

Modeling and forecasting electricity loads: A comparison



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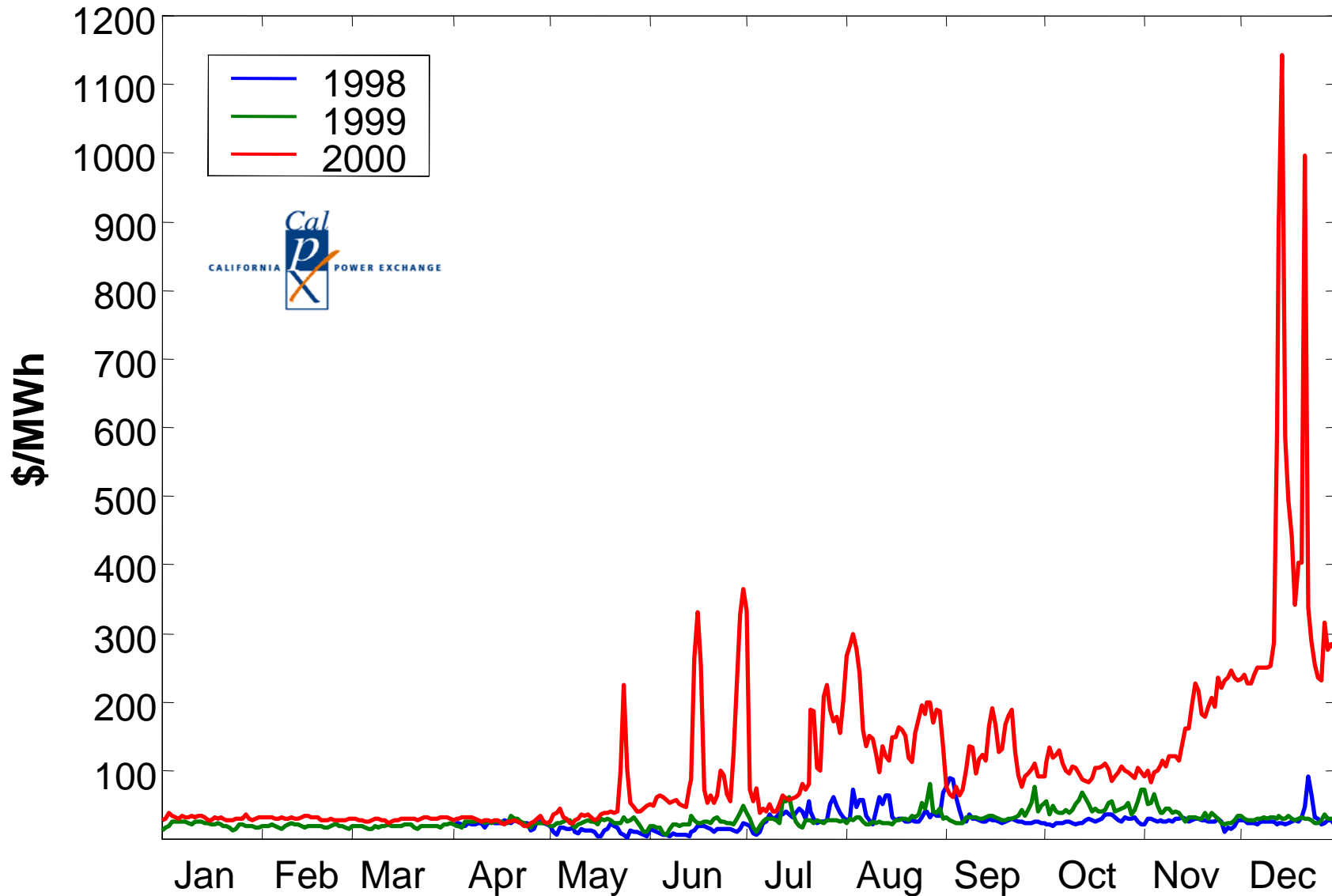
Analyzed data



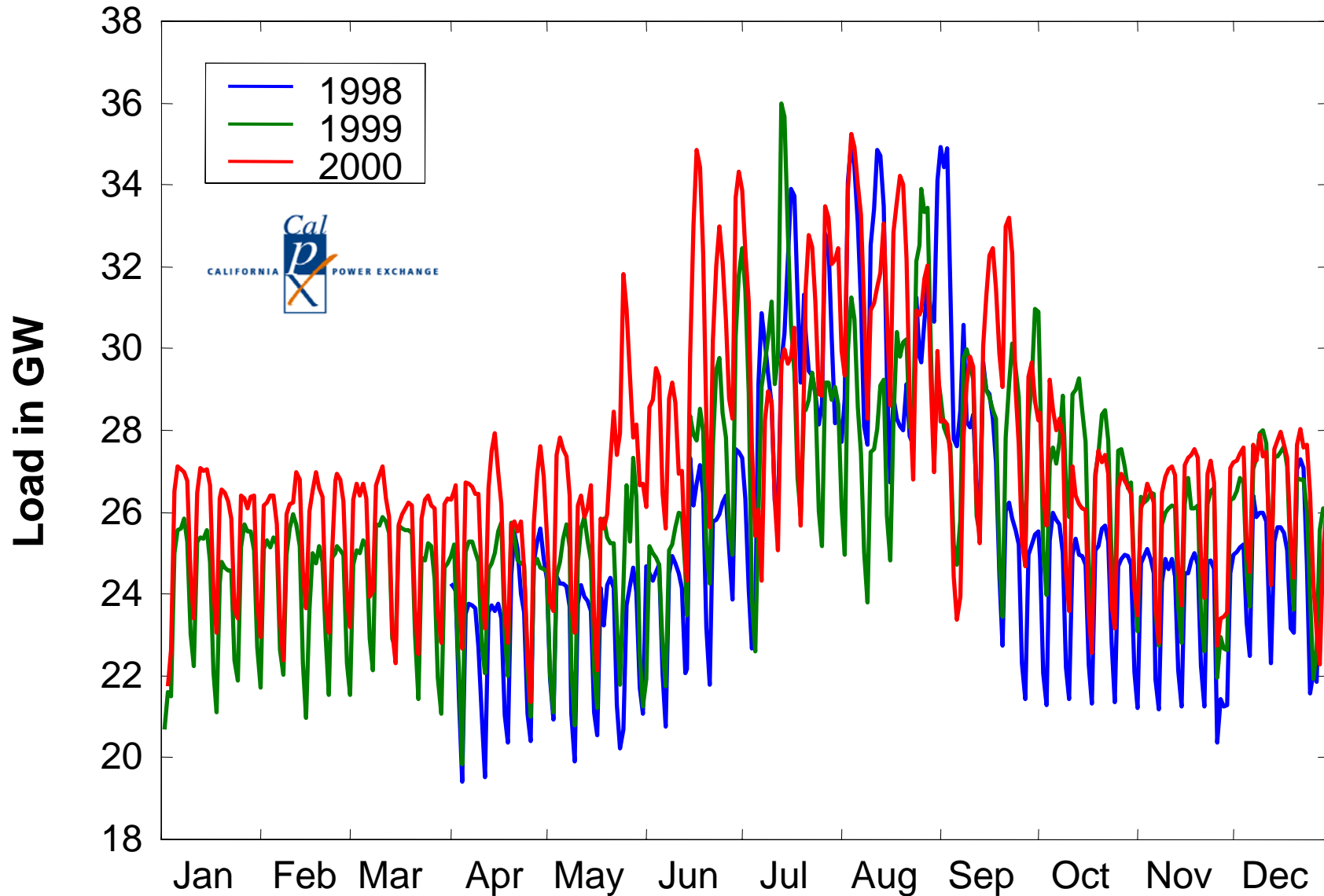
- California power market system-wide load from the period 1.4.1998 – 31.12.2001
- Due to the daily cycle we analyze daily load
- 1999-2000 data used for calibration (2 full cycles), 2001 data used for out-of-sample testing



