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Wavelet-based ARMA model Application in Power Network

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Abstract: The theoretical properties of the ARMA model and the modeling process, then, the Shanghai power network and Shenzhen power network in China were established ARMA model and wavelet-based ARMA model fitting, prediction, and finally, to fit forecast The results were compared. It can be seen, combined with relatively good forecasting effect after wavelet.

1 ARMA Model

Assuming $\{\varepsilon_t\}$ is white noise: $\mathrm{WN}(0,\sigma^2)$, Real coefficients Polynomial $A(z)$ and $B(z)$ has no public root, satisfy $b_0 = 1$, $a_p b_q \neq 0$ and

$$A(z) = 1 - \sum_{j=1}^{p} a_j z^j \neq 0, \quad |z| \leq 1$$
$$B(z) = \sum_{j=0}^{q} b_j z^j \neq 0, \quad |z| < 1 \tag{1}$$

We call the difference equation

$$X_t = \sum_{j=1}^{p} a_j X_{t-j} + \sum_{j=0}^{q} b_j \varepsilon_{t-j}, \quad t \in \mathrm{Z} \tag{2}$$

It is an autoregressive moving average model, named $\mathrm{ARMA}(p,q)$ model。Satisfied stationary time series $\{X_t\}$ of the equation（2）as stationary solution or $\mathrm{ARMA}(p,q)$ series. Named $a = (a_1, a_2, \cdots, a_p)^T$ is the regression coefficient of $\mathrm{ARMA}(p,q)$ model, $b = (b_1, b_2, \cdots, b_q)^T$ is the moving average coefficient of $\mathrm{ARMA}(p,q)$ model.

1.1 Model identification and order determination

An observation sequence is from each model family, select a match with the actual process model structure, model identification is asked Problems. Model identification methods on many commonly used is the Box-Jenkins model identification method that is based on the sample autocorrelation, partial autocorrelation. Correlation functions of the cut-off tail, tail of the initial model to determine the appropriate model of the sequence $\{X_t\}$.

If the autocorrelation function $\{X_t\}$ of a smooth exponential decay, partial autocorrelation function truncated, then it becomes the model $\mathrm{AR}(p)$; if the autocorrelation function $\{X_t\}$ of stationary series truncation, partial autocorrelation function of exponential decay, then it becomes for the model $\mathrm{MA}(q)$; if the autocorrelation function $\{X_t\}$ of stationary series, partial autocorrelation functions are exponential decay, then it becomes the model $\mathrm{ARMA}(p,q)$.

It is worth noting, the use of AIC criteria, we need to order the maximum pre-specified range. Upper limit of the general experience of the order is taken as the ratio of N or a multiple of log*N*, the former more than the case for N is smaller, the larger N for the latter. If the upper edge of the AIC can not determine the minimum point, should increase the cap to calculate the new calculated by comparing the AIC values and minima. In addition, the general consistency of AIC given order is not, and sometimes over-orders.

Order determination criteria BIC

In order to overcome the order determination of non-AIC Consistency，BIC function is sometimes recommended order determination：

$$\mathrm{BIC}(p,q)=\ln\hat{\sigma}^2(p,q)+\frac{(p+q)\ln N}{N}$$

BIC and AIC in the same symbolic meaning. Order determination is the consistency of the BIC, but when is not very large, sometimes with the BIC will underestimate given the order of order.

When doing linear prediction, often using the AIC given order, as AIC given a lot of bands do not overestimate, slightly over-estimated that the order does not cause serious consequences, as well as help more with historical data, and underestimate Order often leads to more errors and the inappropriate choice of model. But in doing research on the model structure, it should be estimated using BIC.

1.2 The estimated model parameters

Least squares estimation is the most commonly used linear model estimation method, it has the advantages of simple computation, this paper ARMA(*p,q*) model to the least squares estimation method, note

$$\tilde{\beta}=(a_1,\cdots,a_p,b_1,\cdots,b_q)$$
$$F_t(\tilde{\beta})=a_1x_{t-1}+\cdots+a_px_{t-p}-b_1\varepsilon_{t-1}-\cdots-b_q\varepsilon_{t-p}$$

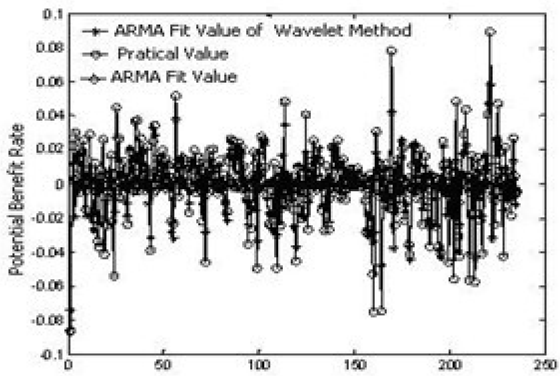
Residual term is： $\varepsilon_t=x_t-F_t(\tilde{\beta})$； Residual sum of squares and for：

$$Q(\tilde{\beta})=\sum_{t=1}^{n}\varepsilon_t^2=\sum_{t=1}^{n}(x_t-a_1x_{t-1}-\cdots-a_px_{t-p}-b_1\varepsilon_{t-1}-\cdots-b_q\varepsilon_{t-q})$$

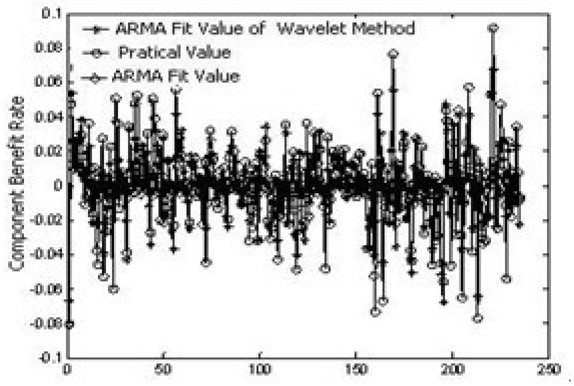
Made to minimize the residual sum of squares of that group are $\tilde{\beta}$ the least squares parameter estimates.

