구조물에 작용하는 풍압력의 시계열 분석

Time Series Analysis of Wind Pressures Acting on a Structure

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요 지

한 구조물에 작용하는 풍압력 시계열이 자기회귀 이동평균(ARMA) 모델을 사용하여 모델화 된다. AR 과정에서 시계열의 현재 값은 유한한 수의 이전 값들의 선형적 결합과 한 백색잡음에 의해 나타난다. MA 과정에서 시계열의 현재 값은 유한한 수의 이전 백색잡음들에 선형적이다. ARMA 과정은 AR과 MA 과정의 결합이다. 본 논문에서, AR, MA와 ARMA 모델이 풍압력 시계열에 적용되고, 데이터를 나타내기에 가장 적합한 ARMA 모델을 선정하는 과정이 소개된다. 모델의 변수들은 최대 가능도법을 사용하여 산정되고, 압력 시계열의 시간적 복잡성의 척도인 모델 차수를 최적화하기 위해 AICC 모델 선정 기준이 사용된다. 또한, 모델의 유효성을 조사하기 위해 LBP 검사가 사용된다. 본 연구로부터, AR 과정이 풍압력 시계열을 나타내기에 가장 적합하다는 결론이 얻어진다.

핵심용어 : 풍압력, 자기회귀 이동평균 모델링, AICC 기준, LBP 검사, 풍동 데이터

Abstract

Time series of wind-induced pressure on a structure are modeled using autoregressive moving average (ARMA) model. In an AR process, the current value of the time series is expressed in terms of a finite, linear combination of the previous values and a white noise. In a MA process, the value of the time series is linearly dependent on a finite number of the previous white noises. The ARMA process is a combination of the AR and MA processes. In this paper, the ARMA models with several different combinations of the AR and MA orders are fitted to the wind-induced pressure time series, and the procedure to select the most appropriate ARMA model to represent the data is described. The maximum likelihood method is used to estimate the model parameters, and the AICC model selection criterion is employed in the optimization of the model order, which is assumed to be a measure of the temporal complexity of the pressure time series. The goodness of fit of the model is examined using the LBP test. It is shown that AR processes adequately fit wind pressure time series.

Keywords : *wind pressure, autoregressive moving average modeling, AICC criterion, LBP test, wind tunnel data*

1. Introduction

Simulation of wind-induced pressure on structures is important in the field of wind engineering. Wind pressure time series acquired in wind tunnel are sampled uniformly and they can be analyzed in time domain using parametric modeling techniques including autoregressive moving

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• 이 논문에 대한 토론을 2001년 3월 31일까지 본 학회에 보내주시면 2001년 6월호에 그 결과를 게재하겠습니다.

average (ARMA) process, Brockwell and Davis[1]. The ARMA model is one of the discrete models and is represented as stochastic linear difference equations of finite order.

The ARMA model has been applied to various fields of study including the field of wind engineering. In wind engineering, there have been endeavors to identify wind velocity or pressure signals using the ARMA model. Reed and Scanlan[2] used ARMA models to describe the full-scale data of wind velocity and wind pressure signals collected on cooling towers. Iannuzzi and Spinelli[3] used normally distributed random numbers in AR filters for the simulation of wind speed. Simple time series models were developed for the description of pressure coefficients measured on monoslope roofs by Stathopoulos and Mohammadian[4]. They showed that a simple AR model was adequate for the simulation of pressure coefficients. Maeda and Mäkino[5] satisfactorily simulated the gust components of the Karman's turbulence using the ARMA model. AR models were also used to investigate wind speed data collected in the field (Smith and Mehta[6]). Schrader[7] computed the statistical scatter of integral scales of the longitudinal component of wind velocity in a turbulent boundary layer through simulation using the AR model. Niemann and Hoffer[8] represented the buffeting aerodynamic loads, which are non-linearly related to flow turbulence, using the AR model. Jeong and Bienkiewicz[9] applied the AR process to model time series of pressure on a low-rise building. ARMA models have been also employed in other engineering applications: earthquake engineering, Ólafsson and Sigbjörnsson[10], ocean engineering, Spanos[11], and others.

Most of the above papers related to wind engineering dealt with the full-scale or experimental data of wind velocity and pressure for ARMA modeling. Relatively low-order AR models were fitted for the data, and the residuals of the fitted model were used to check the adequacy of the model. In this paper, the ARMA model is used to investigate the temporal complexity of the wind-induced pressure on a model of the Texas Tech University test building, and attention is restricted to second order properties, such as mean and autocorrelation function, of time series. ARMA models with several different combinations of the AR and MA orders are fitted to the wind pressure, and the procedure to select the most appropriate ARMA model to represent the data is described. The order of the fitted ARMA model is assumed to be a measure of complexity of the wind-induced pressure. In this paper, important model selection criteria, such as the AICC, BIC and FPE, are employed in the optimization of the model order. The AICC includes a penalty factor for inclusion of additional parameters in the model. Also, the Ljung-Box Portmanteau (LBP) test, which pools the sample autocorrelations of the residuals, is employed to check the adequacy of the model.