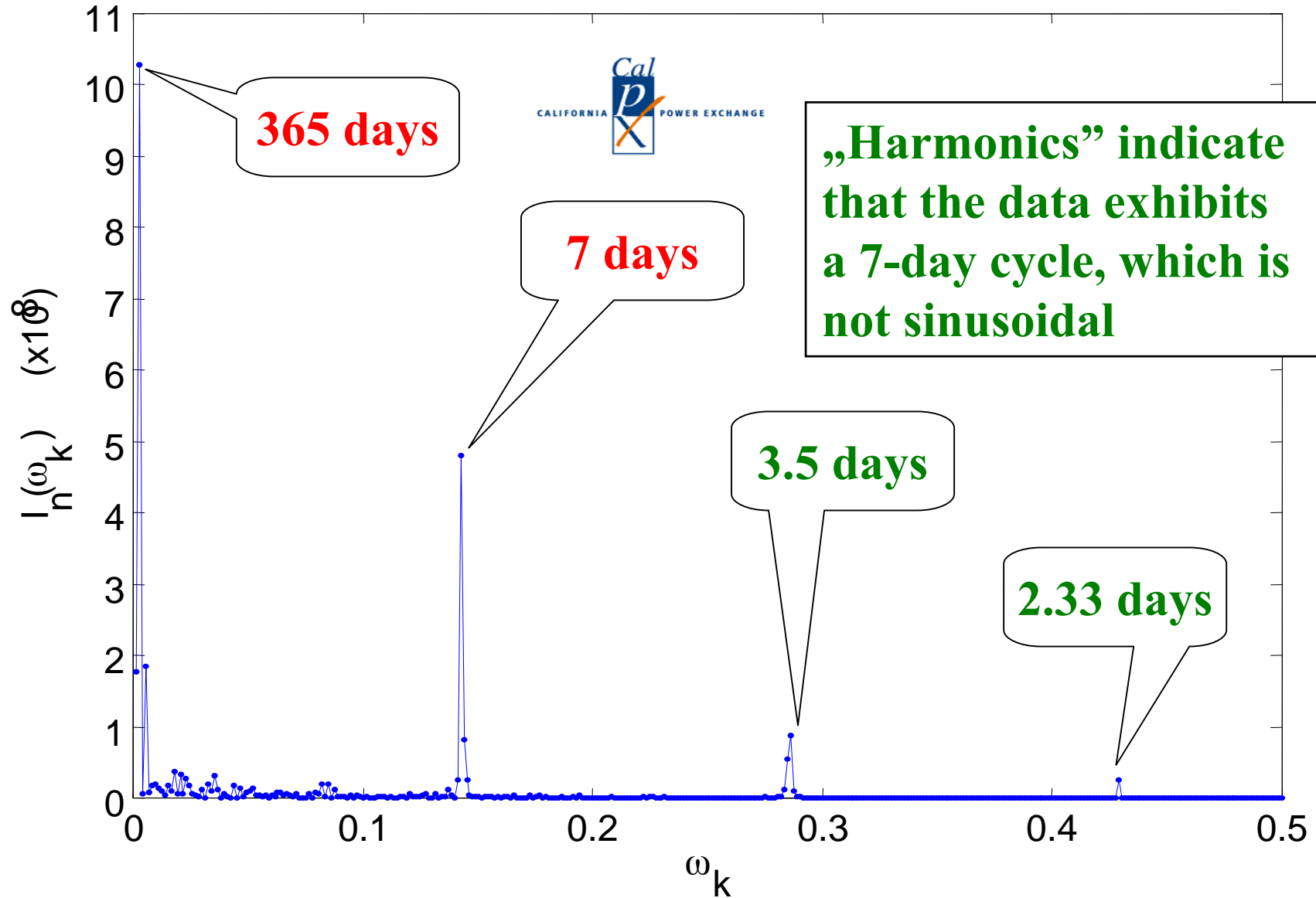
Average daily CalPX system electricity prices



Average daily system-wide load in California



Periodogram of the average daily load since 1.4.98 until 31.12.00



General statistical approach



- Load Z_t is modeled as a sum of two components:
 - ◆ deterministic (or seasonal) X_t
 - ◆ stochastic Y_t
- The stochastic component $Y_t = Z_t - X_t$
 - ◆ AR, ARMAX, FARIMA, GARCH, FIGARCH, etc.
 - ◆ ARMA $(p, q, \phi_1, \dots, \phi_p, \theta_1, \dots, \theta_q, \sigma^2)$

$$Y_t - \phi_1 Y_{t-1} - \dots - \phi_p Y_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q}$$

$$\{\varepsilon_t\} \sim \text{iid}(0; \sigma^2)$$

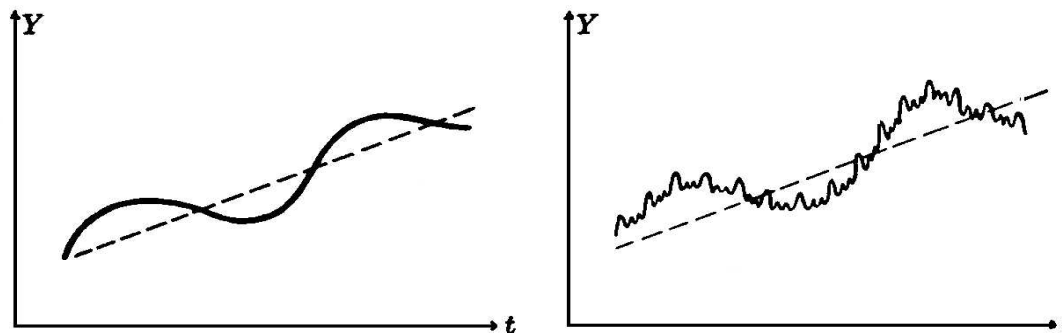
Seasonality reduction techniques



- Differencing

- ◆ e.g. $X_t = Z_t - Z_{t-7}$

- Fitting a sinusoid or a sum of sinusoids



- Moving average method

- Seasonal volatility technique

Model A - Differencing



■ Seasonal component

$$X_t = \frac{1}{N} \sum_{i=1}^N Z_{t-iT} + \frac{1}{M} \sum_{j=1}^M Z_{t-jD} - \frac{1}{NM} \sum_{i=1}^N \sum_{j=1}^M Z_{t-iT-jD}$$

where

- ◆ $T = 168$ hours (i.e. one week)
- ◆ $D = 24$ hour (i.e. one day)
- ◆ $N = 4$ or 5 is the number of weeks used for calibration
- ◆ $M = 7$ is the number of days in a week

Model B

- Moving average method



- For a vector $\{x_1, \dots, x_{730}\}$ calculate a 7-day moving average $m_t = (x_{t-3} + \dots + x_{t+3})/7$
- For each $k = 1, \dots, 7$ calculate mean w_k of deviations $(x_{k+7j} - m_{k+7j})$ and rescale it so that w_k sum to zero
- The time series with eliminated weekly cycle is given by $x_t - w_t$
- Unfortunately this method cannot be used to remove the annual cycle since data covers only two full cycles

Model B

- Seasonal volatility method



- Calculate a 25-day rolling volatility for the vector $\{x_1, \dots, x_{730}\}$

$$v_t = \sqrt{\frac{1}{24} \sum_{i=0}^{24} (R_{t+i} - \bar{R}_t)^2}$$

- Calculate the average annual volatility

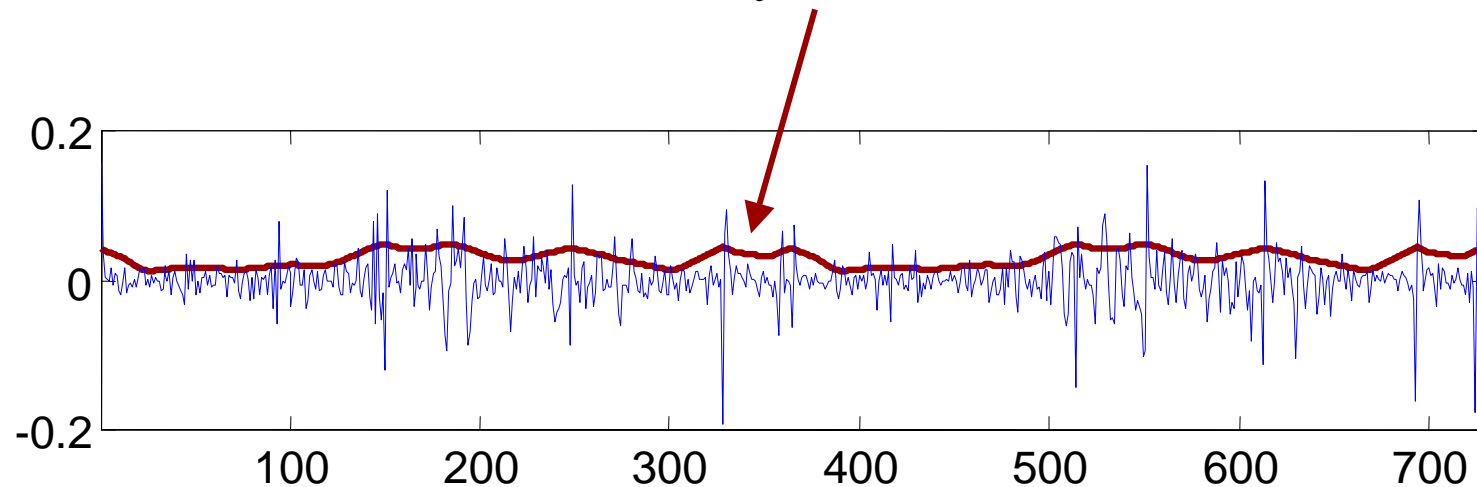
$$\sigma_t = (v_t^{1999} + v_t^{2000})/2$$

- Smooth the volatility by taking a 25-day moving average of σ_t

Seasonal volatility method cont.