2 Results comparision

ARMA model, respectively, and the use of wavelet-based ARMA model for the Shanghai Index and Shenzhen power network Index sequences were studied, following the results of the two model fitting to compare predicted to yield fit results shown in Figure 1, the raw data, such as predictive Figure 2.

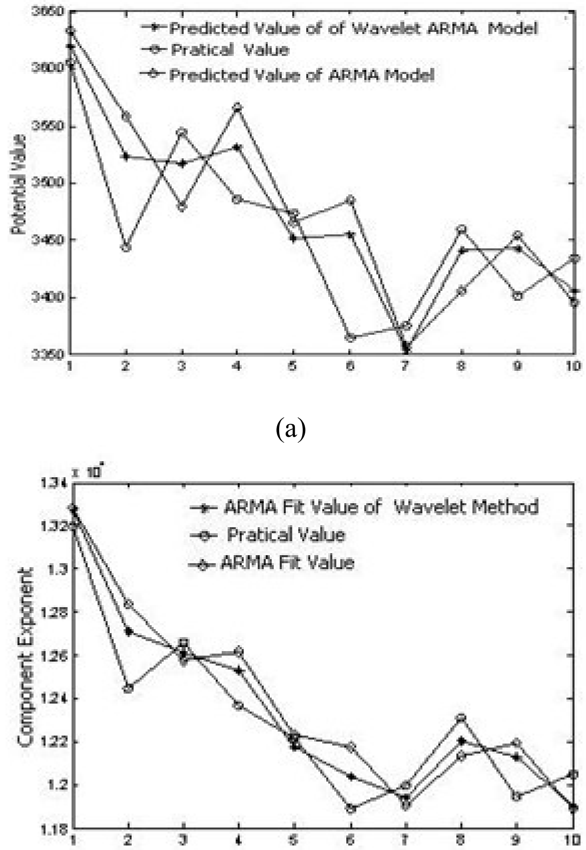


(a)



(b)

Fig.1 The fitting effect sketches of two models



(a)

(b)

Fig.2 The predictive effect sketches of two models

The fitting results of two models from the figure, we can intuitively see the ARMA model fitted values are mostly concentrated in the middle part of the less volatile, fitting is ineffective, while the wavelet-based ARMA model to the relative volatility Large, relatively good fitting effect, but not too satisfactory. The following are given and the Shanghai Index and Shenzhen power network Index of the predictive value and relative error.

Table1 Comparisons of actual value and estimations of Shanghai power network index

Trading Day	Actual value on the card index	ARMA prediction	Relative error (%)	Predictive value of wavelet	Relative error (%)
2008-5-19	3604.76	3632.58	-0.7716	3619.88	-0.4195
2008-5-20	3443.16	3558.56	-3.3515	3523.50	-2.3334
2008-5-21	3544.19	3479.16	1.8350	3517.29	0.7591
2008-5-22	3485.63	3566.23	-2.3124	3531.45	-1.3147
2008-5-23	3473.09	3465.13	0.2293	3451.64	0.6177
2008-5-26	3364.54	3484.92	-3.5779	3454.39	-2.6704
2008-5-27	3375.41	3356.81	0.5510	3353.12	0.6604
2008-5-28	3459.03	3405.59	1.5451	3441.19	0.5158
2008-5-29	3401.44	3453.85	-1.5407	3442.81	-1.2163
2008-5-30	3433.35	3394.98	1.1175	3405.86	0.8005

The Shenzhen power network Index on the Shanghai index and by fitting the predicted results we can know that wavelet-based ARMA model fitting, prediction is better than a simple ARMA model fitting, better than forecast.

3 Conclusions

This paper gives the modeling of ARMA prediction model, then, the main stock indexing China were established ARMA model and wavelet-based ARMA model, and fitting, prediction, and finally, to the fitting, the predicted results Compared. It can be seen, combined with relatively good forecasting effect after wavelet.

References

[1] Tong H. Nonlinear time series analysis since 1990: some personal reflections [J]. Acta Mathematical Applicatae Sinica, English Series, 2002, 18 (2): 177-184.

[2] Härdle W., Lütkepohl H. Chen R. A review of nonparametric time series analysis [J]. International Statistical Review, 1997, 65: 49-72.

[3] Cai Z. and Fan J. Average regression surface for dependent data [J]. Multivariate Anal, 2000, 75: 112-142.

[4] Tsay R.S. Detecting and modeling nonlinearity in univariate time series analysis [J]. Statistical Sinica, 1991, 1: 431-451.

[5] Gao J. and Tong H. Semiparametric non-linear time series model selection[J]. Journal of the Royal Statistical Society Series B, 2004, 66(2): 321-336.