2. Background

A time series C_t having zero mean is an autoregressive process of order p, denoted as AR(p), if it is stationary and satisfies the difference equation

$$C_t = \phi_1 C_{t-1} + \phi_2 C_{t-2} + \cdots + \phi_p C_{t-p} + \varepsilon_t \qquad (1)$$

where $\phi_1, \cdots, \phi_p$ are the autoregressive coefficients and ε_t is a white noise process with zero mean and variance σ_ε^2. In an AR model, the current value of the time series is expressed in terms of a finite, linear combination of the previous values of the time series and a white noise ε_t.

In a moving average model, the value of the time series is linearly dependent on a finite number q of the previous white noise ε's. The moving average process of order q, denoted as MA(q), can be expressed as

$$C_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \qquad (2)$$

where $\theta_1, \cdots \theta_q$ are the moving average coefficients.

The autoregressive moving average process, which is a combination of the autoregressive and moving average processes, of orders p and q, denoted as ARMA(p,q), can be expressed as

$$C_t = \phi_1 C_{t-1} + \phi_2 C_{t-2} + \cdots + \phi_p C_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \qquad (3)$$

The model parameters are related to the autocorrelation function (ACF) and the partial autocorrelation function (PACF). The ACF is a measure of the serial dependence of a time series. The PACF is a measure of the dependence between residuals of the two observations, which result from removal of the effects of intervening observations. The PACF is the pth autoregressive coefficient in the AR process of order p. The plots of the ACF and PACF suggest an approximate ARMA model for the data. If the values of the PACF of the data C_t are negligible for lags greater than p, then an autoregressive model of order p, AR(p), is suggested. Also, if the values of the ACF of C_t vanish for lags greater than q, then a moving average model of order q, MA(q), is suggested.

Estimation of the model parameters is made after a model has been identified. Initial prediction of the parameters, typically made for AR models using the Yule-Walker equations, can be subsequently refined using the least squares and maximum likelihood methods, Brockwell and Davis[1].

Avoiding the problem of overfitting in ARMA modeling is needed. One way in which this can be done is to minimize the final prediction error (FPE), Brockwell and Davis[1]. The FPE for pure autoregressive models is expressed as

$$\text{FPE} = \hat{\sigma}_\varepsilon^2 \frac{n+p}{n-p} \qquad (4)$$

where $\hat{\sigma}_\varepsilon^2$ is the maximum likelihood estimator of the white noise variance σ_ε^2 of the AR(p) model and n is the number of observations.

As a more general criterion, the Akaike information criterion (AIC) of Akaike, or its bias corrected version (AICC), Brockwell and Davis[1], is used. The AICC is expressed as

$$\text{AICC}(\hat{\phi}, \hat{\theta}, \hat{\sigma}_\varepsilon^2) = -2 \ln \text{L}(\hat{\phi}, \hat{\theta}, \hat{\sigma}_\varepsilon^2) + 2(p+q+1)n/(n-p-q-2) \qquad (5)$$

where $L(\hat{\phi}, \hat{\theta}, \hat{\sigma}_\varepsilon^2)$ is the likelihood of the data, under the Gaussian ARMA model with parameters $(\hat{\phi}, \hat{\theta}, \hat{\sigma}_\varepsilon^2)$. In Eq.(5), the second term is a penalty factor for inclusion of additional parameters in the model. In model selection, the ARMA models of orders p and q minimizing AICC are selected.

The Bayesian information criterion (BIC) is another criterion which attempts to correct the overfitting nature of the AIC. The BIC, as defined by Akaike[12], is written as

$$\text{BIC} = (n-p-q)\ln[n\,\hat{\sigma}_\varepsilon^2/(n-p-q)] + n(1+\ln\sqrt{2\pi}) + (p+q)\ln[(\sum_{t=1}^{n} z_t^2 - n\,\hat{\sigma}_\varepsilon^2)/(p+q)] \qquad (6)$$

The three criteria - AICC, BIC and FPE - are used to optimize the order of ARMA models in the paper. It is known that order selection by minimization of the FPE, AIC or AICC is asymptotically efficient for autoregressive models.

