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ON STOCHASTIC MODELLING OF WATER CONSUMPTION AND WASTEWATER DISCHARGE

Stochastic modelling of water consumption, wastewater discharge and water and wastewater quality is of great importance in sanitary engineering. It is connected with control of the water and wastewater treatment. This paper gives stochastic models of hourly tap water consumption and wastewater inflow to a municipal sewage treatment plant through a separate sewer system. First-order autoregressive seasonal models (with period $S = 24$ h) give a good approximation of hourly water consumption. The application of such models for the sewage inflow to the treatment plant yields worse approximating effects because of irregular disturbance due to the rainfall. Taking this disturbance into account enables us to obtain a model which improves the approximation. The same holds when wastewater inflow is correlated with water consumption.

1. INTRODUCTION

The wide spectrum of problems dealt with in water and wastewater management includes among others modelling of flow and quality parameters. Models of that kind may have a number of various applications. They are employed to predict water consumption [1] or to describe variations of water flow and water quality in streams and rivers [2], [3]. Such models may be efficient tools enabling interpretation of operating data from wastewater treatment plants [4]–[7], analysis of their dynamics [7], [8], and description of the water treatment process for the needs of control [9].

In this paper, stochastic models of tap water consumption and wastewater inflow to a municipal sewage treatment plant have been presented. Analyses of data included hourly water consumption in two different housing estates (one of these is situated in a large city [10], the other one in a small town [11]) and hourly wastewater flow entering the sewage treatment plant of the same town through a

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separate sewer system [12]. The separate sewer system receives illicitly precipitation water from many inlets. The models enable to obtain forecasts, which can be used in water supply and wastewater treatment processes control.

2. TIME SERIES ANALYSIS AND SOME FUNDAMENTAL NOTIONS

The methods used in this study are those developed by BOX and JENKINS [13].

In engineering practice, we often have to deal with series of interrelated observations (time series), which are realizations of a given stochastic process. The objective of time series analysis is to discover and to quantify the relations that occur among the elements of the series. This enables construction of stochastic models. Typical examples of time series (which are of great importance in sanitary engineering) are hourly water consumption, wastewater flow, and wastewater load.

The model for a stationary stochastic process acquires the form

$$\bar{Z}_t = \varphi_1 \bar{Z}_{t-1} + \varphi_2 \bar{Z}_{t-2} + \ldots + \varphi_p \bar{Z}_{t-p} + a_t. \tag{1}$$

It is referred to as autoregressive model (AR) of order p, and may be defined as AR(p). Thus, AR(1) denotes a first-order model, and henceforth

$$\bar{Z}_t = \varphi_1 \bar{Z}_{t-1} + a_t. \tag{2}$$

The term $\bar{Z}_t$ included in formulae (1) and (2) indicates the deviation of the point value from the average of the stochastic process μ and may be written as $\bar{Z}_t = Z_t - \mu$, whereas a_t denotes white noise (i.e., a series of independent random impulses with an average value zero, and a constant variance σ_a^2). Substitution of the backward shift operator $BZ_t = Z_{t-1}$ (viz. $B^m Z_t = Z_{t-m}$) into model (1) gives

$$\varphi(B)\bar{Z}_t = a_t. \tag{3}$$

Model

$$\bar{Z}_t = (1 - \Theta_1 B - \Theta_2 B^2 - \ldots \Theta_q B^q) a_t, \tag{4}$$

which may also be formulated as

$$\bar{Z}_t = \Theta(B) a_t, \tag{5}$$

is referred to as a moving average model of order q, MA(q).

It is advisable to use models as simple as possible, i.e., those including the least possible number of parameters. These may sometimes be achieved by using a combined autoregressive-moving average model of order p, q (viz. ARMA (p, q)):

$$\varphi(B)\bar{Z}_t = \Theta(B) a_t. \tag{6}$$

It may frequently happen that the processes under analysis fail to be stationary. If so, we are sometimes able to make them stationary by differentiation in terms of the backward difference operator ∇ or seasonal backward difference operator ∇_s. Thus, we can write

$$\nabla Z_t = Z_t - Z_{t-1} = (1-B) Z_t = W_t, \tag{7}$$

$$\nabla_s Z_t = Z_t - Z_{t-s} = (1-B^s) Z_t = W_t. \tag{8}$$

Whenever necessary, we have to repeat the differentiation procedure d times.

Models of ARMA type may be fitted to the W_t series. They are then referred to as integrated autoregression-moving average processes, ARIMA (p, d, q), and can be expressed as

$$\varphi(B) W_t = \varphi(B) \nabla_s^d Z_t = \varphi^* Z_t = \Theta(B) a_t. \tag{9}$$

Having two correlated time series at hand (X_t and Y_t), it is possible to model one of these by making use of the information included in the other. This way, we have obtained the transfer function model with added noise

$$\delta(B) Y_t = \omega(B) X_{t-b} + N_t \tag{10}$$

where X_t denotes input and Y_t indicates output.

Selecting the process ARIMA (p, d, q) for the purpose of modelling noise N_t we can write

$$Y_t = \delta^{-1}(B) \omega(B) X_{t-b} + \varphi^{*-1}(B) \Theta(B) a_t. \tag{11}$$

Making use of the model (11), it is necessary to choose a delay b in addition to the coefficients in operators δ, ω, φ, Θ, and noise variance δ_a^2. The choice of an appropriate model to describe a given time series is an iterative procedure which involves identification, estimation of parameters, and diagnostic checks.

