SHORT-TERM AND LONG-TERM WATER LEVEL PREDICTION AT ONE RIVER MEASUREMENT LOCATION

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Abstract

Global hydrological cycles mainly depend on climate changes whose occurrence is predominantly triggered by solar and terrestrial influence, and the knowledge of the high water regime is widely applied in hydrology. Regular monitoring and studying of river water level behavior is important from several perspectives. On the basis of the given data, by using modifications of general approaches known from literature, especially from investigation in hydrology, the problem of long- and short-term water level forecast at one river measurement location is considered in the paper. Long-term forecasting is considered as the problem of investigating the periodicity of water level behavior by using linear-trigonometric regression and short-term forecasting is based on the modification of the nearest neighbor method. The proposed methods are tested on data referring to the Drava River level by Donji Miholjac, Croatia, in the period between the beginning of 1900 and the end of 2012.

Key words: *Water level prediction, Long-term prediction, Short-term prediction, Nearest neighbor method*

1. INTRODUCTION

Many cyclic phenomena have been noted on a global level that are largely triggered by solar and terrestrial influence. According to (Chapanov and Gambis, 2010), a global model of water redistribution can be analyzed by means of a variety of databases. These are e.g. the data on the rotation of the Earth (recorded since the year 1623), the data on total solar irradiance (since 1610), the data on the occurrence of sunspots (since 1700), the data on mean sea level (since 1774), and the data on sea ice thickness (recorded since the year 1622). The impact of the 11-year sunspot cycle and the 45-year equatorially symmetric solar cycle is especially observed. It is clear that these impacts are also locally transmitted to individual areas with smaller or larger variations.

Knowing the surface water regime has a wide range of applications in life. Regular monitoring and studying of river water level behavior is important from several perspectives, i.e. supply of drinking and wastewater to the population, various industrial applications, managing water for sustainable agriculture, especially irrigation and drainage, timely forecasting of floods and dry spells, transport connections, etc., and this is exemplified by numerous references (Chinh *et al*., 2009; Koutroulis *et al*., 2010; del Valle Venencio and García, 2011). In this sense, the analysis of the change in water level as well as water level forecast have been subjects of numerous research activities. Trigonometric regression, Fourier analysis and wavelet theory are most commonly used for long-term prediction, and Artificial Neural Network (ANN) (Maier *et al*., 2010; Sabo, Scitovski, Vazler and Zekić-Sušac, 2011; Wu *et al*., 2008; Wei, 2012) is also frequently used. For the purpose of short-term prediction, ANN, Nearest Neighbor (NN) method, different moving averages methods and cluster analysis are also most commonly used (Sabo, Scitovski, Vazler and Zekic-Sušac, 2011; Wu *et al*., 2008, 2010).

By using modifications of general approaches known from literature, especially from investigation in hydrology, Section 2 proposes an efficient method for periodicity analysis of data time series by using linear-trigonometric (LT) regression. The method is illustrated on synthetic data and tested on empirical data on temporal changes in water level of the Drava River by Donji Miholjac. In Section 3, a modification of the NN method for short-term prediction is proposed. The method is also tested on the previously mentioned data set.

2. LONG-TERM PREDICTION AND PERIODICITY ANALYSIS

Let us consider time series $(t_i, y_i), i = 1, \dots, N,$ where t_i are time intervals (days, months, etc.), and y_i measured water level values at some place of the river flow. For example, Fig. 1a shows the measured water level values of the Drava River by Donji Miholjac from 1 January 1900 to 1 February 2012. Fig. 1b shows seasonality of water level values throughout the year for this data set by means of the so-called Burn diagram (see Koutroulis *et al*. (2010); Parajka *et al*. (2010)), i.e. by the set

$$\mathcal{B} = \{y_i(\cos\tau_i, \sin\tau_i) \in \mathbb{R}^2 : \tau_i = 2\pi t_i (mod\ 2\pi), i = 1, \dots, N\}.$$

A mathematical model for describing the periodicity of water level is defined in form of LT regression

$$f(t;\alpha,\beta,a) = \alpha + \beta t + \sum_{j=1}^{n} a_j \sin(b_j t + c_j), \quad a = (a_1, b_1 c_1, \dots, a_n, b_n c_n) \qquad (1)$$