The fitted ARMA models are validated through examination of the residuals which are the rescaled one-step prediction errors. The residuals are defined as

$$\hat{e}_t = (C_t - \hat{C}_t)/\sqrt{r_{t-1}} \qquad (7)$$

where $\hat{C}_t$ is the ARMA(p,q) based predicted values of C_t based on the observations up to time t-1, r_{t-1} is defined by $E(C_t - \hat{C}_t)^2/\sigma_\varepsilon^2$, where E is the expectation operator, and σ_ε^2 is the white noise variance of the fitted model. If the fitted ARMA model is appropriate, then the residuals $\hat{e}_t$ should be approximately like a white noise process with mean zero and variance σ_ε^2. This property is verified by inspecting the ACF of the residuals.

The Ljung-Box Portmanteau (LBP) test is also used to examine the goodness of fit of the model in this paper. The LBP test pools the sample autocorrelations of the residuals instead of looking at them individually. The LBP test statistic $\tilde{Q}_e$, defined by Ljung and Box[13], is

$$\tilde{Q}_e = n(n+2)\sum_{k=1}^{h} \hat{\rho}_e^2(k)/(n-k) \qquad (8)$$

where $\hat{\rho}_e(k)$ is the sample autocorrelation of the residuals at lag k, and h is a maximum number of lags. h=20 is a commonly used value. If the model is fitted correctly, then $\tilde{Q}_e$ is approximately chi-squared (χ^2) with h-p-q degrees of freedom. The adequacy of the model is rejected at level α_{port} if $\tilde{Q}_e$ is larger than the (1-α_{port}) quantile of the χ^2_{h-p-q} distribution.

3. Results and discussion

The ARMA modeling of wind-induced pressure was performed for laboratory time series of pressure, on the roof of a 1:50 geometrical scale model of the Texas Tech University test building. The experimental data was acquired during a wind-tunnel study performed in a

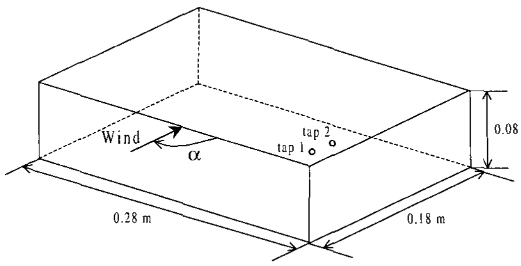


Fig. 1 Model of a structure and representative pressure tap locations

boundary-layer wind tunnel at the Fluid Dynamics and Diffusion Laboratory, Colorado State University.

ARMA models with several different combinations of the orders p and q were fitted to the pressure, and then the most appropriate ARMA model for each data was selected. The point pressure at tap 1 and at tap 2 on the roof of the building model were utilized for the analysis, given as Fig. 1. Two wind directions, cornering wind (α=45°) and wind normal to the longer edge of the building (α=90°), are employed. The time series of the considered pressure are depicted in Fig. 2. The sampling frequency of the pressure records was 500Hz. The length of a continuous record of the pressure data was 9000 points. The first 4000 points were used in the ARMA modeling. Fig. 3 depicts the probability density functions (PDFs) of the four pressure time series shown in Fig. 2. The PDF is plotted versus the fluctuating pressure divided by the square root of the mean square value of pressure. It is shown in Fig. 3 that the PDFs do not deviate significantly from Gaussian. In this paper, non-Gaussian pressure characteristics is not considered, and attention is restricted to second order properties of time series.

Model matching was accomplished by using the time series computing package ITSM (Interactive Time Series Modeling) developed by Brockwell and Davis[14]. The autocorrelation