Autocorrelation function and partial autocorrelation function are two useful tools for the identification of ARIMA models. Using the autocorrelation function, we can define the differentiation of the time series, which is a prerequisite to obtain a stationary process. The autocorrelation function of a stationary process as well as the partial autocorrelation function enable the orders of the autoregression operators and of the moving average to be determined tentatively. The autocorrelation function allows a rough evaluation of the coefficients of the model. More accurate calculations are carried out during nonlinear estimation of parameters. Noise a_t is assumed to be white and to display a normal distribution. The optimization criterion adopted at the stage of nonlinear estimation comprises a minimum error mean-square for the residuals of the model (difference between model and data).

Once its parameters have been estimated, the model is subject to diagnostic checking for determining its adequacy. If the model is found to be inadequate, the iteration cycle must be repeated either in full or in part.

There are two basic factors which decide whether or not the model is adequate — the degree of deviation from the adopted independence of residuals and the degree of deviation from normal distribution. To assess the independence of residuals it is convenient to use their autocorrelation function which may be evaluated by checking the goodness of fit by test Q. Another convenient tool is the cumulative periodogram.

The identification of the transfer function model involves the cross-correlation function of series X_t and Y_t. The analysis of the function enables rough evaluation of the orders of operator δ, operator ω (r and s, respectively), and delay b. The coefficients of the model should be estimated by the same method as those of the ARIMA model. The same holds for the method of determining the adequacy of the model. There is, however, one more thing to do – to check the independence of the residuals and the input. The most convenient tool to investigate this independence is the cross-correlation function of residuals and input, which may be evaluated when checking the goodness of fit by test S. More details on it and forecasting procedures can be found in BOX and JENKINS [13].

3. DISCUSSION OF RESULTS

3.1. WATER CONSUMPTION

Figure 1 (solid line) gives hourly water consumption Z_t for the housing estate of Wrocław (Series A). Raw data were logged prior to further processing ($X_t = \ln Z_t$). The autocorrelation function of Series A is shown in fig. 2. The apparent 24-hour seasonal component substantiates the necessity of using the seasonal differentiating operator ∇_{24} to make the series stationary. Figures 3 and 4 illustrate the autocorrelation function and the partial autocorrelation function for the differentiated series ($\nabla_{24} X_t$), respectively. The rapid fade-away of the autocorrelation function substantiates the stationary nature of the series. The break of the partial autocorrelation function at $k > 1$ suggests an autoregression model of first order (AR(1)). The results of fitting are listed in tab. 1. Figures 5 and 6 give the autocorrelation function of noise and the cumulative periodogram of model residuals, respectively. Analysing the plots of the figures and taking into account the data of tab. 1, we have good evidence that the selected model is adequate. Test χ^2 gives good support to the normal distribution of the residuals ($\bar{a} = 0.006$, $SD = 0.157$, $\chi^2 = 11.9$, $D.f. = 9$)*.

Figure 1 gives a comparison of data and one-step-ahead forecasts calculated by making use of the model. The agreement is very good. Taking into account the presence of the operator ∇_S, all forecasts which are more than one step ahead will be adjusted to the seasonal nature of the time series.

The results from the study of hourly water consumption for the housing estate of town R (Series B) are plotted in figs. 7–12. The model to be fitted was found to be

* a – mean, SD – standard deviation, $D.f.$ – degree of freedom.

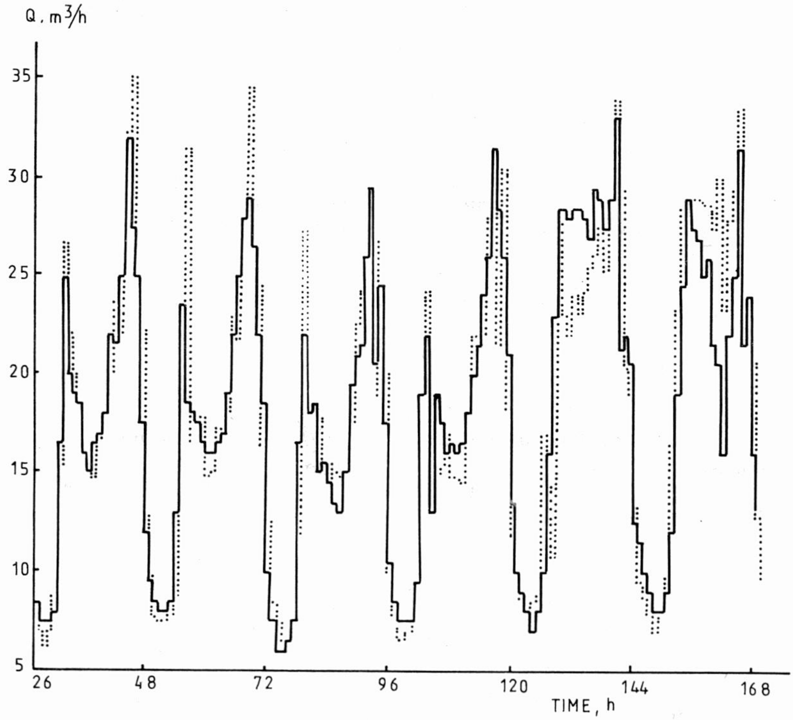

Fig. 1. Hourly water consumption and forecast for the housing estate of a large city (Series A, Z_t)

that for Series A. The results of fitting are listed in tab. 2. The data of tab. 2 as well as the plots in figs. 10–12 indicate that the model is adequate. There is a good agreement between one-step-ahead forecasts and the data involved.