(a) Time series (b) Burn diagram

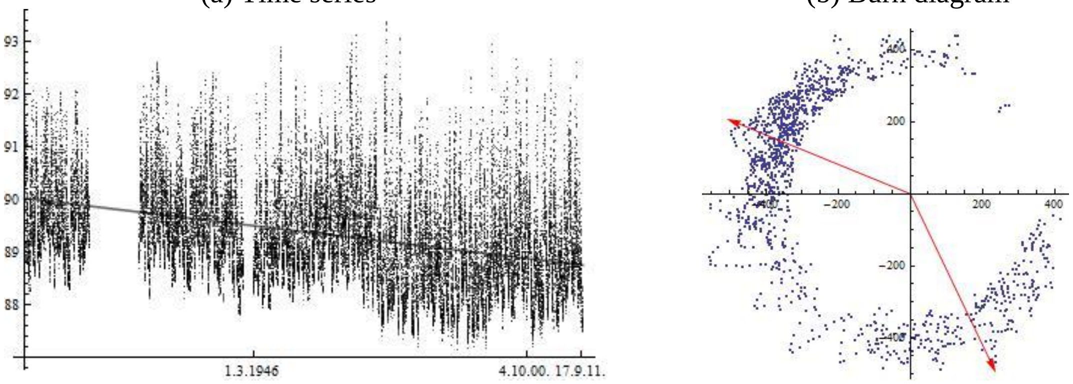

Figure 1: Water level values of the Drava River by Donji Miholjac from 1 January 1900 to 1 February 2012

where $t \mapsto \alpha + \beta t$ is a linear part in the model, and $t \mapsto a_j \sin(b_j t + c_j)$ describe the j-th periodic influence with amplitude a_j, frequency b_j, delay c_j and basic period $T_j = \frac{2\pi}{b_j}$. Optimal parameters $\alpha^*,\ \beta^* \in \mathbb{R}$ and $a^* \in \mathbb{R}^n$ should be determined such that

$$(\alpha^*, \beta^*, a^*) = \operatorname*{argmin}_{\alpha,\beta\in\mathbb{R}, a\in\mathbb{R}^n} F(\alpha,\beta,a), \qquad F(\alpha,\beta,a) = \sum_{i=1}^{N} \big(y_i - f(t_i;\alpha,\beta,a)\big)^2. \qquad (2)$$

Optimization problem (1)-(2) is a complex nonlinear separable least squares (LS) problem with many parameters for the solution of which we may use some of the well-known iterative methods such as the Levenberg-Marquardt method (Bonnans *et al*., 2006). It is thereby extremely important to have a good initial approximation.

2.1 Initial approximation method

The following algorithm gives a very good initial approximation for optimization problem (1)-(2).

Algorithm 1. (Initial Approximation)

Step 1: (Linear LS-problem) Input $n > 0,\ N \gg n,\ (t_i, y_i), i = 1, \dots, N$

Determine $(\hat{\alpha}, \hat{\beta}) \in \mathbb{R}^2$ by solving a simple linear least squares problem

$$(\hat{\alpha}, \hat{\beta}) = \operatorname*{argmin}_{\alpha,\beta\in\mathbb{R}} \sum_{i=1}^{N} (y_i - \alpha - \beta t_i)^2; \qquad (3)$$

Set $\hat{y}_i = y_i - \hat{\alpha} - \hat{\beta} t_i, i = 1, \dots, N;$ Set j=1;

Step 2: (Nonlinear LS-problem) By solving a nonlinear least squares problem determine

$$(\hat{a}_j, \hat{b}_j, \hat{c}_j) = \underset{a,b,c\in\mathbb{R}}{\operatorname{argmin}} \sum_{i=1}^{N} (\hat{y}_i - a\sin(bt_i + c))^2, \tag{4}$$

Step 3: If j < n, set $\hat{y}_i = \hat{y}_i - \hat{a}_j \sin(\hat{b}_j t_i + \hat{c}_j), i = 1, \dots, N;$

Set j = j+1 and go to *Step 2*; Else STOP.

A nonlinear LS-problem from Step 2 will be solved by using the DIRECT method for global optimization (Jones *et al.*, 1993; Neumaier, 2006). First, solving optimization problem (1)-(2) by using Algorithm 1 is illustrated by the following simple example.