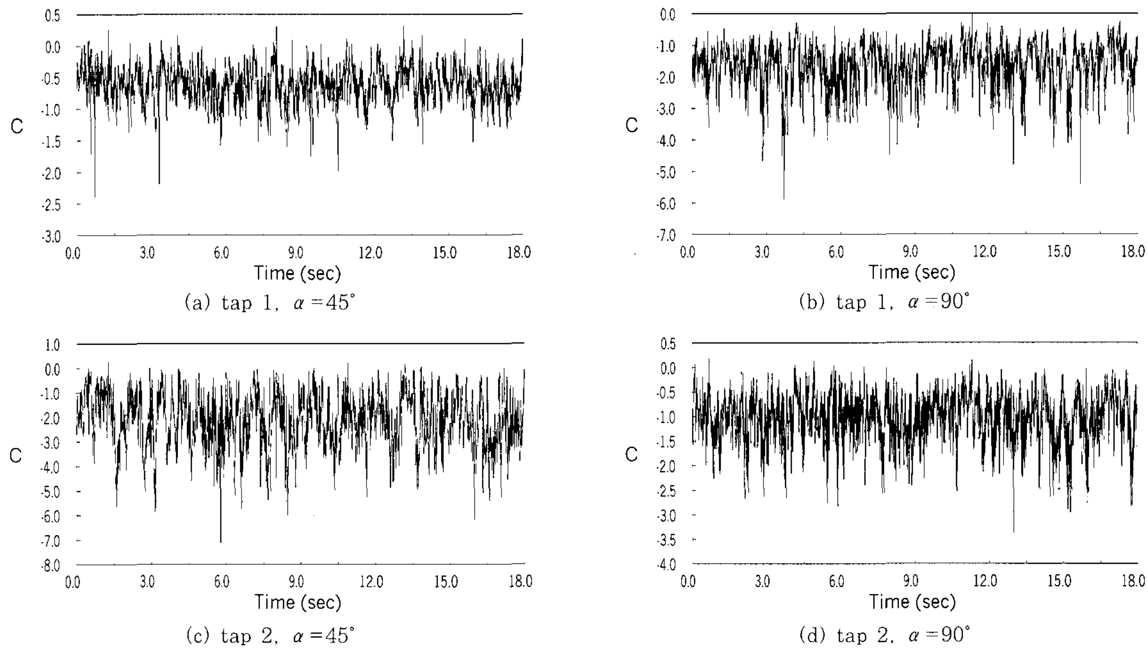


Fig. 2 Time series of pressure

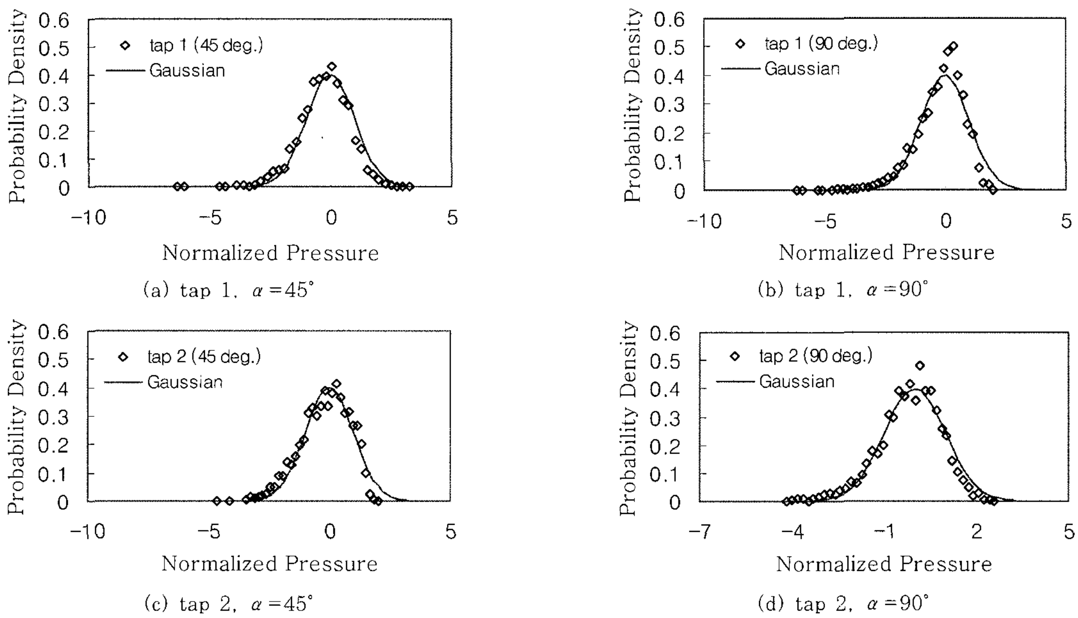


Fig. 3 Probability density functions of pressure

function (ACF) and the partial autocorrelation function (PACF) were computed first. They are shown for the pressure at two representative taps and two wind directions ($\alpha=45°$ and $\alpha=90°$) in Fig. 4. The horizontal lines on the graph display approximate 95% bounds for the autocorrelations of a white noise sequence. Examination of the PACF suggests an approximate