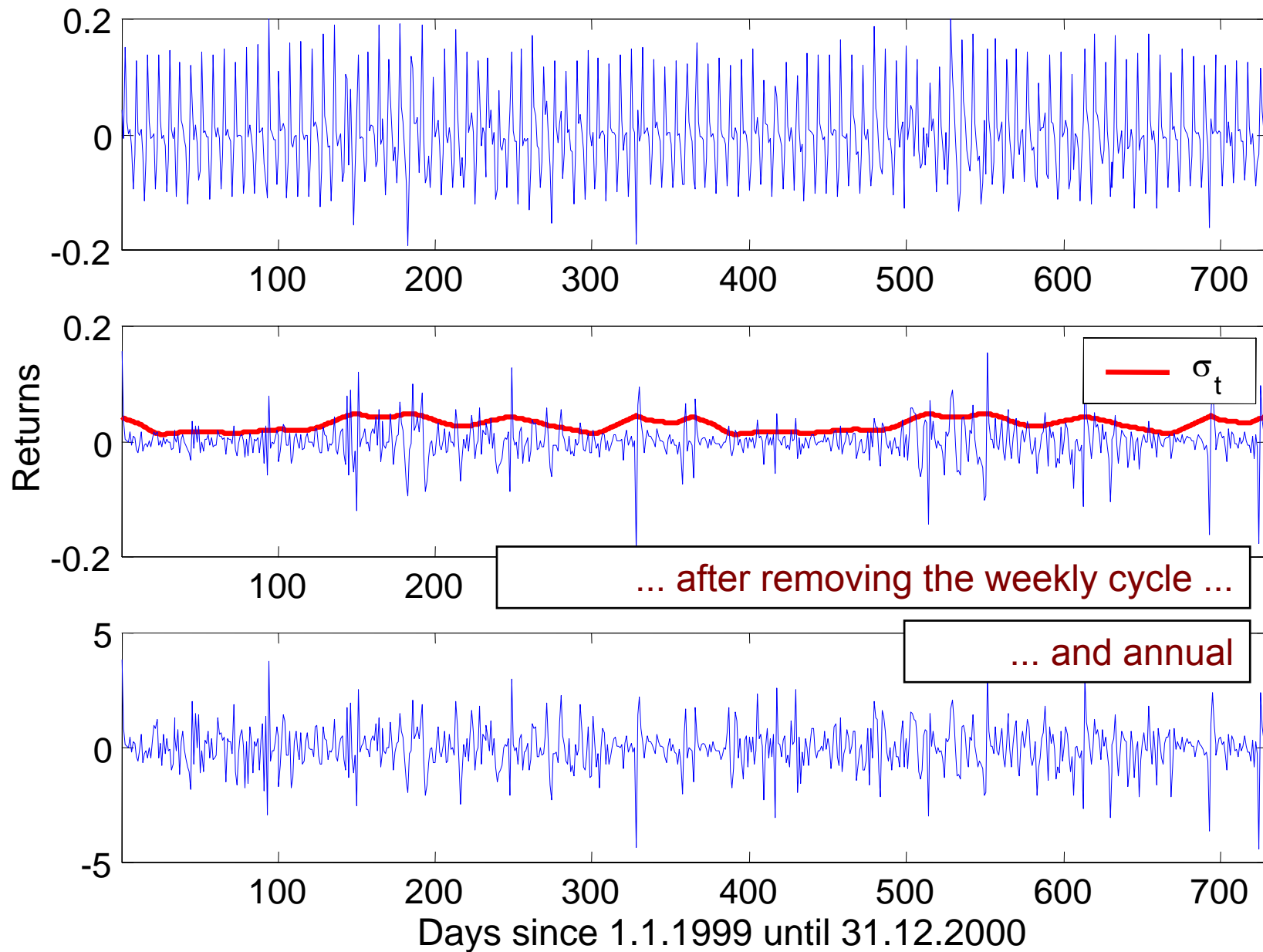


- Finally rescale the returns by dividing them by the smoothed annual volatility $\bar{\sigma}_t$

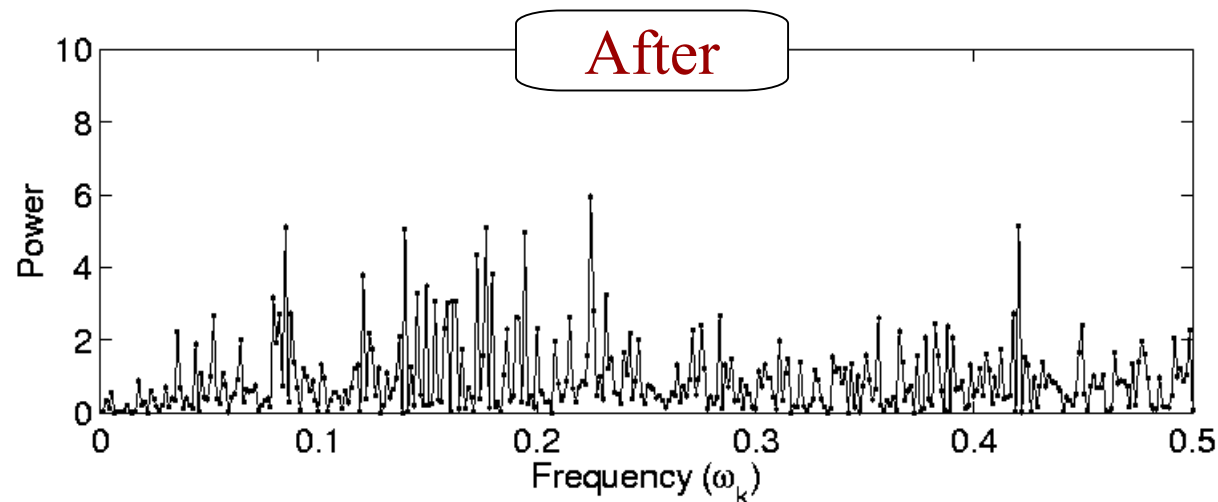
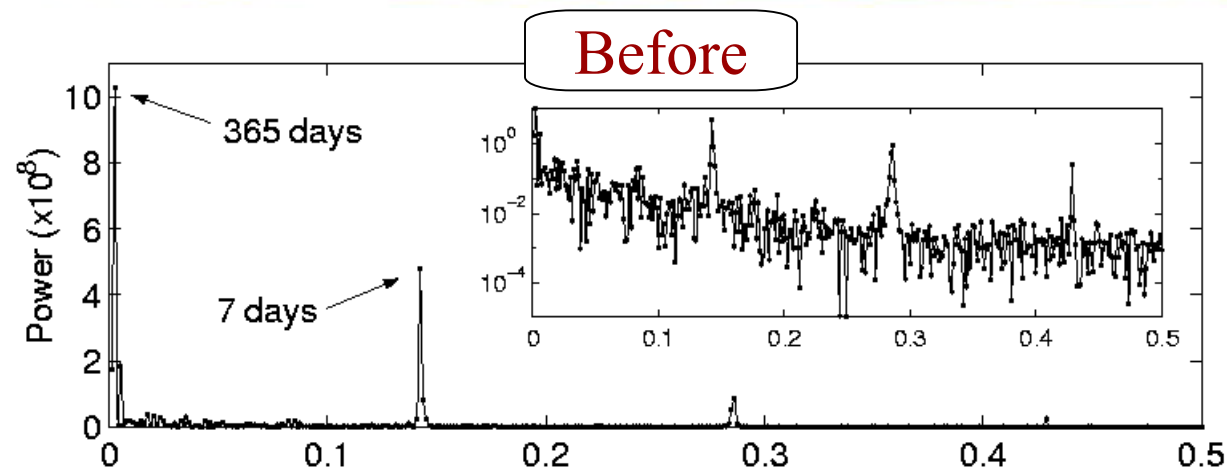


- The obtained time series does not exhibit the annual cycle

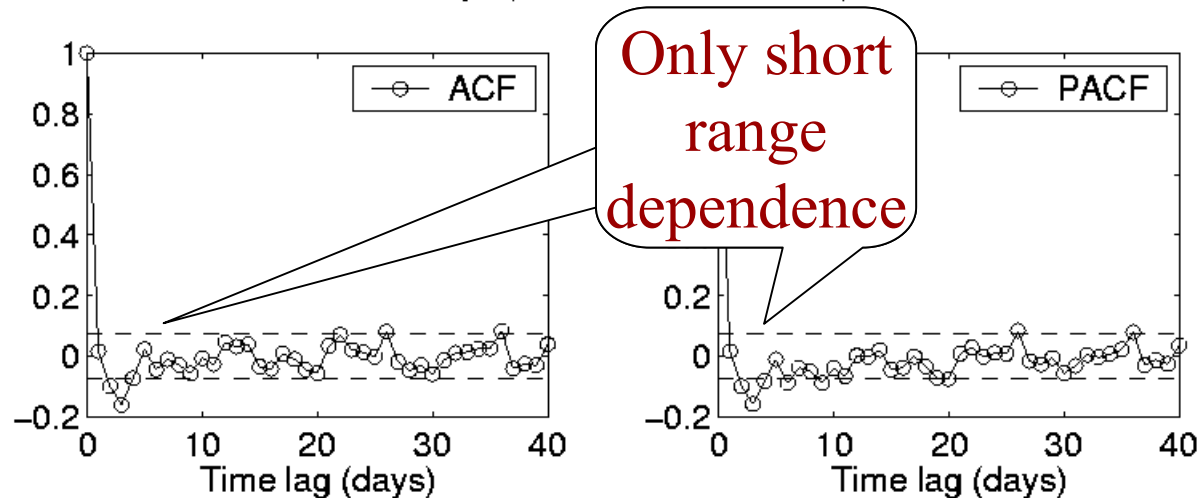
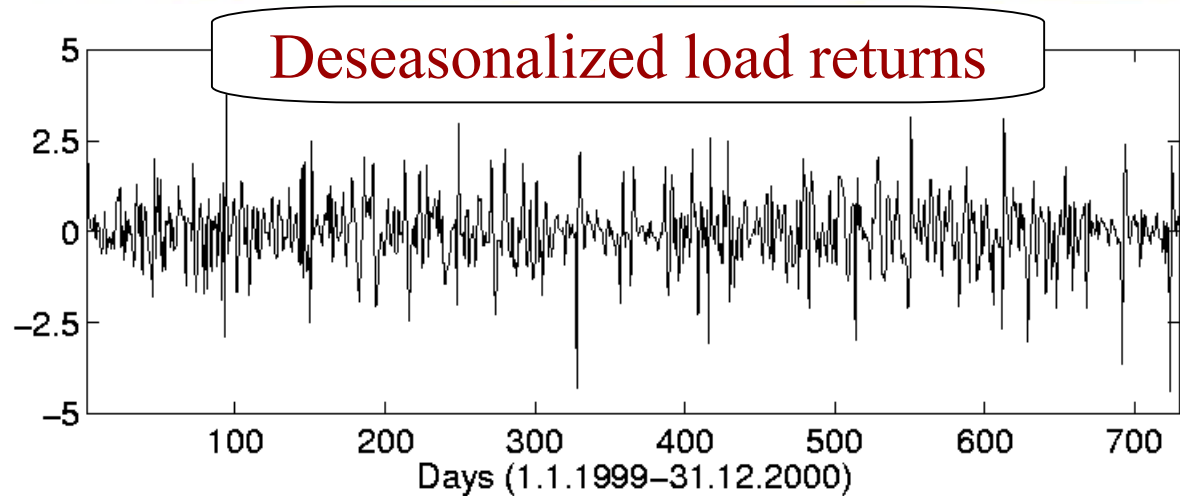
Returns of daily load ...