(a) Graph of function *f* and approximations (b) Contour Plot

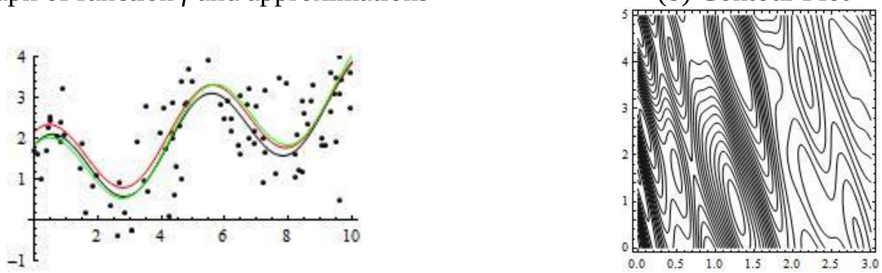

Figure 2: Illustration of Algorithm 1 by function $f:[0,10] \to \mathbb{R}, f(t) = 1 + 0.2t + \sin\left(\frac{2\pi}{5}t + 1\right)$

Example 1. *Let the function* $f:[0,10] \to \mathbb{R}, f(t) = 1 + 0.2t + \sin\left(\frac{2\pi}{5}t + 1\right)$ *be given (black curve in Fig 2a). We define* $N = 100$ *data in the following way*

$$t_i \sim \mathcal{U}(0,10), \qquad i = 1, \dots, N$$

$$y_i = f(t_i) + \epsilon_i, \qquad \epsilon_i \sim \mathcal{N}(0,1).$$

On the basis of these data optimal parameters of the mathematical model $f(t; \alpha, \beta, a) = \alpha + \beta t + a_1 \sin(b_1 t + c_1)$ *should be determined.*

First, in Step 1, by solving linear LS-problem (3) *we obtain* $\hat{\alpha} = 1.25707$, $\hat{\beta} = 0.1899$ *with* $F(\hat{\alpha}, \hat{\beta}, 0,0,0,) = 123.63$. *After that, by solving nonlinear LS-problem* (4) *in Step 2 we obtain* $\hat{a}_1 = 0.96182$, $\hat{b}_1 = 1.22644$, $\hat{c}_1 = 1.13393$ *with* $F(\hat{\alpha}, \hat{\beta}, \hat{a}_1, \hat{b}_1, \hat{c}_1) = 85.56$. *The red curve in Fig 2a shows a corresponding graph. The local optimal values of parameters are obtained by solving nonlinear LS-problem* (1)-(2) *by using the obtained initial approximation. We get*

$$\alpha^* = 0.87026, \quad \beta^* = 0.25065, \quad a^* = (1.04741, 1.21013, 1.16257), \quad F(\alpha^*, \beta^*, a^*) = 82.69.$$

The green curve in Fig 2a shows the corresponding graph. The Contour Plot of minimizing function (4) *with* $b = b_1^*$ *is shown in Fig. 2b, where several local minima are observed. This implies that in this case it would be appropriate to apply some global optimization method (see e.g.* Jones *et al*., 1993; *Neumaier, 2006). However, by using the DIRECT method we obtain a global optimal* solution that coincides with the one previously obtained.

2.2 Periodicity analysis of the water level of the Drava River by Donji Miholjac

The data on absolute water level values for the period between 1 January 1900 and 1 February 2012 were used for the water level analysis of the Drava River by Donji Miholjac. Since observations referring to the period of 12 years are missing (World War I and II), we have $N = 36\,524$ daily data for the last 100 years at that location (see Fig. 1a).

The impact of the linear factor and n=3 dominant periodic factors whose characteristics we would like to investigate will be analyzed on the basis of water level changes. Initial approximation values of parameters are obtained by using Algorithm 1, and LS-optimal parameters are obtained by solving optimization problem (1)-(2) by using a modified Levenberg-Marquardt method (Bonnans *et al.*, 2006). The application of the DIRECT method for global optimization confirms the obtained LS-optimal parameter values. The graph of the obtained LT regression with the basic periods of 10.32 years and 39.37 years and time periods with high water level is shown in Fig. 3.