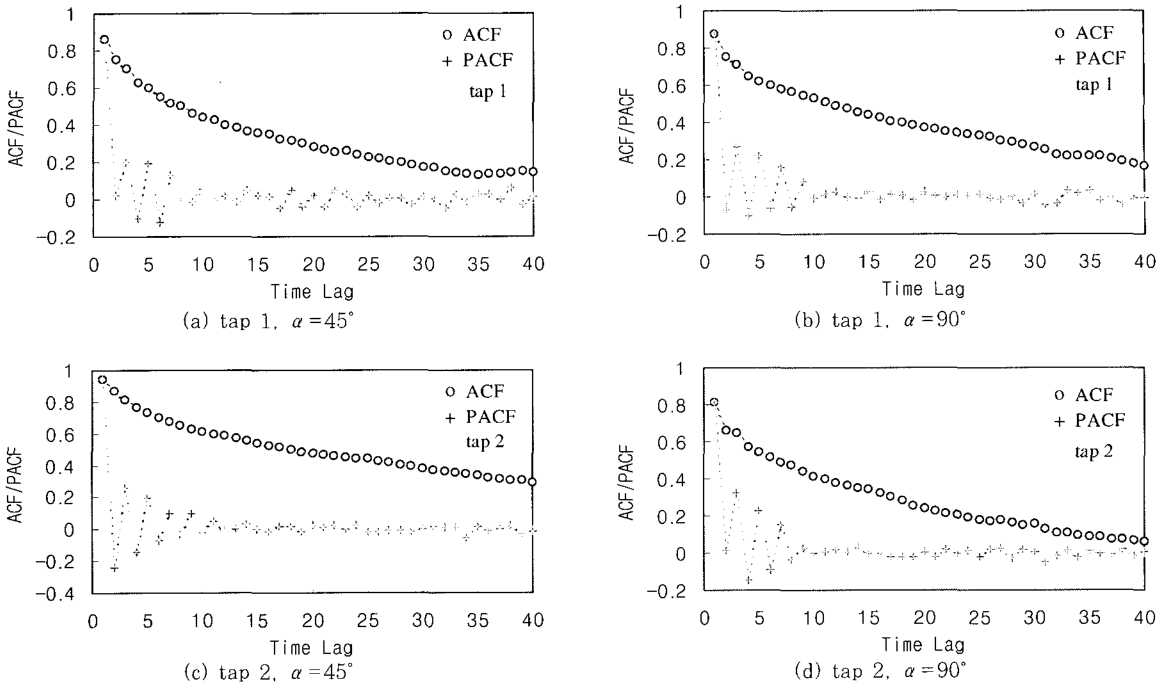


Fig. 4 ACF and PACF of pressure

order of the AR model for the pressure.

The model parameters were established using the maximum likelihood method. The AICC and BIC criteria were employed in the optimization of the model order. The FPE criterion was also used in the optimization of the AR model order. Several ARMA models fitted to the pressure are presented in Tables 1 and 2. The values of model selection criteria, AICC and BIC are shown in these tables.

The value of the statistic $\tilde{Q}_e$ used in the Ljung-Box portmanteau (LBP) test is 83 for the AR(7) model fitted to the pressure at tap 1 and the wind direction of 45°, Table 1. Since this value is larger than $\chi^2_{0.95}(27-7)=31.4$ at level α_{port} =0.05 with 20 degrees of freedom, the residuals do not pass the test. For the residuals from the AR(9) model fitted to the pressure at tap 2 and the wind direction of 90°, Table 2, the value of $\tilde{Q}_e$ is 22.6, which is less than $\chi^2_{0.95}(20)=31.4$. Thus this model is a good fit to the data.

The order of the minimum-AICC AR model for the residuals is shown in Tables 1 and 2. If the fitted model is satisfactory, the residuals of the model should have the order of zero. The AR order of the residuals of the AR(7) model fitted to the pressure at tap 1 and the wind direction of 45° is not zero as shown in Table 1. This suggests that some correlation remains in the residuals, and that the residuals come from some other identifiable process.

The model which did not satisfy the LBP test was excluded from model selection. Also, the model was not selected if the residuals of the model came from a clearly identifiable process. All the MA models in Tables 1 and 2 have high AICC values and do not satisfy the LBP test. Also, the residuals of the MA models show non-whiteness. Thus the MA models were rejected in model selection. Most of the ARMA models with non-zero orders p and q in these tables fail to satisfy the LBP test or the mini-