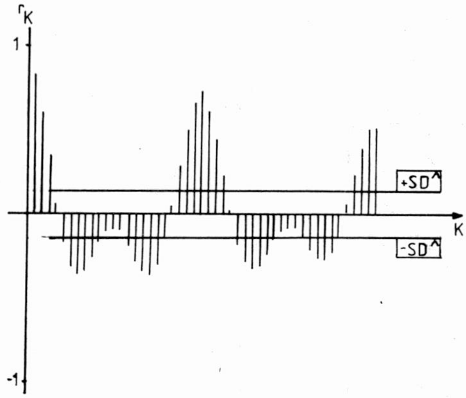

Fig. 2. Autocorrelation function for Series A ($X_t = \ln Z_t$)

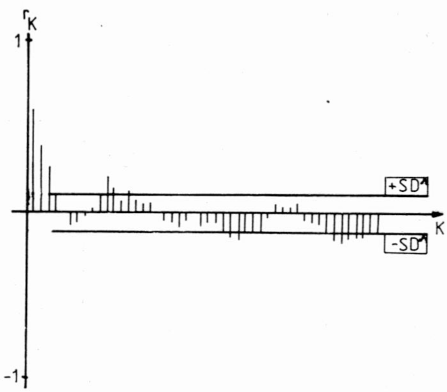

Fig. 3. Autocorrelation function for differentiated Series A ($\nabla_{24} X_t$)

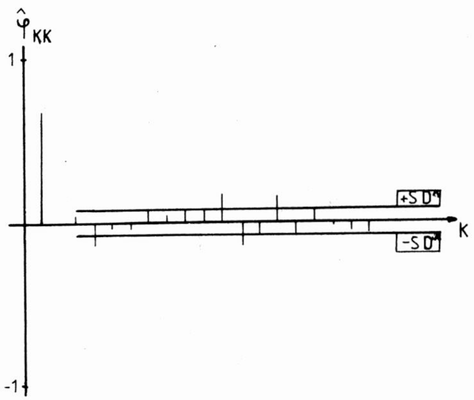

Fig. 4. Partial autocorrelation function for differentiated Series A ($\nabla_{24} X_t$)

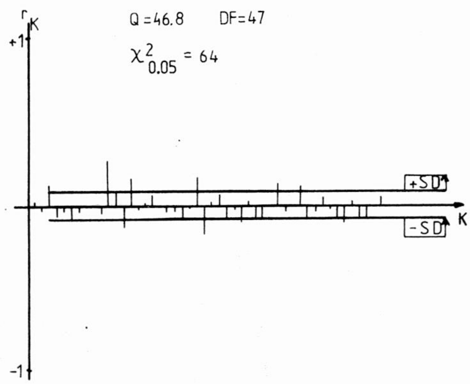

Fig. 5. Autocorrelation function for residuals of model $(1-\varphi_1 B)\nabla_{24} X_t = a_t$ (Series A)

Table 1

Fitting of model $(1-\varphi_1 B)\nabla_{24} X_t = a_t$ to Series A ($X_t = \ln Z_t$)

Variance X_t σ_X^2	Variance of residuals σ_a^2	Parameters of model	Test Q / $D.f.$ / $\chi^2_{0.05}$
0.209	0.025	$\varphi_1 = 0.65 \pm 0.06$	46.8
	$R = 0.94$		47
	(coefficient of correlation)		64

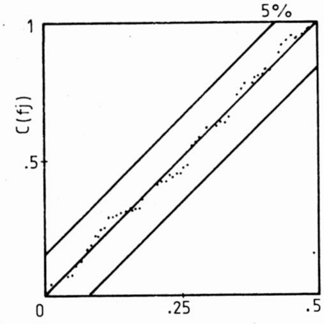

Fig. 6. Cumulative periodogram for residuals of model $(1-\varphi_1 B)\nabla_{24} X_t = a_t$ (Series A)

Table 2

Fitting of model $(1-\varphi_1 B)\nabla_{24} X_t = a_t$ to series B ($X_t = \ln Z_t$)

Variance X_t σ_X^2	Variance of residuals σ_a^2	Parameters of model	Test Q / *D.f.* / $\chi^2_{0.05}$
0.0783	0.0121	$\varphi_1 = 0.39 \pm 0.08$	31.0
	$R = 0.92$		47
			64

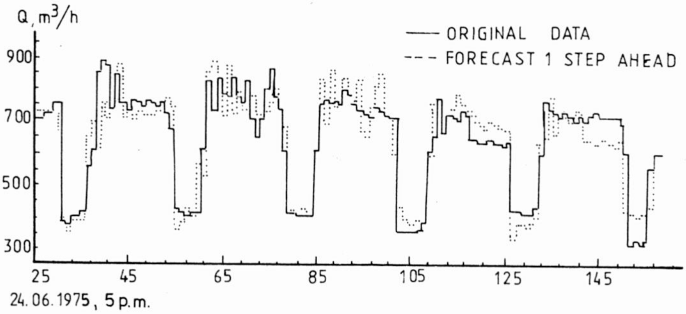

Fig. 7. Hourly water consumption and forecast for town R (Series B, Z_t)

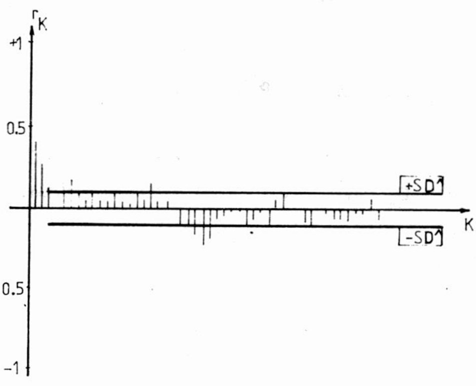

Fig. 8. Autocorrelation function for differentiated Series B ($\nabla_{24} X_t$; $X_t = \ln Z_t$)