Periodogram before and after seasonality reduction



Deseasonalized load returns can be modeled by ARMA time series



Stochastic components



■ Model A

◆ ARMA(3,2)

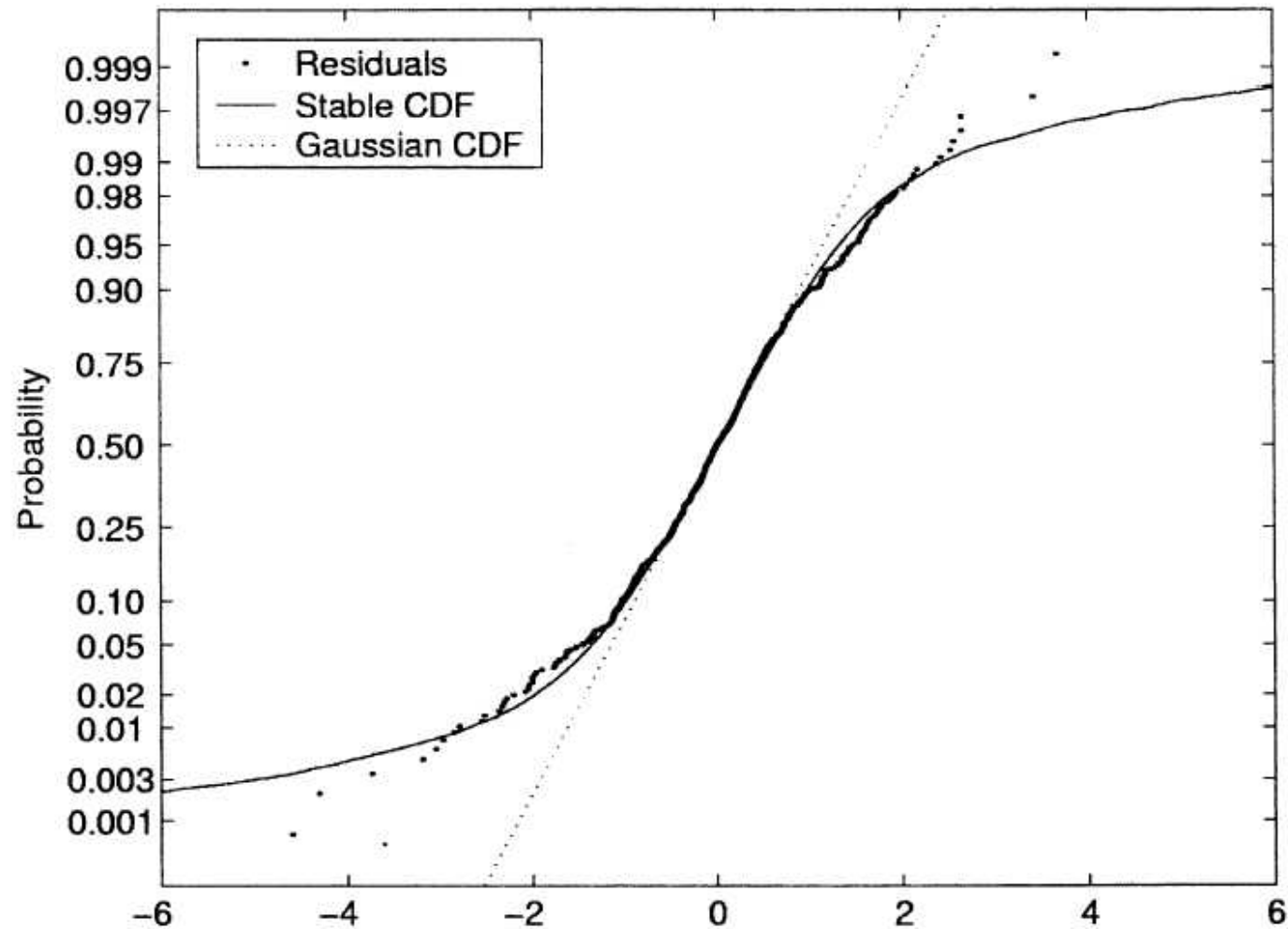
■ Model B

Table 1
AICC values for the best AR, MA and ARMA models

Model class	Best model	AICC value	Model class	Best model	AICC value
AR(-)	AR(11)	1965.226	MA(-)	MA(4)	1959.299
ARMA(1, -)	ARMA(1, 6)	1956.294	ARMA(2, -)	ARMA(2, 3)	1960.312
ARMA(3, -)	ARMA(3, 3)	1962.037	ARMA(4, -)	ARMA(4, 4)	1963.028
ARMA(5, -)	ARMA(5, 3)	1962.045	ARMA(6, -)	ARMA(6, 2)	1966.060
ARMA(7, -)	ARMA(7, 3)	1967.511	ARMA(8, -)	ARMA(8, 1)	1967.844
ARMA(9, -)	ARMA(9, 1)	1965.556	ARMA(10, -)	ARMA(10, 1)	1967.628
ARMA(11, -)	ARMA(11, 1)	1968.005			

"-" denotes an integer from the interval [1,11].

ARMA models with hyperbolic noise



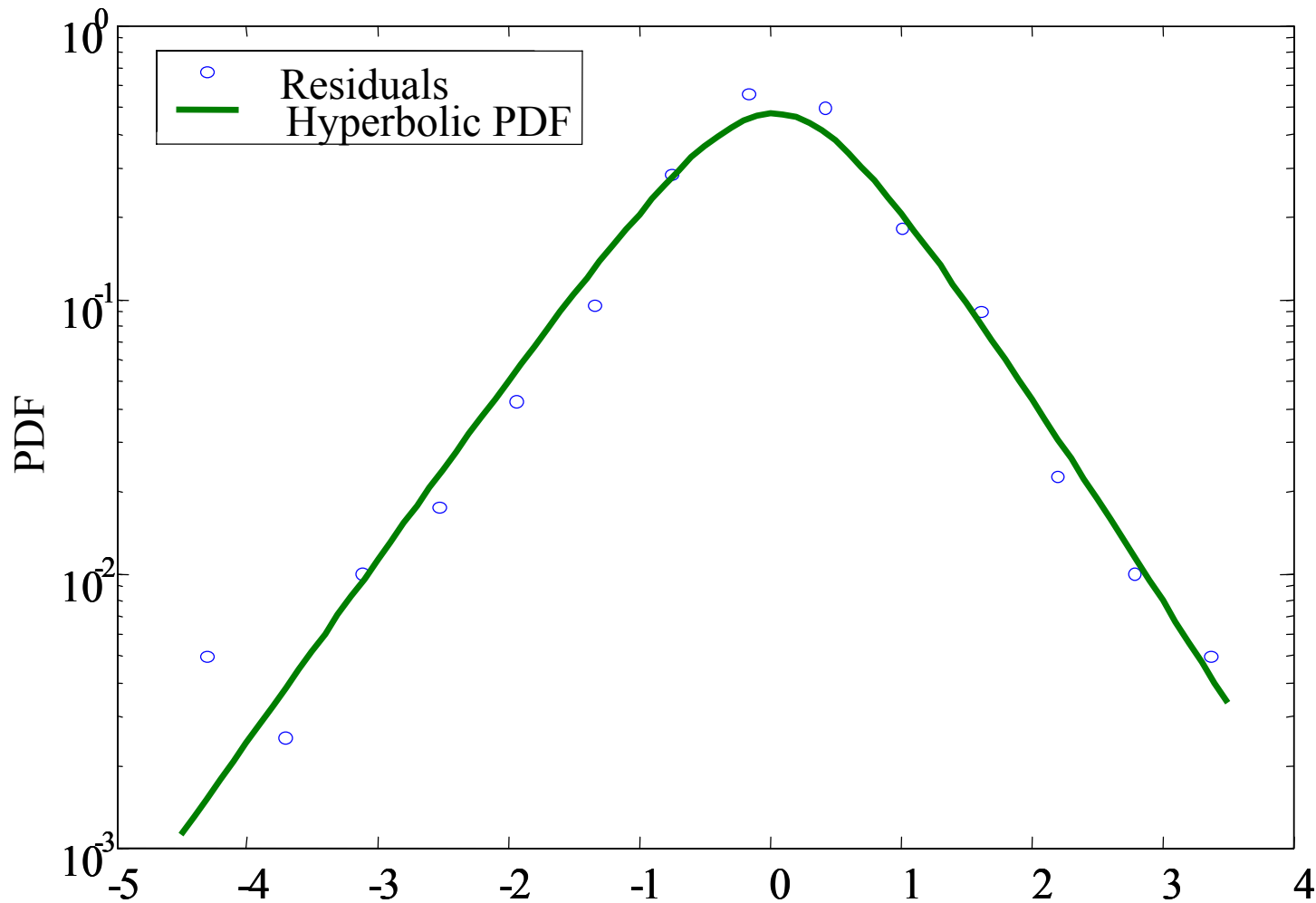
ARMA models with hyperbolic noise cont.



$$\begin{aligned} f(x; \alpha, \beta, \delta, \mu) &= \frac{\sqrt{\alpha^2 - \beta^2}}{2\alpha\delta K_1(\delta\sqrt{\alpha^2 - \beta^2})} \exp\{-\alpha\sqrt{\delta^2 + (x - \mu)^2} \\ &\quad + \beta(x - \mu)\}, \end{aligned} \tag{13}$$

where $\delta > 0$ is the scale parameter, $\mu \in R$ is the location parameter and $0 \leq |\beta| < \alpha$. The latter two parameters— α and β —determine the shape, with α being responsible for the steepness and β for the skewness.