Table 1 ARMA model results for pressure, 8-second record subsets, $\alpha=45°$

Wind direction	Tap	Model	AICC	BIC	Ljung-Box portmanteau test (df=20)	AR order of residuals
45°	1	AR(7)	-4864.1	-4821.9	83.0	23
		AR(10)	-4872.6	-4814.2	66.2	23
		AR(14)	-4877.6	-4799.0	67.2	23
		AR(18)	-4892.5	-4794.8	64.4	0
		AR(22)	-4909.2	-4793.3	48.6	0
		AR(24)	-4915.6	-4790.8	40.8	0
		AR(26)	-4914.1	-4780.6	40.5	0
		MA(5)	-4125.2	-4095.4	1464.0	25
		MA(15)	-4796.3	-4713.3	195.6	23
		MA(20)	-4862.5	-4755.8	104.0	26
		ARMA(2,2)	-4731.2	-4706.6	229.1	23
		ARMA(6,6)	-4872.9	-4804.4	71.0	23
		ARMA(12,12)	-4991.1	-4884.5	64.2	12
		ARMA(15,9)	-4967.6	-4873.1	78.3	16
	2	AR(9)	2476.2	2538.4	34.7	0
		AR(11)	2466.1	2541.0	23.0	0
		MA(3)	4439.7	4458.9	7884.0	12
		MA(6)	3227.8	3269.2	2733.0	16
		MA(9)	2952.7	3013.9	1265.0	18
		ARMA(2,2)	2504.2	2532.2	55.9	12
		ARMA(3,3)	2481.8	2524.0	45.5	13
		ARMA(6,6)	2477.5	2558.6	33.2	0
		ARMA(7,4)	2474.7	2549.6	32.0	0
		ARMA(8,3)	2478.7	2553.5	34.5	0

mum-AICC AR models fitted to their residuals do not have the order of zero. Tables 1 and 2 show that the AR model having a minimum BIC value, such as AR(7) for the pressure at tap 1 and $\alpha=45°$, is unsatisfactory because the residuals of the model neither pass the LBP test nor show whiteness.

The ARMA model having a minimum AICC value, satisfying the LBP test, and satisfying the hypothesis that the residuals are observations from a white noise sequence was selected as the most appropriate model for the pressure. It is shown in Tables 1 and 2 that the minimum-AICC AR models fitted to the pressure satisfy the LBP test, and that their residuals are compatible with a realization of a white noise sequence. Thus it is concluded that the minimum-AICC AR model is quite adequate for modeling the pressure data. For the pressure at tap 1 and the wind direction of 45°, the ARMA model of AR order (p=12) and MA order (q=12) has a minimum AICC value, as shown in Table 1. However, this model does not pass the LBP test and the AR order of the residuals of the model is not zero. For that reason, the minimum-AICC AR model of order 24 was selected as the best-fitting model for the pressure. The value of $\hat{Q}_e$ for this model is 40.8 and this does not exceed $\chi^2_{0.95}(20)=31.4$ significantly. Thus this model is considered to be a good fit.

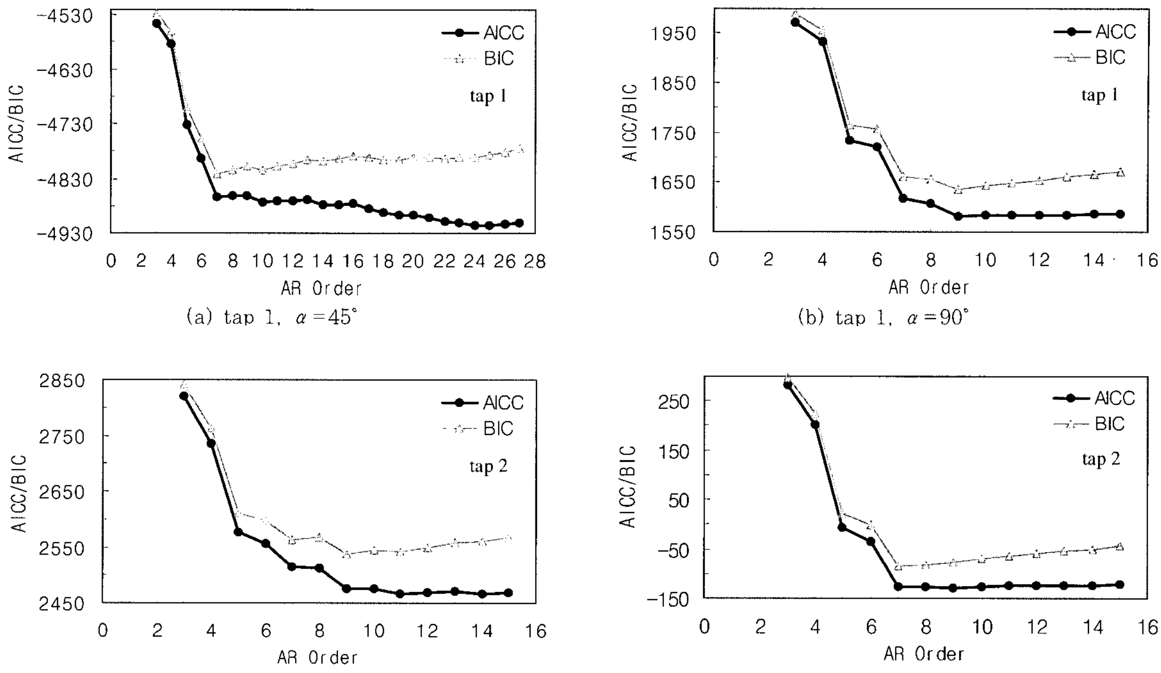
Table 2 ARMA model results for pressure, 8-second record subsets, $\alpha=90^\circ$