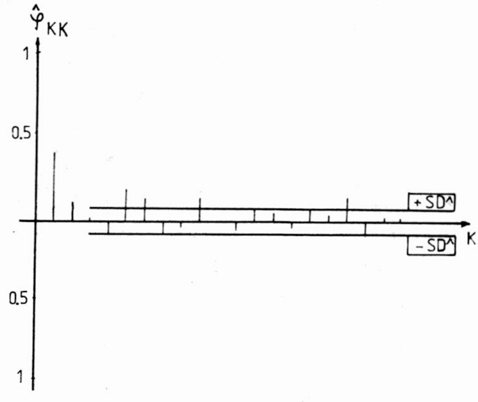

Fig. 9. Partial autocorrelation function for differentiated Series B ($\nabla_{24} X_t$)

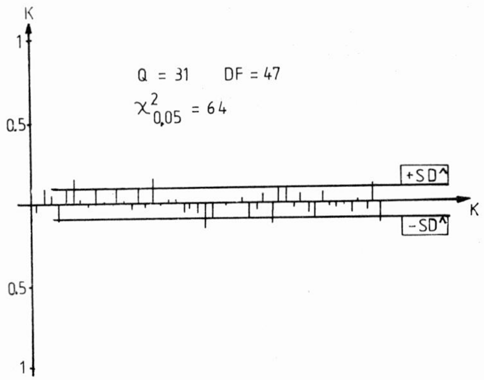

Fig. 10. Autocorrelation function for residuals of model $(1-\varphi_1 B)\nabla_{24} X_t = a_t$ (Series B)

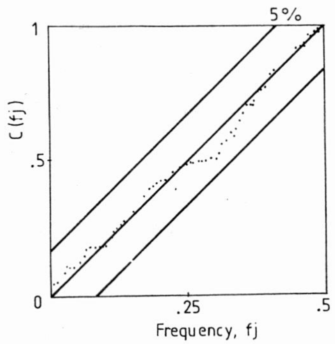

Fig. 11. Cumulative periodogram for residuals of model $(1-\varphi_1 B)\nabla_{24} X_t = a_t$ (Series B)

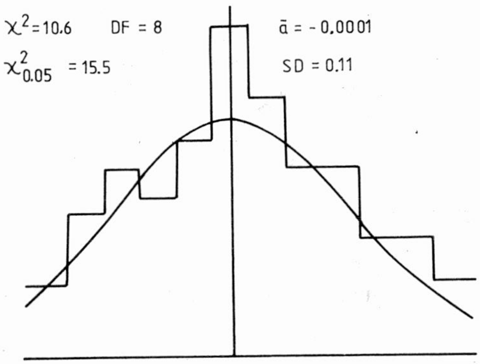

Fig. 12. Histogram for residuals of model $(1-\varphi_1 B)\nabla_{24} X_t = a_t$ (Series B)

3.2. WASTEWATER INFLOW TO THE SEWAGE TREATMENT PLANT OF TOWN R

Figure 13 shows inflow rate variations for the sewage treatment plant of town R (Series C, Z_t) and periods of rainfall R received by this area. The autocorrelation function and partial autocorrelation function (after transformation of $X_t = \ln Z_t$ and $\nabla_{24} X_t$) are shown in figs. 14 and 15, respectively. The form of the autocorrelation function suggests that model

$$(1-\varphi_1 B)\nabla_{24} X_t = a_t \text{(referred to as M1)}$$

may be suitable.

The results of fitting are gathered in tab. 3, and the results of the analysis of the model M1 residuals are plotted in figs. 16–18. Neither test Q nor the periodogram

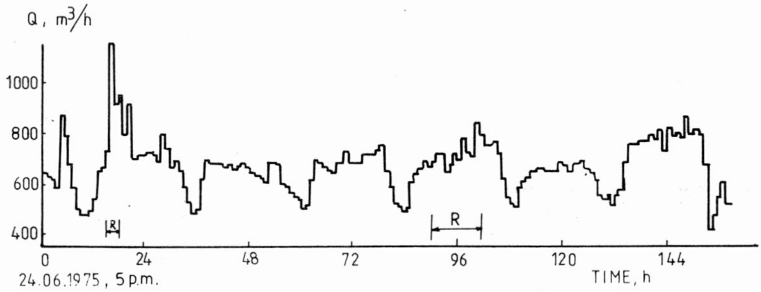

Fig. 13. Inflow to sewage treatment plant of town R (Series C, Z_t)

call the independence of residuals in question and their distribution may be considered normal at the significance level between 0.025 and 0.05. Comparison of the data with one-step-ahead forecasts (fig. 19) reveals significant discrepancies at 40 h. These should be attributed to the high inflow rate experienced the day before as a result of heavy rain. When transforming model M1 it becomes obvious that the actual forecasts are influenced by the inflow rate measured the preceding day. Hence, we obtain

$$X_t = 0.72\,X_{t-1} + X_{t-24} - 0.72_{X-25} + a_t.$$

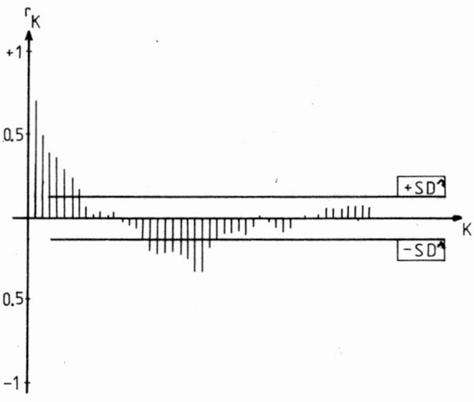

Fig. 14. Autocorrelation function for differentiated Series C ($\nabla_{24} X_t$)

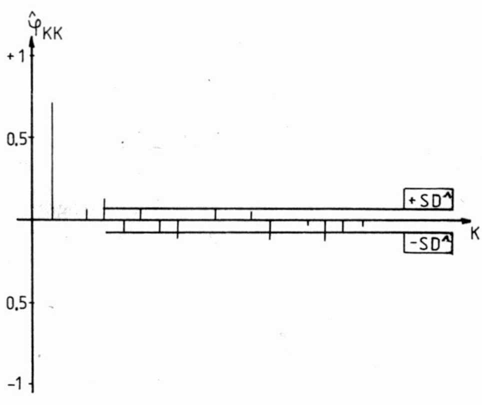

Fig. 15. Partial autocorrelation function for differentiated Series C ($\nabla_{24} X_t$)

If the hourly inflow rates measured within the preceding 24 h are different from normal, their influence on the future inflow values disappears after a time shorter than 24 h. The model M1 fails to include this effect.

