Modeling and forecasting cumulative average temperature and heating degree day indices for weather derivative pricing

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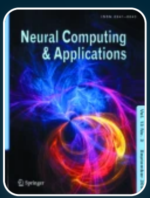

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Abstract

In this paper, we use wavelet neural networks in order to model a mean-reverting Ornstein–Uhlenbeck temperature process, with seasonality in the level and volatility and time-varying speed of mean reversion. We forecast up to 2 months ahead out of sample daily temperatures, and we simulate the corresponding Cumulative Average Temperature and Heating Degree Day indices. The proposed model is validated in 8 European and 5 USA cities all traded in the Chicago Mercantile Exchange. Our results suggest that the proposed method outperforms alternative pricing methods, proposed in prior studies, in most cases. We find that wavelet networks can model the temperature process very well and consequently they constitute an accurate and efficient tool for weather derivatives pricing.

Finally, we provide the pricing equations for temperature futures on Cooling and Heating Degree Day indices.

Notes

1. Atlanta, Detroit, New York, Baltimore, Houston, Philadelphia, Boston, Jacksonville, Portland, Chicago, Kansas City, Raleigh, Cincinnati, Las Vegas, Sacramento, Colorado Spring, Little Rock, Salt Lake City, Dallas, Los Angeles, Tucson, Des Moines, Minneapolis-St. Paul, Washington, D.C.

2. Amsterdam, Barcelona, Berlin, Essen, London, Madrid, Paris, Rome, Stockholm, Oslo.

3. Tokyo, Osaka.

4. Calgary, Montreal, Vancouver, Edmonton, Toronto, Winnipeg.

5. http://www.engr.udayton.edu/weather/.

6. The *t* test assumes that the population is normally distributed. This assumption

for the two indices is justified in many papers, in [68] for example.

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