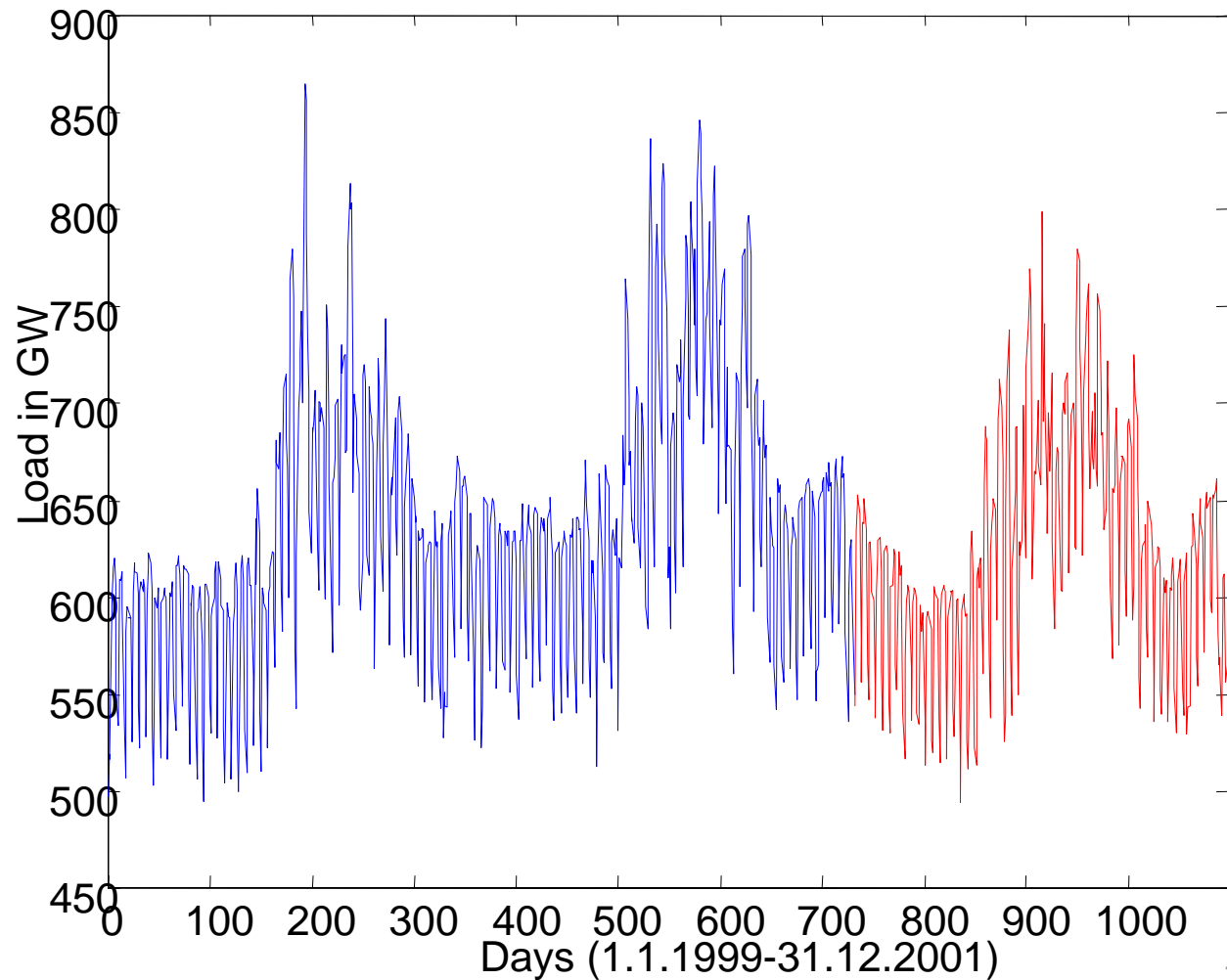
ARMA models with hyperbolic noise cont.

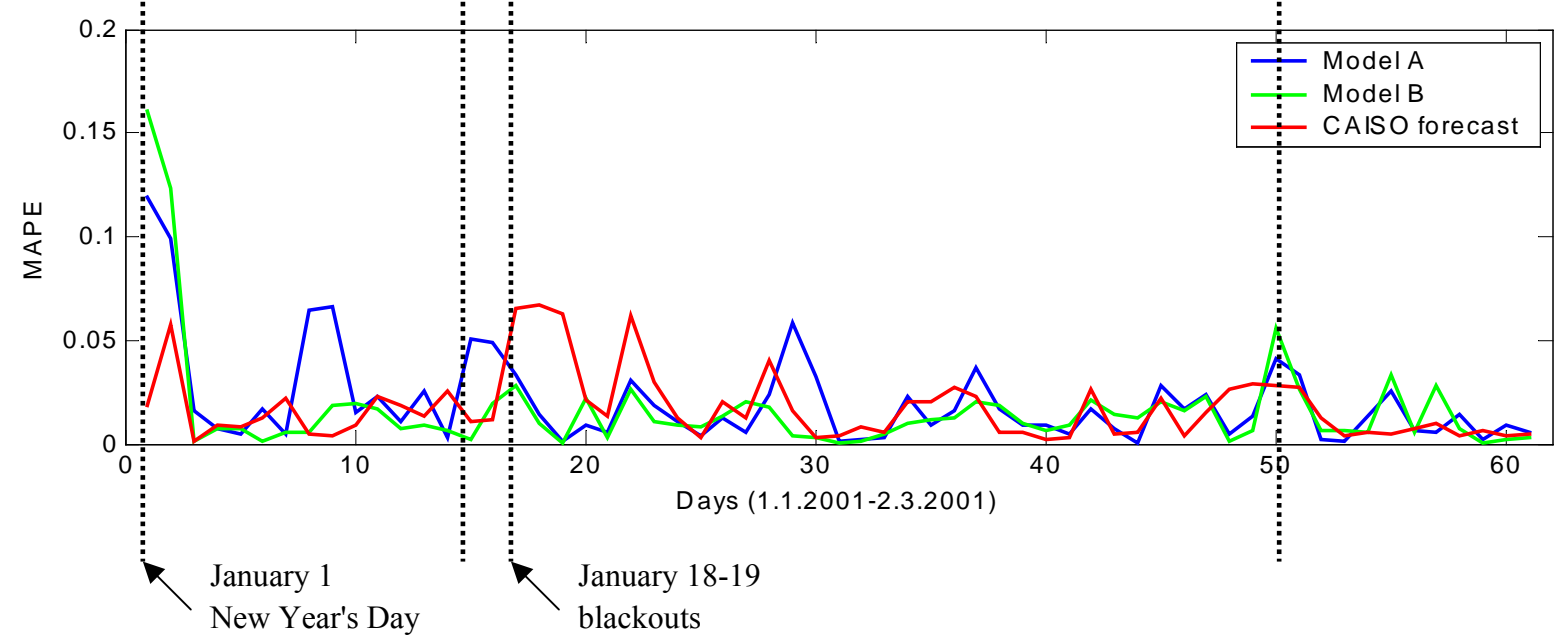
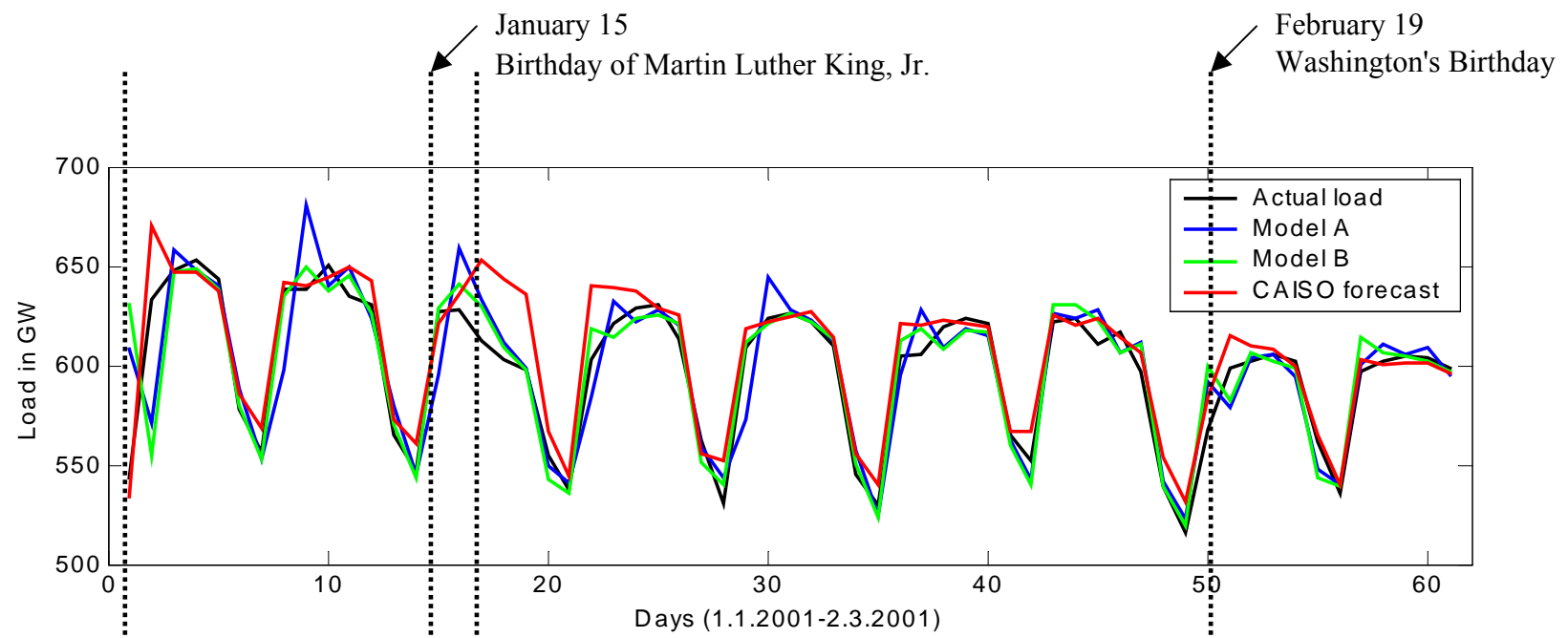