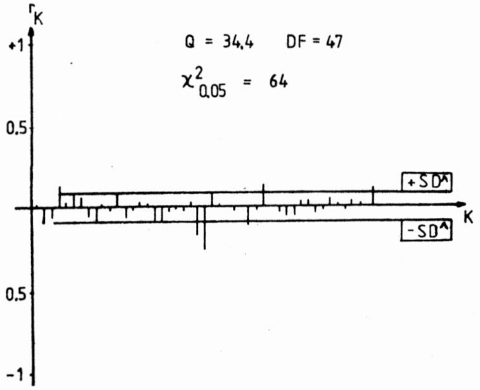

Fig. 16. Autocorrelation function for residuals of model M1

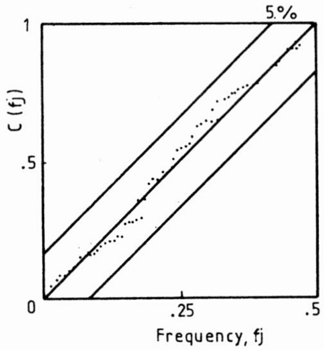

Fig. 17. Cumulative periodogram for residuals of model M1

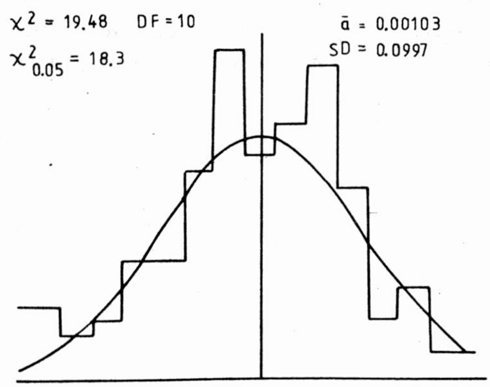

Fig. 18. Histogram for residuals of model M1

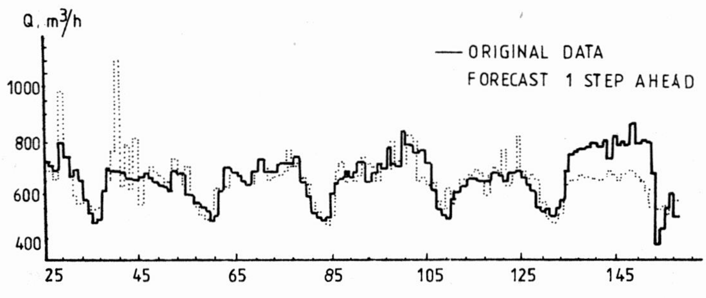

Fig. 19. Inflow to sewage treatment plant of town R and forecast of model M1

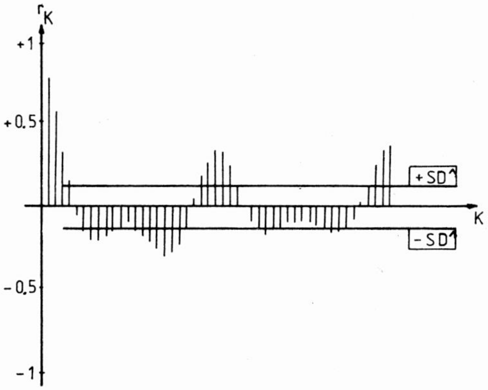

Fig. 20. Autocorrelation function for Series C (X_t)