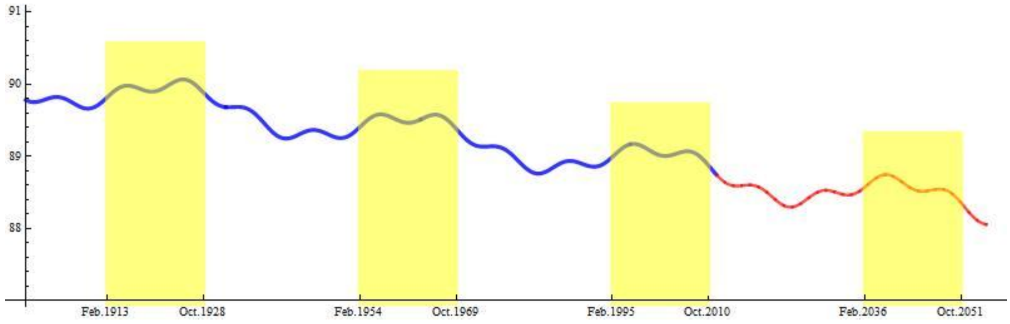

Figure 3: LT regression and high water level intervals

On the basis of the obtained results, we can conclude that water level values of the Drava River by Donji Miholjac are predominantly affected by the following three periodic factors:

- periodic factor with the basic period of one year and the amplitude 56.73 cm expressed by the function $t \mapsto 56.7346 \sin\left(\frac{2\pi}{365.4} t + 11.24\right)$;
- periodic factor with the basic period of 10.32 years and the amplitude 8.90 cm expressed by the function $t \mapsto 8.90664 \sin\left(\frac{2\pi}{3766.8} t + 1.4459\right)$;
- periodic factor with the basic period of 39.37 years and the amplitude 24.00 cm expressed by the function $t \mapsto 24.0033 \sin\left(\frac{2\pi}{14369} t + 10.193\right)$;

In addition, from the linear part $t \mapsto 90.0276 - 0.0000312\, t$ of the obtained model function it can be seen that the average water level values of the Drava River by Donji Miholjac in the observed period is about 90.027 cm above sea level[1] and that it has an average annual decreasing trend of approximately 1.13 cm (see a straight line in Fig. 1a).

3. SHORT-TERM PREDICTION

Extensive research has been conducted especially in the last two decades for the purpose of short-term prediction of a water level at some place of river flow, with special stress placed on river flood protection. Rainfall prediction and the like are considered similarly.

Numerous methods have been developed in the hydrologic literature, which are based on general time series prediction methods (see e.g. Chatfield, 2000; Davis and Brockwell, 1999), and which can generally be classified into three groups: Nearest Neighbor (NN) methods (Wu *et al*., 2008, 2010; Toth *et al*., 2000), Artificial Neural Network (ANN) (Leahy *et al*., 2008; Maier *et al*., 2010; Wu *et al*., 2010), and Support Vector Regression (SVR) (Vapnik, 2010; Wu *et al*., 2008).

3.1 Modification of the NN method

One of the first papers that consider the NN method is Toth et al. (2000). Later on, this approach appears in many other papers (see e.g. (Wu et al., 2008, 2010)). In this paper, we propose a modification of the NN method which includes the basic idea of the SVR method. The method gives very acceptable short-term prediction, and it is tested on the aforementioned water level data of the Drava River by Donji Miholjac.

3.1.1 A day in advance prediction

First, we consider a simplest case - a day in advance prediction. The available data set is divided into a training data set $(t_i, y_i), i = 1, \dots, M$ and a testing data set $(\tau_i, \eta_i), i = 1, \dots, m$. Suppose that $t_{i+1} - t_i = 1, i = 1, \dots, M-1,$ $\tau_{i+1} - \tau_i = 1, i = 1, \dots, m-1,$ and $t_M < \tau_1$. Therefore, a training data set and a testing data set can be written simpler: $(y_1, \dots, y_M)$ and $(\eta_1, \dots, \eta_m)$.