Wind direction	Tap	Model	AICC	BIC	Ljung-Box portmanteau test (df=20)	AR order of residuals
90°	1	AR(9)	1581.2	1635.6	21.4	0
		MA(2)	3370.0	3381.2	6531.0	13
		MA(4)	2335.1	2359.6	2311.0	13
		MA(6)	2062.0	2098.5	1270.0	13
		ARMA(1,1)	2240.9	2253.0	532.8	18
		ARMA(2,2)	1646.5	1671.5	92.1	13
		ARMA(3,3)	1615.1	1652.3	68.0	11
		ARMA(5,2)	1593.2	1636.2	37.5	0
		ARMA(6,1)	1625.0	1668.1	63.2	13
		ARMA(8,1)	1592.8	1647.2	33.1	0
	2	AR(7)	-125.7	-85.5	29.1	0
		AR(9)	-128.0	-77.5	22.6	0
		MA(2)	1242.1	1252.7	3888.0	8
		MA(4)	413.6	436.6	1355.0	11
		MA(6)	215.1	249.4	725.3	11
		ARMA(2,2)	-44.0	-20.7	111.5	11
		ARMA(3,3)	-108.1	-73.4	44.6	8
		ARMA(5,2)	-114.5	-74.4	39.4	9
		ARMA(5,5)	-123.3	-67.9	33.2	0
		ARMA(6,1)	-100.4	-60.3	53.3	16

For the pressure at tap 2 and the wind direction of 45°, the minimum-AICC AR model of order 11 was selected. The minimum-AICC AR model of order 9 for the pressure at tap 1 and the wind direction of 90° was selected as the best-fitting model, shown as Table 2. Also, for the pressure at tap 2 and the wind direction of 90°, the minimum-AICC AR model of order 9 was selected.

The AICC and BIC criteria for the pressure at two representative taps and two wind directions ($\alpha=45^\circ$ and $\alpha=90^\circ$) are shown as a function of the AR model order in Fig. 5. The AR order associated with the minimum of a given criterion for the pressure at two taps and two wind directions is shown for AICC, BIC and FPE in Table 3, columns 2 through 4. It is found from this table that the order resulting from minimizing the AICC is similar to that from the FPE, that the BIC leads to a relatively low order of the model, and that the AR order based on the BIC is equal to that implied by the PACF. The AR model order which was finally selected was based on the AICC criterion. It is shown in column 5 of Table 3. The model order for the pressure ranges from 9 through 24.

The results of the LBP test, column 6 of Table 3, indicate a good fit of the AR models. This conclusion is confirmed by the inspection of the residuals and by the comparison of both the ACF and PACF of the model and sample, respectively. The ACF of the residuals for the pressure at a representative location (tap 2) and two wind directions are depicted in Fig. 6. The ACF of the residuals appears to be compatible with the hypothesis that the residuals constitute a white noise sequence.



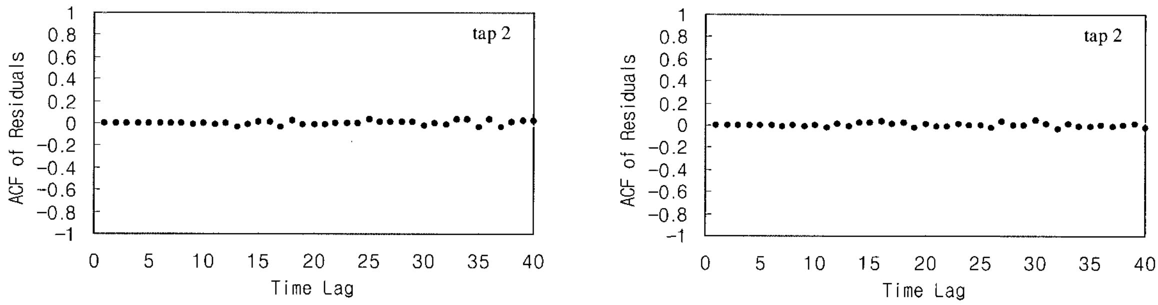
(a) tap 1, $\alpha=45°$ (b) tap 1, $\alpha=90°$