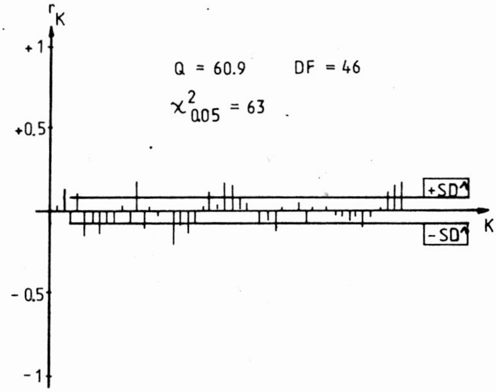

Fig. 21. Autocorrelation function for residuals of model M2

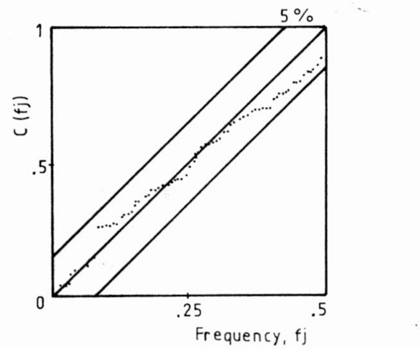

Fig. 22. Cumulative periodogram for residuals of model M2

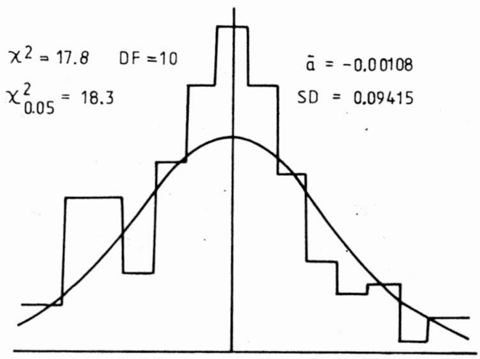

Fig. 23. Histogram for residuals of model M2

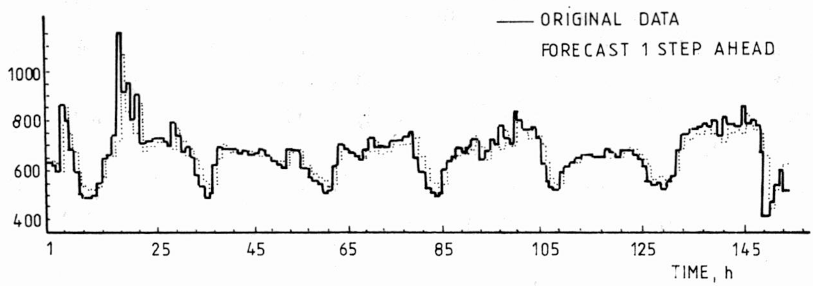

Fig. 24. Inflow to sewage treatment plant of town R and forecast of model M2

Table 3

Fitting of models M1, M2 to series C ($X_t = \ln Z_t$)

Variance X_t σ_X^2	Model	Variance of residuals σ_a^2	Parameters of the model and correlation of parameters for it	Test Q / $D.f.$ / $\chi^2_{0.05}$
0.02343	M1	0.00997	$\varphi_1 = 0.72 \pm 0.06$	34.4
		$R = 0.76$		47
				64
	M2	0.00892	1. $\varphi_1 = 0.75 \pm 0.07$	60.9
		$R = 0.79$	2. $\Theta_1 = -0.12 \pm 0.10$	46
			$R_{1,2} = 0.60$	63

Irrespective of the fact that the autocorrelation function of Series C (X_t) presented in fig. 20 fails to suggest such an approach, model M2

$$(1-\varphi_1 B) X_t = (1-\Theta_1 B) a_t \tag{M2}$$

was also checked for our purpose. The results of fitting are shown in tab. 3 and figs. 21–23. Comparing the one-step-ahead forecasts with the data in fig. 24, it becomes obvious that there are no disturbances which were present in model M1.

3.3. RAINFALL: AN ADDITIONAL VARIABLE OF THE MODEL

It may be expected that when the relationship between the influent sewage stream and the precipitation volume is taken into account, the model displays a smaller variance of residuals. Unfortunately, no measured values of the rain volume received by the area of interest were at hand when recording the influent sewage rate Y_t'. The only information available then was whether or not it rained on a given day. Thus, the rainfall periods (R in fig. 13) were assigned unity, whereas the periods with no precipitation were assigned zero. The series obtained via this route, $D(X_t')$, consisted of a number of 0 and 1, thus enabling the approximate representation of rainfall phenomena in the investigated period.

Series C was transformed by logging and substracting the mean ($Y_t = \ln Y_t' - \overline{\ln Y_t'}$), and Series D by detracting the mean alone ($X_t = X_t' - \bar{X}_t'$). Model M4

$$Y_t = \frac{\omega_0}{1-\delta_1 B} X_{t-b} + \frac{1}{1-\varphi_1 B - \varphi_2 B^2} a_t \tag{M4}$$

was fitted, and the results are listed in tab. 4.

Table 4

Fitting of model M4

Output variance (ln Y_t') σ_y^2	Variance of residuals σ_a^2	Parameters of the model and correlation of parameters for it	Test Q / $D.f.$ / $\chi^2_{0.05}$	Test S / $D.f.$ / $\chi^2_{0.05}$
	0.00801	$b = 2$		
0.02343	$R = 0.81$	1. $\delta_1 = -0.56 \pm 0.15$		
		2. $\omega_0 = 0.17 \pm 0.04$	37.7	19.7
		3. $\varphi_1 = 0.95 \pm 0.08$	34	35
		4. $\varphi_2 = -0.20 \pm 0.08$	48.6	49.8
		$R_{1,2} = 0.63$; $R_{1,3} = -0.06$		
		$R_{1,4} = 0.05$; $R_{2,3} = -0.08$		
		$R_{2,4} = 0.08$; $R_{3,4} = -0.79$		