Furthermore, for $n < min\{M, m\}$ define sets

$$\{(a_i, y_i) \in \mathbb{R}^{n+1} : a_i = (y_{i-n}, \dots, y_{i-1}) \in \mathbb{R}^n, y_i \in \mathbb{R}, i = n+1, \dots, M\}, \tag{5}$$

$$\mathcal{A} = \{a_i = (y_{i-n}, \dots, y_{i-1}) \in \mathbb{R}^n : i = n+1, \dots, M\}. \tag{6}$$

In the set $\mathcal{A}$, we will search for all $a \in \mathcal{A}$ that are by their form up to $\epsilon > 0$ similar to the vector $\eta = (\eta_r, \eta_{r+1}, \dots, \eta_{r+n-1})$ for some $r \in \{1, \dots, m-n+1\}$, whose components represent water level

[1] River surface level "0" corresponds to 88.57cm above sea level

values at moments $\tau_r, \ldots, \tau_{r+n-1}$. For that purpose, all data should be normalized and some similarity function $d: \mathcal{A} \times \mathbb{R}^n \longrightarrow \mathbb{R}$ should be chosen (Berry *et al.*, 1999; Zhang *et al.*, 2011), as e.g.

$$d(a,\eta) = 1 - \frac{(a,\eta)}{\|a\|\|\eta\|}, \quad a, \eta \in \mathbb{R}^n \text{ (cos similarity function).} \tag{8}$$

Note that the given $a \in \mathcal{A}$ can be said to be up to ϵ near/similar to the vector η if $(a,\eta) < \epsilon$.

For the given $\epsilon > 0$, by applying similarity function d we obtained a set of vectors up to ϵ near/similar to the vector η

$$\hat{\mathcal{A}} = \{\hat{a}_j = (\hat{y}_{j-n}, \ldots, \hat{y}_{j-1}) \in \mathcal{A} : \hat{a}_j \text{ is up to } \epsilon \text{ } d\text{-similar to } \eta\}, \qquad |\hat{\mathcal{A}}| = k.$$

After that to each vector $\hat{a}_j \in \hat{\mathcal{A}}$ we associate datum $\hat{y}_j$ which in the sequence $y_1, \ldots, y_M$ follows immediately after $\hat{y}_{j-1}$.

Remark 1. Components $\hat{y}_{j-n}, \ldots, \hat{y}_{j-1}$ of vector $\hat{a}_j$ and the value $\hat{y}_j$ can be understood as water level values at moments $t - \mathrm{n}, \ldots, t-1, t$. In accordance with (Toth *et al.*, 2000; Wu *et al.*, 2008), the set $\hat{\mathcal{A}}$ can be defined as the set of the *k*-nearest neighbor to the vector η, and the simple arithmetic mean of the data $\hat{y}_1, \ldots, \hat{y}_k$ can be taken as predicted behavior at the moment τ_{n+1}.

Our modification implies that predicted behavior at the moment t on the basis of behavior at moments $t-n, \ldots, t-1$ is defined by using linear regression $f: \mathbb{R}^n \longrightarrow \mathbb{R}$,

$$f(x_{t-1}, \ldots, x_{t-n}) = \zeta_1 x_{t-1}, \ldots, \zeta_n x_{t-n}, \tag{9}$$

with parameters $\zeta_1, \ldots, \zeta_n \in \mathbb{R}$. Optimal parameters $\zeta_1^*, \ldots, \zeta_n^*$ of linear regression (9) will be determined as a solution of a linear Least Absolute Deviation (LAD) (*p* = 1) or LS (*p* = 2) problem

$$\underset{\zeta_1 \in \mathbb{R}}{argmin} \sum_{j=1}^{k} \left|\hat{y}_j - \zeta_1 \hat{y}_{j-1} - \cdots - \zeta_n \hat{y}_{j-n}\right|^p, \quad p = 1 \text{ or } p = 2, \tag{10}$$

and a day in advance water level prediction on the basis of behavior at previous moments is defined as

$$\hat{\eta}_{r+n} = \zeta_1^* \eta_{r+n-1} + \cdots + \zeta_n^* \eta_r. \tag{11}$$