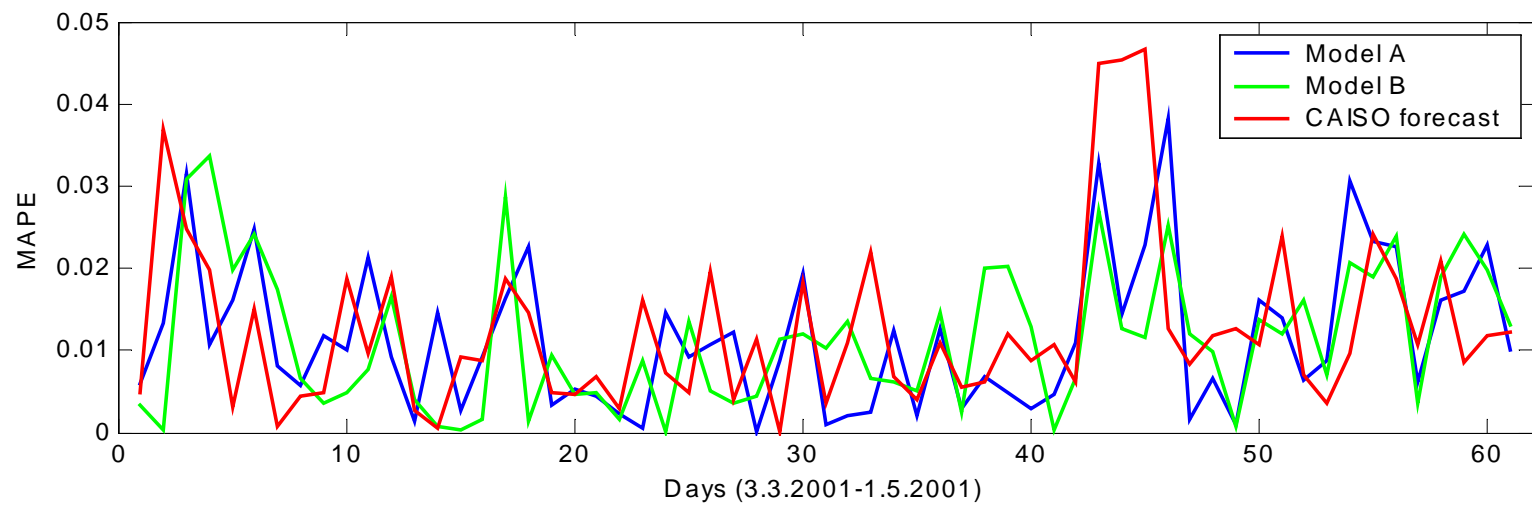
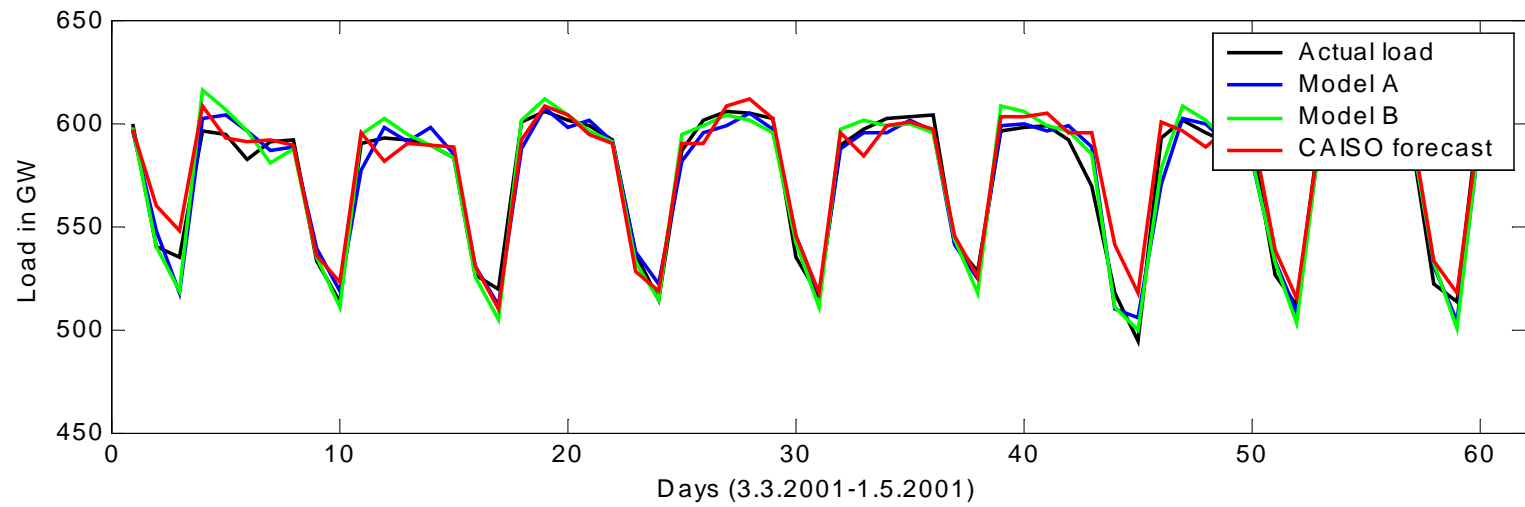
Out-of-sample tests

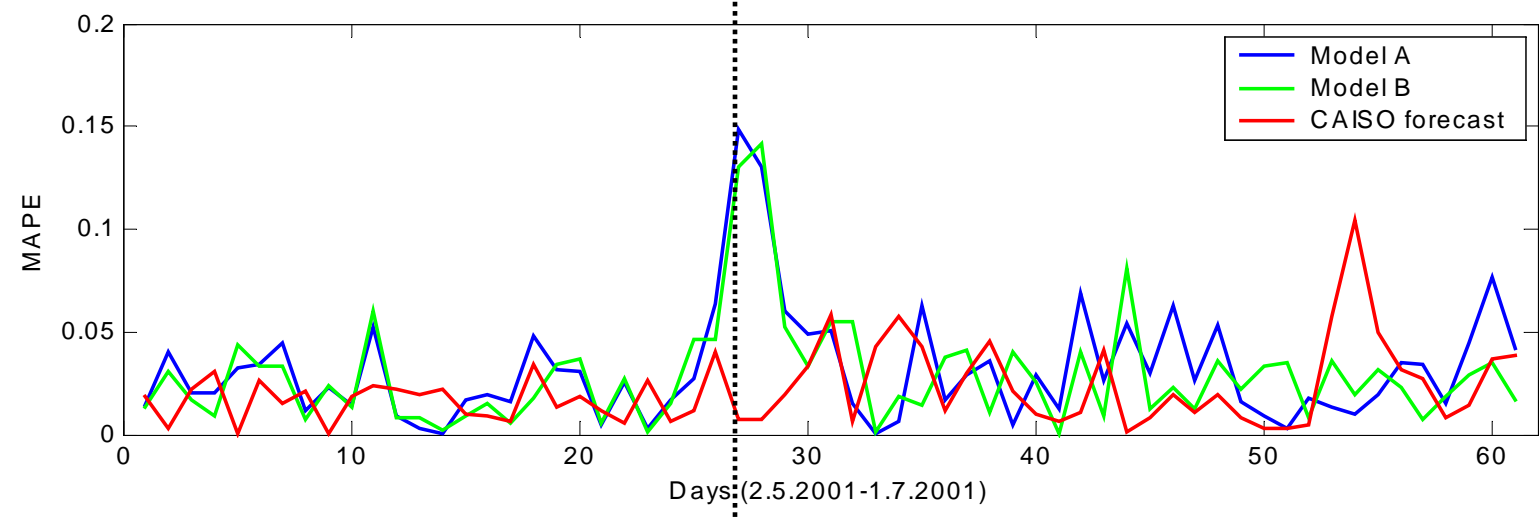
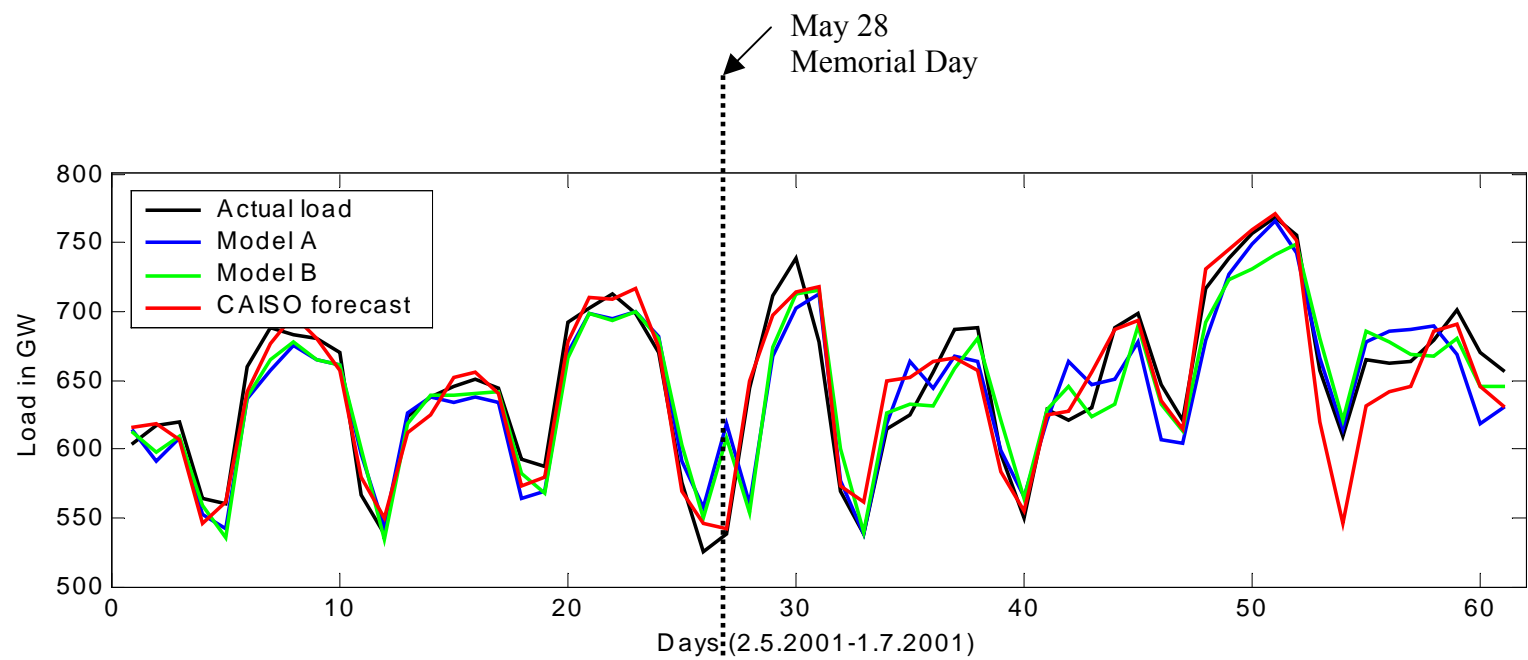