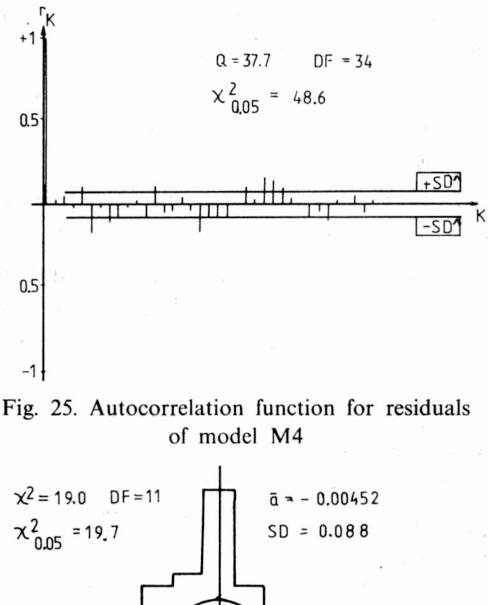

Fig. 25. Autocorrelation function for residuals of model M4

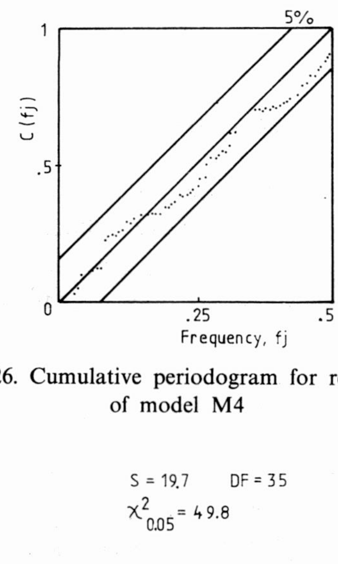

Fig. 26. Cumulative periodogram for residuals of model M4

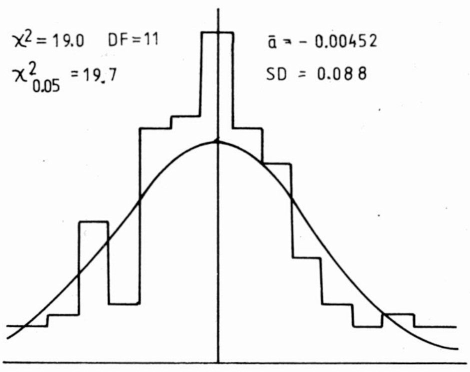

Fig. 27. Histogram for residuals of model M4

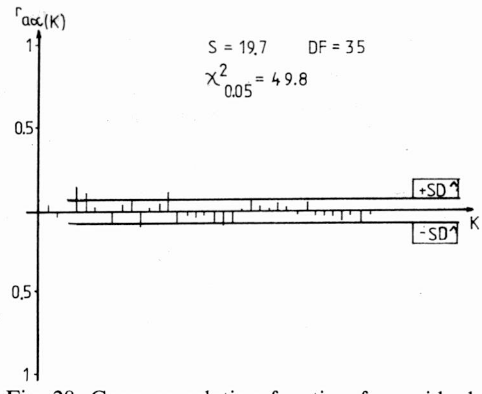

Fig. 28. Cross correlation function for residuals of model M4 and prewhitened input

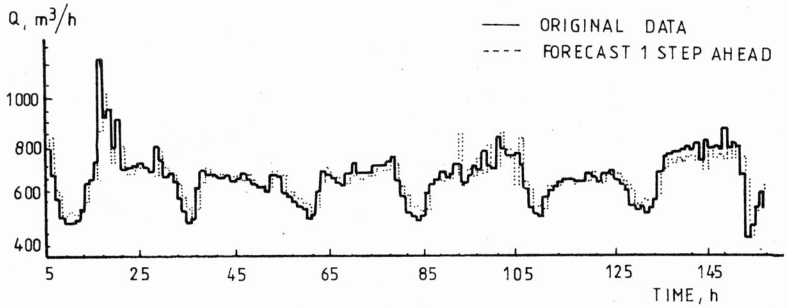

Fig. 29. Inflow to sewage treatment plant of town R and forecast of model M4

As shown by the data in figs. 25–27, the residuals of the model are independent and display a normal distribution. The assumed independence of noise and prewhitened input X_t has also been confirmed (fig. 28). The comparison of one-step-ahead forecasts for model M4 with the available data (fig. 29) reveals that even a rough estimation of the precipitation volume is sufficient to improve the forecast established in the 16th hour of measurement (see fig. 24).

3.4. WATER CONSUMPTION INCLUDED AS AN ADDITIONAL VARIABLE OF THE MODEL

The application of data on water consumption (Series B (X'_t)) to the modelling of sewage inflow Y'_t is exemplified by model M5. Series B and C were transformed by logging and by substracting the mean ($Y_t = \ln Y'_t - \overline{\ln Y'_t}$; $X_t = \ln X'_t - \overline{\ln X'_t}$). Analysis of correlations and, later on, the estimation of parameters have revealed that the best

Table 5

Fitting of model M5

Input variance ($\ln Y'_t$) σ_y^2	Variance of residuals σ_a^2	Parameters of the model and correlation of parameters for it	Test Q / $D.f.$ / $\chi^2_{0.05}$	Test S / $D.f.$ / $\chi^2_{0.05}$
		$b = 0$		
	0.00698	1. $\delta_1 = 0.68 \pm 0.07$	19.9	22.9
		2. $\omega_0 = 0.18 \pm 0.03$	35	35
0.02343	$R = 0.84$	3. $\varphi_1 = 0.65 \pm 0.06$	49.8	49.8
		$R_{1,2} = -0.58$		
		$R_{1,3} = 0.02$		
		$R_{2,3} = -0.01$		

