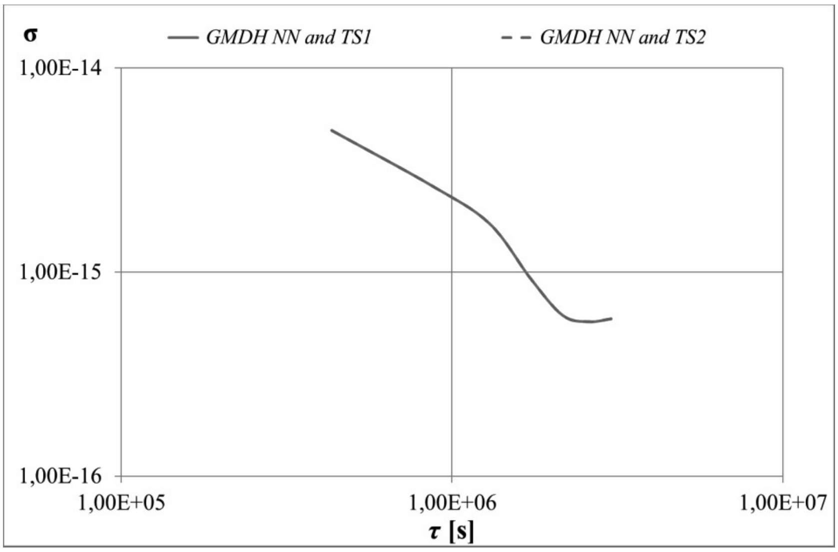


Fig. 8. The relationship MDEV of averaging time (τ) for GMDH neural network with time series TS1 and TS2 for UTC(NPL).
Rys. 8. Zależność MDEV od czasu uśredniania (τ) dla sieci neuronowej GMDH dla szeregów czasowych TS1 oraz TS2 dla UTC(NPL).

Table 1.
Prediction quality measure values for UTC(PL) and UTC(NPL) for TS1 and TS2 time series.

Quality measure of prediction	**UTC(PL) for TS1**	**UTC(PL) for TS2**	**UTC(NPL) for TS1**	**UTC(NPL) for TS2**
max (ns)	16	17	3.6	3.6
min (ns)	-3.3	-14	-2.7	-2.7
ME (ns)	6.9	0.4	0.4	0.4
MAE (ns)	7.2	4.1	1.4	1.4
MSE (ns^2)	66	39	2.6	2.6
MSE_1 (ns^2)	48	0.2	0.2	0.2
MSE_2 (ns^2)	0.8	0.3	0.03	0.03
MSE_3 (ns^2)	17	38	2.4	2.4
RMSE (ns^2)	8.1	6.2	1.6	1.6

The following conclusions have been drawn from the research results presented in Fig. 4 to Fig. 8 and Table 1:

1. The comparison of the values of all the prediction quality measures indicates that better-quality predictions have been obtained in the case of the UTC(NPL) scale.

2. The analysis of $xb(t)$ deviation values shows that in the case of the UTC(NPL) scale we are dealing with deviation values not exceeding single ns, where in the case of the UTC(PL) scale the deviation values in the worst case exceed the value of -50 ns.
3. In the case of the UTC(PL) scale, in 19 cases out of 23 the obtained residuals values are within ±10 ns for the TS1 time series, and in 20 cases out of 23 for time series TS2. The highest absolute residual value achieved for the TS1 time series is 15.35 ns. In the case of data defined by the TS2 time series, the highest absolute value of residual achieved is 17.05 ns
4. In the case of the UTC(NPL) scale, all the obtained residuals values are within ±4 ns for the TS1 and TS2 time series. The highest absolute residual value achieved for both the time series TS1 and TS2 is 3.52 ns.
5. In the case of the UTC(NPL) scale for the TS1 and TS2 time series, the same residuum values have been obtained. This is due to the method of realizing the UTC(NPL) scale and the constant value of the phase time $xa(t)$, between UTC(NPL) and the active hydrogen maser realizing this scale.
6. The comparison of the error values ME, MAE and MSE_1 shows that in the case of the UTC(PL) scale and the TS1 time series, the predictions are biased. The obtained prediction values are lower than the observed values. For the UTC(PL) scale and TS2 time series, as well as the UTC(NPL) scale and TS1 and TS2 series, the predictions are unbiased. The observed residual values are multidirectional.
7. In the case of the UTC(NPL) scale there are very small values of the MSE_2 and MSE_3 components. This means better prediction of the variability of the predicted values in relation to the variability of the observed values and a high consistency of the direction of changes in the prediction as compared to the direction of changes in the prediction value. This is due to the very high stability of the UTC(NPL) scale.
8. In the results obtained for the UTC(PL) scale and TS1 and TS2 time series there are cases of large residuals. This is due to two factors. The first one is related to changes in the direction of the trend of $xb(t)$ deviations determined according to the UTC scale, resulting from the control of the time scale. Hence, for these time series there have been large values of the MSE_3 error component. The second factor is the variable prediction horizon which, depending on the prediction date (t_{pred}), ending with the digit 4 or 9, varied from 3 to 7 days.

9. The achieved low residual values for UTC(NPL) scale has made it possible to obtain high time and frequency stability (respectively: 0.86 ns and 5.72·10-16 for $\tau = 30$ days).

5. CONCLUSIONS

The obtained research results have confirmed the possibility of predicting the values of [UTC - UTC(k)] deviations by means of GMDH neural network based on data prepared on the basis of deviations determined according to the UTC and UTCr scales both for UTC(k) time scales based on commercial caesium atomic clocks, as well as UTC(k) time scales based on active hydrogen masers additionally supervised by the primary frequency standard in the form of a caesium fountain.

The research results have shown that better quality of predicting has been obtained for the UTC(NPL) time scale. It is related to the very high stability, as well as the quality of this scale. Currently, an active hydrogen maser is also used for UTC(PL) scale realization, which is the right course of action. Initial results of the UTC(PL) predicting performed by the active hydrogen maser have shown an improvement in the quality of the predicting.

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