3.1.2 *T* days in advance prediction

Let us consider *T* days in advance prediction, i.e. prediction at the moment τ_{n+T} . First, to each vector $\hat{a}_j \in \hat{\mathcal{A}}$ we associate datum $\hat{y}_{j+T-1}$, which in the sequence $y_1, \ldots, y_M$ comes to the *T*-th position after $\hat{y}_{j-1}$. Optimal parameters $\zeta_1^*, \ldots, \zeta_n^*$ of regression (9) should be determined on the basis of the data

$$(\hat{a}_j; \hat{y}_{j+T-1}) = (\hat{y}_{j-1}, \ldots, \hat{y}_{j-n}; \hat{y}_{j+T-1}), \qquad j = 1, \ldots, k,$$

as a solution of the linear LAD or LS-problem (Sabo, Scitovski and Vazler, 2011)

$$\underset{\zeta_1\in\mathbb{R}}{argmin}\sum_{j=1}^{k}\left|\hat{y}_{j+T-1}-\zeta_1\hat{y}_{j-1}-\cdots-\zeta_n\hat{y}_{j-n}\right|^p,\quad p=1\;or\;p=2. \tag{12}$$

T days in advance water level prediction is then

$$\hat{\eta}_{n+T}=\zeta_1^*\eta_{r+n-1}+\cdots+\zeta_n^*\eta_r. \tag{13}$$

3.1.3 Evaluation of model performance

Different measures for model evaluation are proposed in literature (Toth *et al*., 2000; Wu *et al*., 2008, 2010). Suppose that $u_s, s=1,\ldots,r$ are observed, and $v_s, s=1,\ldots,r$ are predicted values, then we can use the following model evaluation

$$RMSE=\sqrt{var},\qquad var=\frac{1}{r}\sum_{i=1}^{r}(v_i-u_i)^2\ \text{(Root Mean Square Error)}, \tag{14}$$

$$MAE=\frac{1}{r}\sum_{i=1}^{r}|v_i-u_i|\quad\text{(Mean Absolute Error)}, \tag{15}$$

$$CC=\frac{cov(u,v)}{\sigma_u\sigma_v}=\frac{\sum(u_i-\bar{u})(v_i-\bar{v})}{\sqrt{\sum(u_i-\bar{u})^2}\sqrt{\sum(v_i-\bar{v})^2}}\ \text{(Pearson Correlation Coefficient)}, \tag{16}$$

$$CE=1-\sum_{i=1}^{r}(u_i-v_i)^2\Big/\sum_{i=1}^{r}(u_i-\bar{u})^2\quad\text{(Coefficient of Efficiency)}, \tag{17}$$

where $\bar{u}=\frac{1}{r}\sum u_s,\ \bar{v}=\frac{1}{r}\sum v_s.$

3.2 Short-term prediction of water level values of the Drava River by Donji Miholjac

We separate a training data set and a testing data set from the aforementioned set of measured water level values of the Drava River by Donji Miholjac from 1 January 1946 to 1 February 2012. First, 20000 data from 1 January 1946 to 4 October 2000 will be taken as a training data set, and $r=100$ times by $n=7$ data from 5 October 2000 to 12 January 2001 will be taken as a testing data set. Fig. 4 and Fig. 5 show prediction of 1, 2 and 3 days in advance for LAD-optimality criterion $(p=1)$ and LS-optimality criterion $(p=2)$, respectively. Table 1 shows evaluations of model performances for 1, 2 and 3 days in advance. Significantly better results are obtained in case of LAD-optimality criterion.