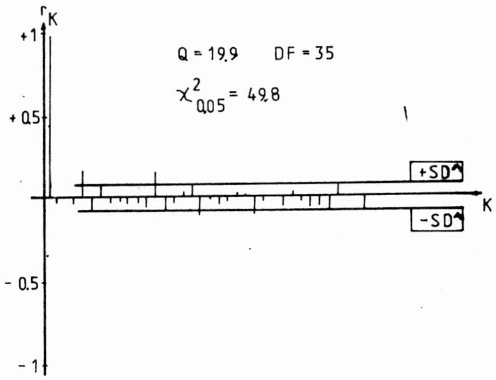

Fig. 30. Autocorrelation function for residuals of model M5

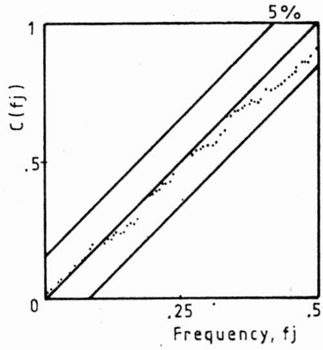

Fig. 31. Cumulative periodogram for residuals of model M5

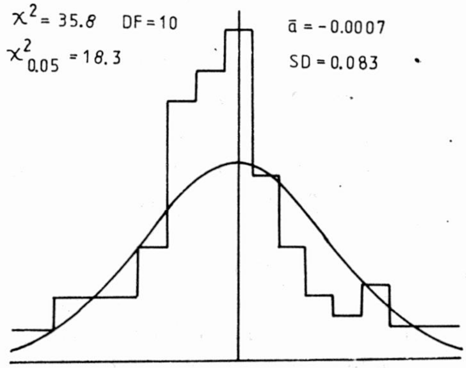

Fig. 32. Histogram for residuals of model M5

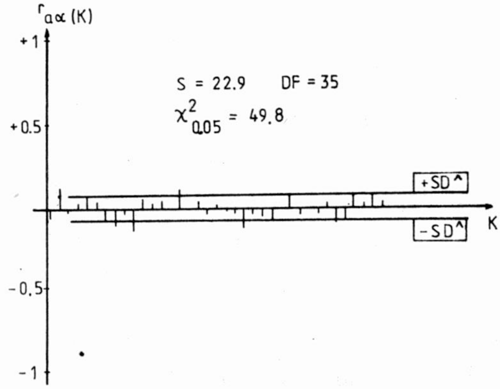

Fig. 33. Cross correlation function for residuals of model M5 and prewhitened input

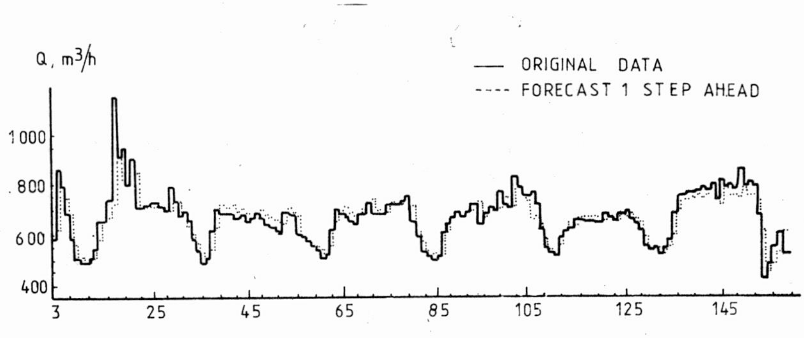

Fig. 34. Inflow to sewage treatment plant of town R and forecast of model M5

results can be achieved by anticipating delay $b = 0$. The fitting procedure was carried out for model M5 of the form

$$Y_t = \frac{\omega_0}{1-\delta_1 B} X_t + \frac{1}{1-\varphi_1 B} a_t. \tag{M5}$$

Table 5 gives the results of fitting for model M5.

Although the residuals of model M5 are independent (which is proved by the analysis of figs. 30 and 31), their distribution fails to be normal (fig. 32). Analysing the cross correlation between noise and prewhitened input X_t (fig. 33), it becomes obvious that the model is well fitted (fig. 34).

4. CONCLUSIONS

First-order autoregression seasonal models give a good approximation of hourly water consumption. The residuals of the models satisfy the condition of independence and display a normal distribution. Residual variances are insignificant, and so are the errors of forecasts with a small number of steps ahead. The presence of the seasonal differentiating operator ∇_S accounts for the periodic nature of the forecast function. That is why forecasts with many steps ahead do not tend to an average value. They have the ability to adjust themselves to the periodic nature of the time series (however, errors associated with many-steps-ahead forecasts are considerable). The application of such models to the description of sewage inflow to the treatment plant through a separate sewer system yields significantly worse approximating effects. The main reason is the considerable disturbance in the behaviour of flow due to the irregularity of rainfall. Such disturbances become particularly distinct when large amounts of precipitation water enter the sewer system illicitly from a great number of inlets. The inclusion of this source of disturbance in the model requires the wastewater inflow to be correlated with the precipitation volume received in the area of interest.

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STOCHASTYCZNE MODELOWANIE ZUŻYCIA WODY I ZRZUTU ŚCIEKÓW

Stochastyczne modelowanie zużycia wody, zrzutu ścieków oraz ich jakości ma duże znaczenie w inżynierii sanitarnej. Wiąże się ono z zaopatrzeniem w wodę i sterowaniem procesami oczyszczania wody i ścieków. Przedstawiono zagadnienia stochastycznego modelowania zużycia wody wodociągowej i dopływu ścieków do oczyszczalni systemem kanalizacyji rozdzielczej. Sezonowe modele autoregresji pierwszego rzędu (z okresem $S = 24$) dobrze przybliżają godzinowe zużycie wody. Zastosowanie ich w modelowaniu godzinowego dopływu ścieków do oczyszczalni nie jest w pełni efektywne z powodu nieregularnych zakłóceń przepływu wywołanych opadami deszczu. Uwzględniając opad deszczu lub zużycie wody jako dodatkową zmienną objaśniającą, uzyskuje się modele dające lepsze efekty aproksymacji.

СТОХАСТИЧЕСКОЕ МОДЕЛИРОВАНИЕ ПОТРЕБЛЕНИЯ ВОДЫ И ОТБРОСА СТОЧНЫХ ВОД

Стохастическое моделирование потребления воды и отброса сточных вод а также их качества имеет большое значение в санитарной технологии. Оно связано со снабжением водой и управлением процессами очистки воды и сточных вод. Представлены вопросы стохастического моделирования потребления водопроводной воды и добегания сточных вод к очистной станции системой раздельной канализации. Сезонные модели авторегрессии первого порядка (с периодом $S = 24$) хорошо приближают потребление воды за час. Их применение для моделирования часового добегания сточных вод к очистной станции не вполне эффективно из-за нерегулярных помех течения вызванных осадками. Учитывая осадки или потребление воды как добавочную разъясняющую переменную получают модели дающие лучшие эффекты аппроксимации.