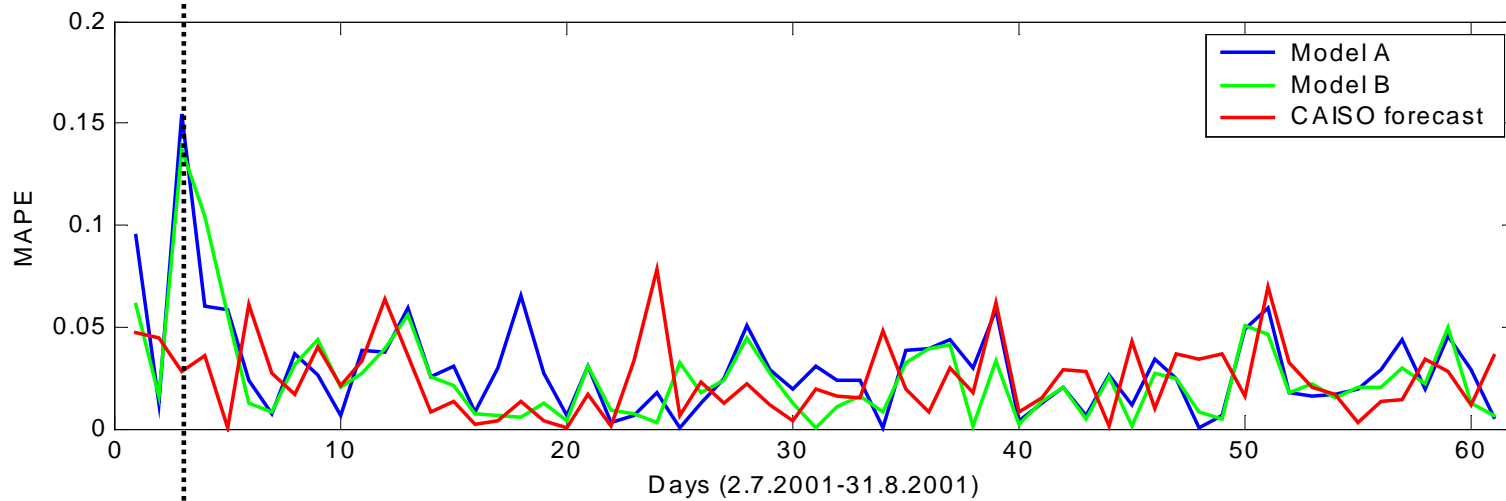
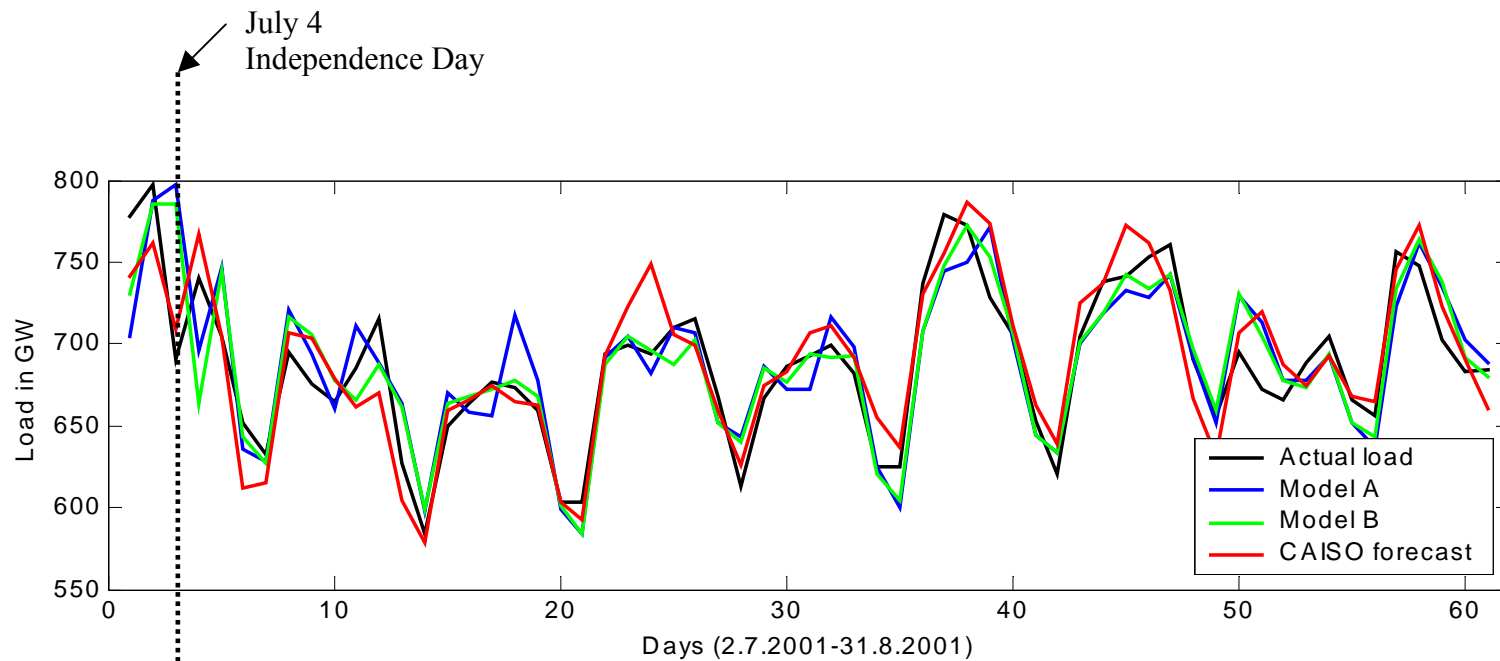
- Day-ahead predictions
- Adaptive scheme