(c) tap 2, $\alpha=45°$ (d) tap 2, $\alpha=90°$

Fig. 5 AICC and BIC criteria for pressure

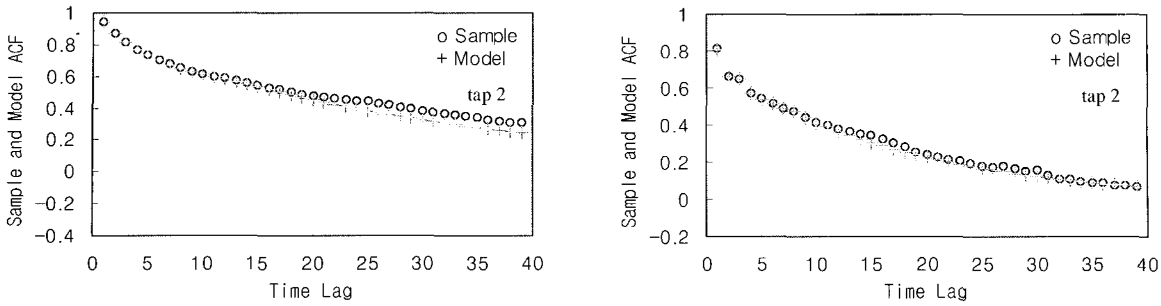
Table 3 Order of AR models for pressure, 8-second record subsets

Wind direction	Tap	AR order (p)				Selected model	
		PACF (1)	AICC (2)	BIC (3)	FPE (4)	AR order (5)	Ljung-Box portmanteau test(df=20) (6)
45°	1	7	24	7	22	24	40.8
	2	9	11	9	11	11	23.0
90°	1	9	9	9	9	9	21.4
	2	7	9	7	7	9	22.6



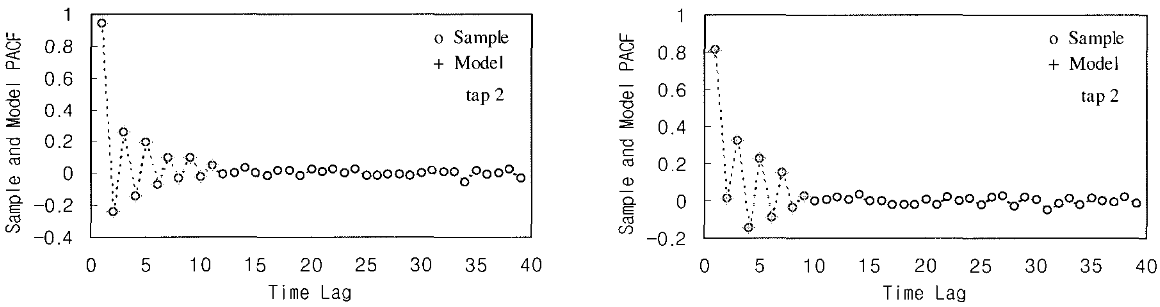
(a) $\alpha=45°$ (b) $\alpha=90°$

Fig. 6 ACF of AR model residuals for pressure



(a) $\alpha=45^{\circ}$ (b) $\alpha=90^{\circ}$

Fig. 7 Sample ACF and model ACF of pressure



(a) $\alpha=45^{\circ}$ (b) $\alpha=90^{\circ}$

Fig. 8 Sample PACF and model PACF of pressure

The sample and model autocorrelation functions for the pressure at a representative location (tap 2) and two wind directions are compared in Fig. 7. The sample and model partial autocorrelation functions for the pressure are also compared in Fig. 8. These comparisons show a good agreement between the sample and model autocorrelation functions. The similarities between the sample and model autocorrelation functions indicate that the model provides a good representation of the data.

4. Conclusions

Autoregressive moving average (ARMA) models with several different combinations of the AR and MA orders were fitted to fluctuations of the wind pressure on a structure, and then the most appropriate ARMA model for each data was selected. In the presented study, the three model selection criteria - AICC, BIC and FPE - were employed in optimization of the order of ARMA models. The adequacy of the ARMA model was examined using the Ljung-Box portmanteau test as well as the residuals of the fitted model.

The presented study showed that from a second-order point of view AR processes adequately fitted the investigated time series of wind pressure. It was concluded that the AR order associated with the minimum of the AICC was optimal, and that the minimum-AICC AR model was adequate for modeling wind pressure.

Acknowledgements

The author would like to express his gratitude to Professor B. Bienkiewicz of Colorado State

University, USA and Dr. Hee-Jung Ham of National Research Council, Canada, for making available to the author the experimental data employed in the paper.

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(접수일자 : 1999. 12. 3)