(a) A day in advance (b) Two days in advance (c) Three days in advance

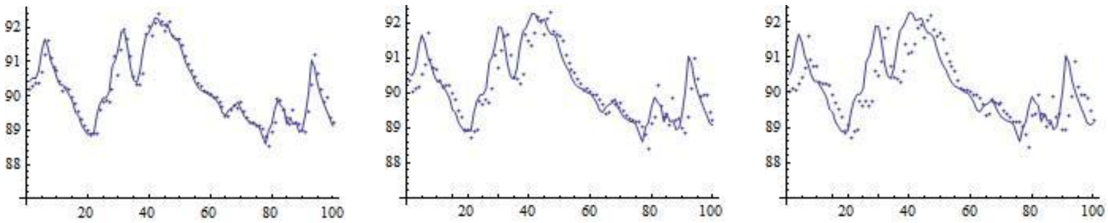

Figure 4: LAD-water level prediction from 5 October 2000 to 12 January 2001

(a) A day in advance (b) Two days in advance (c) Three days in advance

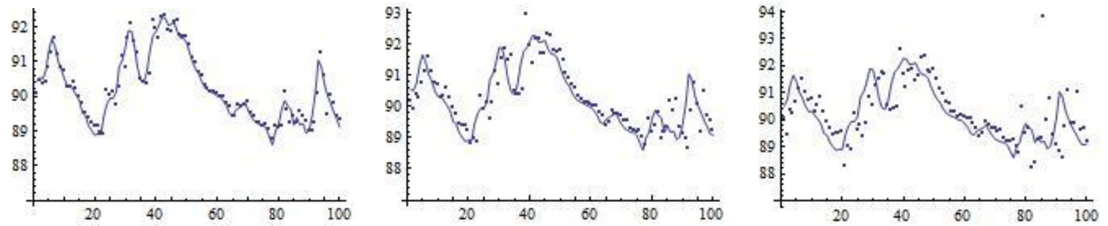

Figure 5: LS-water level prediction from 5 October 2000 to 12 January 2001

Assessment	*LAD* (1)	*LAD* (2)	*LAD* (3)	*LS* (1)	*LS* (2)	*LS* (3)
RMSE	0.26	0.51	0.70	0.28	0.58	0.92
MAE	0.19	0.39	0.55	0.21	0.43	0.68
CC	0.96	0.86	0.73	0.96	0.82	0.58
CE	0.93	0.73	0.49	0.91	0.65	0.13

Table 1: Model evaluation for the data from 5 October 2000 to 12 January 2001

As the second example, 24 000 data from 1 January 1946 to 17 September 2011 will be taken as a training data set, and $r = 100$ times by $n = 7$ data from 18 September 2011 to 26 December 2011 will be taken as a testing data set. Fig. 6 and Fig. 7 show prediction of 1, 2 and 3 days in advance for LAD-optimality criterion $(p = 1)$ and LS-optimality criterion $(p = 2)$, respectively. Table 2 shows evaluations of model performances for 1, 2 and 3 days in advance. Again, significantly better results are obtained in case of LAD-optimality criterion.

(a) A day in advance (b) Two days in advance (c) Three days in advance

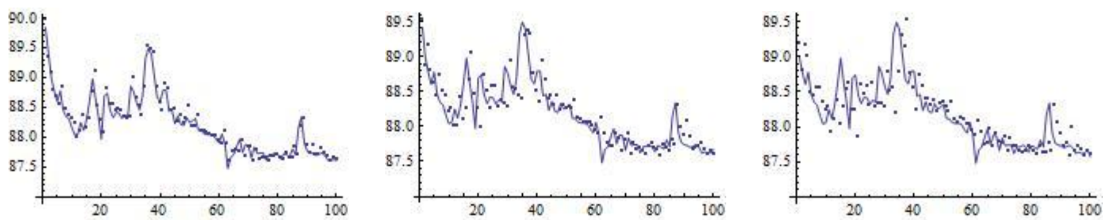

Figure 6: LAD-water level prediction from 18 September 2011 to 26 December 2011

(a) A day in advance (b) Two days in advance (c) Three days in advance

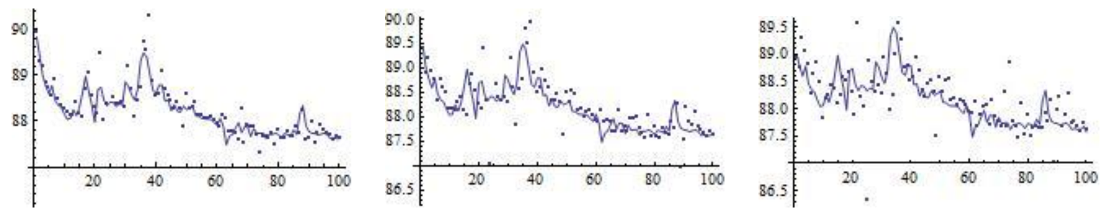

Figure 7: LS-water level prediction from 18 September 2011 to 26 December 2011

Table 2: Model evaluation for the data from 18 September 2011 to 26 December 2011

Assessment	*LAD* (1)	*LAD* (2)	*LAD* (3)	*LS* (1)	*LS* (2)	*LS* (3)
RMSE	0.19	0.30	0.32	0.45	0.60	0.46
MAE	0.14	0.21	0.22	0.23	0.33	0.31
CC	0.93	0.79	0.74	0.72	0.52	0.56
CE	0.84	0.59	0.49	0.14	-0.70	-0.03

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