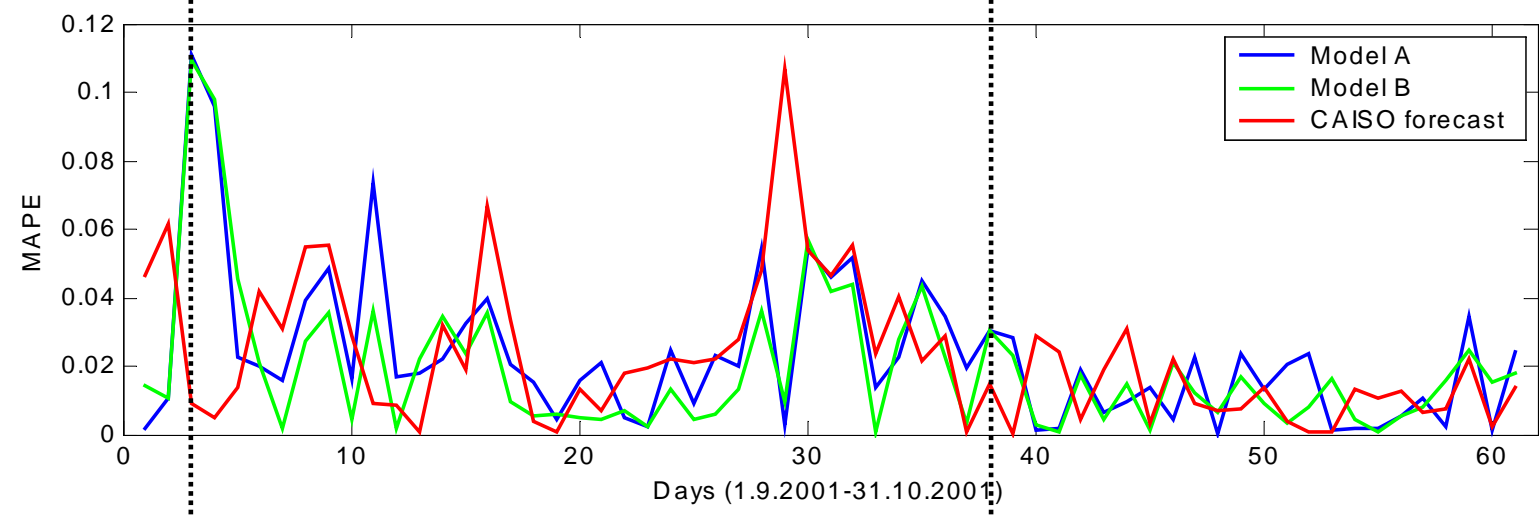
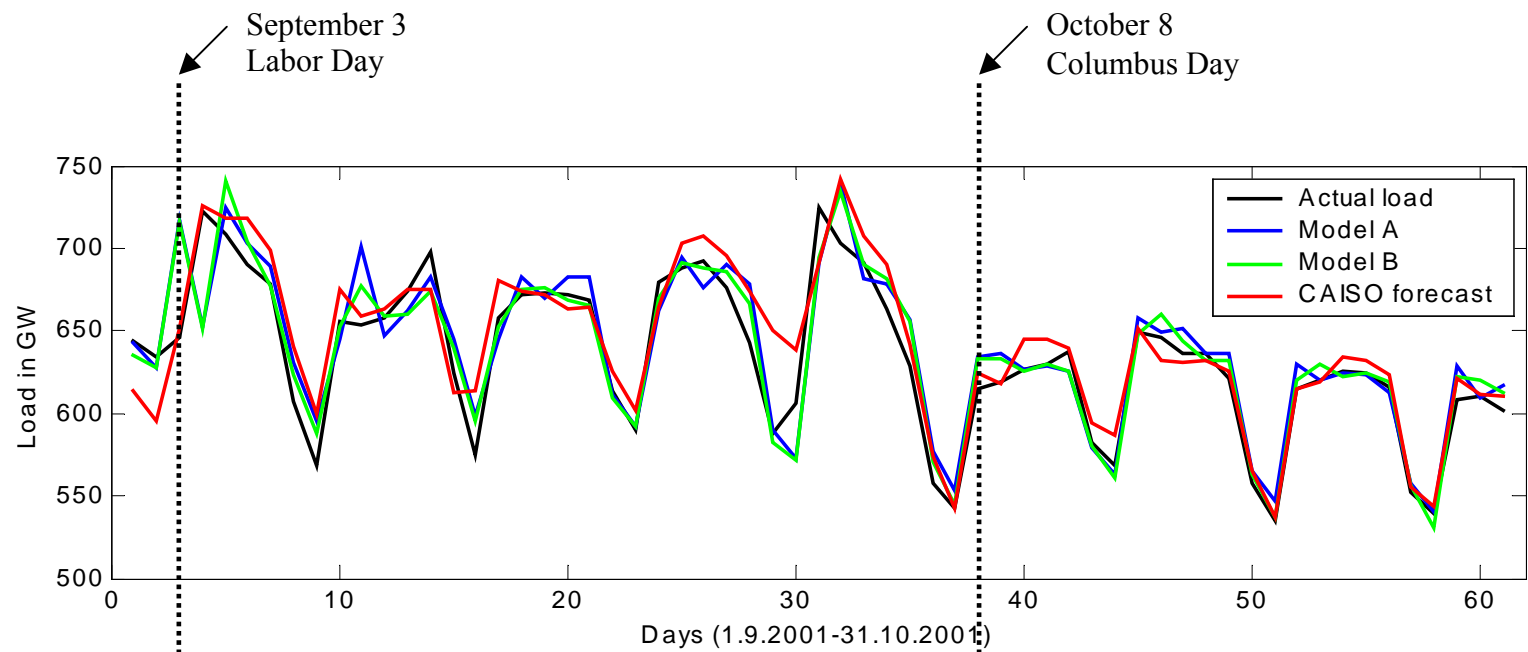


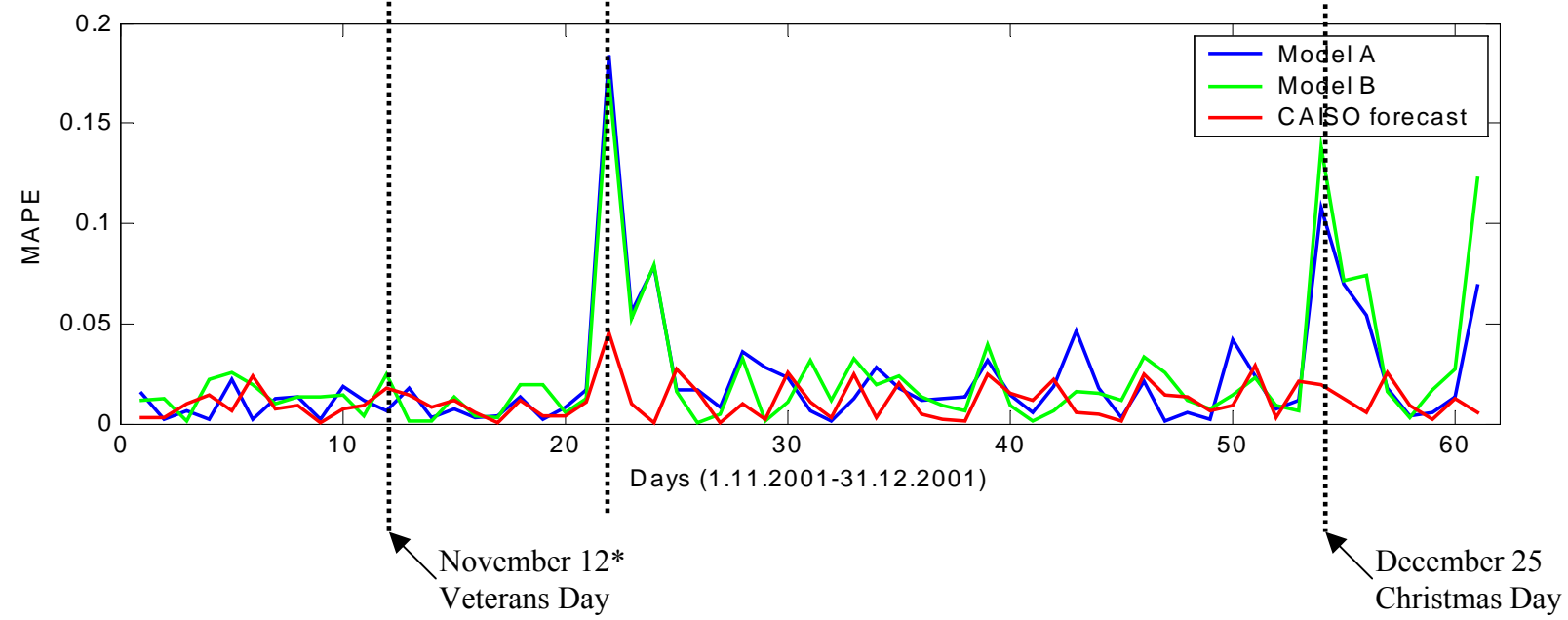
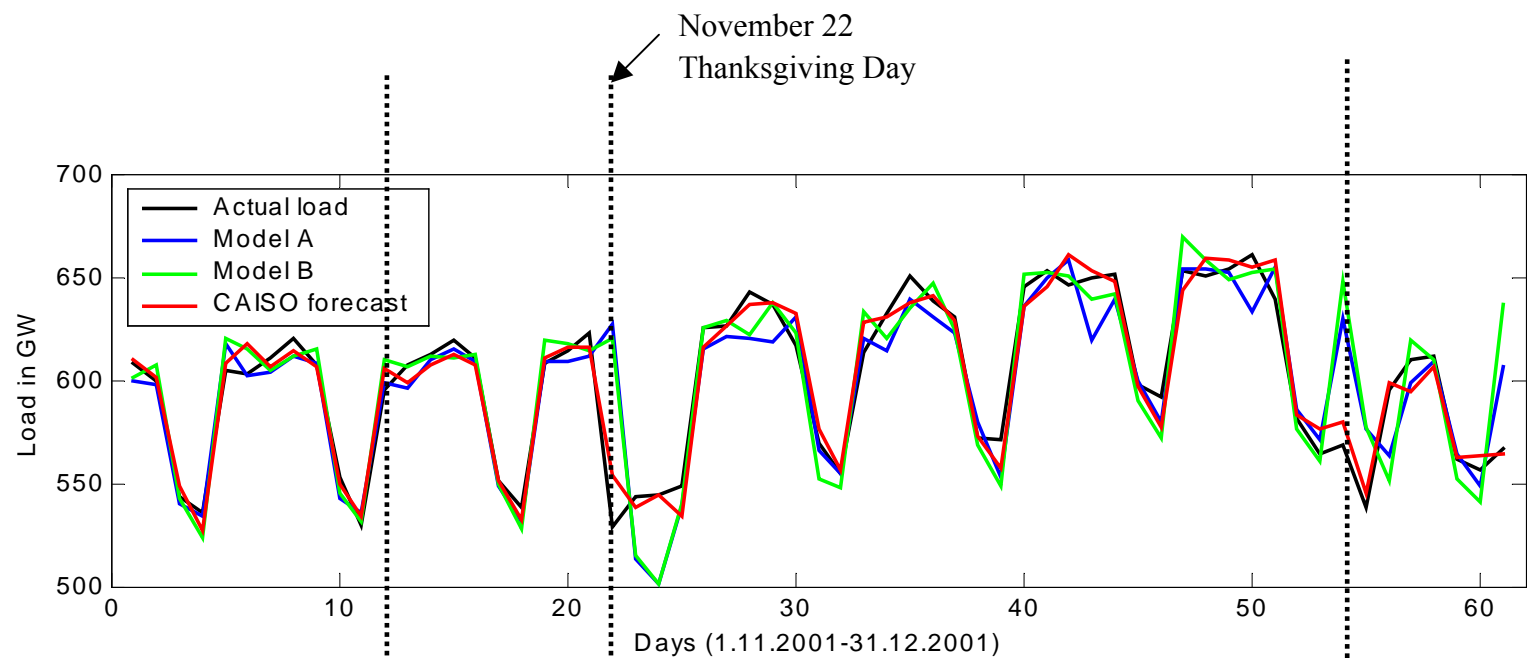












Forecast errors in 2001



MAPE (Jan.-Dec.)	CAISO	Model A	Model B
With holidays	1.84%	2.30%	2.08%
Without holidays	1.77%	1.95%	1.71%

