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Quantum-minimized BWGC/NGARCH approach to financial time series forecast

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ABSTRACT

In this study, a novel approach to time series forecast is introduced in order to overcome the crucial problems of the overshoot phenomenon and the effect of volatility clustering at the same time. The prediction using grey model (GM) has encountered the overshoot phenomenon that results in big residual errors. To the contrary a method called cumulated 3-point least square polynomial model (C3LSP) may yield the underestimated output in the prediction. Thus we can utilize the predicted result from C3LSP to compensate the output of grey prediction so as for reducing the overshoot significantly. It is applicable to combine GM and C3LSP linearly and tune this combination optimally by back-propagation neural network (BPNN). This model denotes BPNN-weighted GM–C3LSP (BWGC). However, an effect of volatility clustering suggests a time series where successive disturbance, even if uncorrelated, are yet serially dependent. Consequently, this effect not only decreases the predictive accuracy but also deteriorates the localization for time series. Thus, incorporating a nonlinear generalized autoregressive conditional heteroscedasticity (NGARCH) into BWGC is proposed so that NGARCH is used to tackle the problem of volatility clustering effect during the time series forecast. For the purpose of simplicity, both BWGC and NGARCH models are composed linearly and then an algorithm called quantum-based minimization (QM) is particularly employed to regularize this composite model BWGC/NGARCH to best fit time series. As a result, the proposed approach can resolve the overshoot and volatility clustering effects simultaneously and outperforms the alternative models for time series forecasts.

1. Introduction

Grey model (GM) [1], quite often, has been applied to non-periodic short-term forecasts and its performance of time series prediction is better than Holt–Winters smoothing, Box–Jenkins, or ARMA models [2,3]. However, GM commonly encounters the overshoot phenomenon [4], whereby huge residual errors emerge at the inflection points of a data sequence [5], i.e., when the slope changes from positive to negative and vice versa. Fig. 1 compares the actual TAIEX stock price monthly-closing indices for 31 months (January 1999 to July 2001) with the GM prediction. The GM predictions (denoted "●") reveal the overshoot at the turning point regions of time series around sample numbers 7, 14, 25, 26, and 27. Clearly, the overshoot phenomenon seriously weakens its prediction accuracy. In order to overcome this drawback, a cumulated 3-point least square prediction (C3LSP) model [4] (denoted "○") with an underestimated result gives us a way to offset an overshoot output from grey prediction. This is because grey prediction outputs an overshoot result, while C3LSP model could produces an underestimated output at the same period. Here comes to a question: how to moderate two distinct predicted outputs? According to our previous work [4], a back-propagation neural network (BPNN) [6] is brought into moderating both outputs linearly and this moderated output yields the satisfactory predicted result. We abbreviate BPNN-weighted GM–C3LSP model to BWGC. As shown in Fig. 1, BWGC (denoted "–∗–") gives better prediction accuracy than GM, C3LSP, and the pure average of both (i.e., GM plus C3LSP) do.

However, the volatility clustering [7,8] possibly degrades the predictive accuracy upon financial time series prediction. Volatility commonly means the risk or uncertainty measure associated with a financial time series and is associated with the standard deviation of time series in general. Volatility clustering commonly associated with financial time series in which large changes tend to follow large changes, and small changes tend to follow small changes. In either case, the changes from one period to the next are typically intractable. For example, a sequence of

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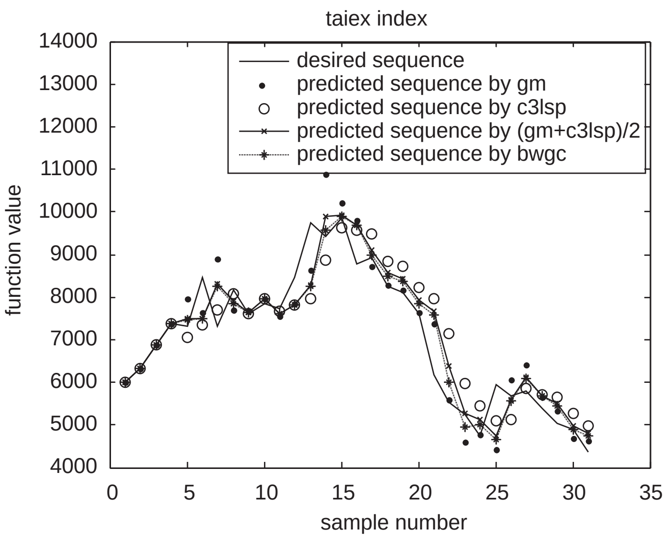

Fig. 1. The desired sequence represents the monthly Taiwan's stock price index for a period of 31 months from January 1999 to July 2001. The outputs of GM model are denoted by "•", revealing the overshoot effect around the turning-point region at sample number 7, 14, 25, 26, and 27. The underestimated predicted outputs, resulted from C3LSP, is denoted by "∘" at sample number 6, 12, 13, 25, and 26. The average between GM and C3LSP is denoted by "– × –" at every sample number, whereas the output of BWGC model is denoted by "–∗–".

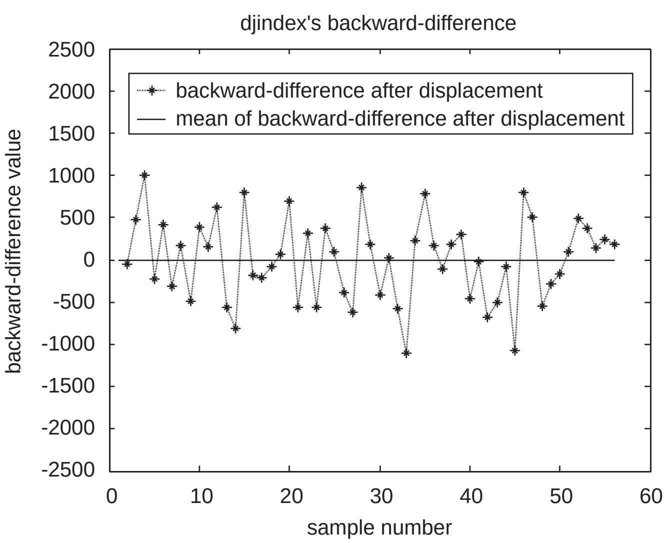

Fig. 2. A sequence of backward-difference from New York D.J. Industrials monthly-closing indices has displaced to its mean value dated from January 1999 to August 2003 for a period of 56 months. This plot shows that big change around the sample numbers 2–4, 12–16, 27–35, and 45–47, whereas small change around the sample numbers 5–11, 17–19, 21–26, 36–44, and 48–56.

backward-difference values of New York D.J. Industrials monthly-closing indices for 56 months (January 1999 to August 2003) are shown in Fig. 2 with zero mean value (solid line). Volatility clustering can be seen in this plot, for example, small change occurs around the sample numbers 5–11, 17–19, 21–26, 36–44, and 48–56, whereas large change occur around the sample numbers 2–4, 12–16, 27–35, and 45–47. Volatility clustering, or persistence, suggests a time series model, where successive disturbances, even if uncorrelated, are yet serially dependent. Thus based on a few historical disturbances, no matter what positive or negative, may be applied to predicting the variance of disturbance at the next period. The remarkable approach—generalized autoregressive conditional heteroscedasticity (GARCH)—is suitable to dealing with the problem of volatility clustering upon financial time series. Frankly speaking, heteroscedasticity is treated as a time-varying variance, i.e., volatility. The word "conditional" suggests a dependence on the observations of the immediate past, while autoregressive represents a feedback to incorporate the past observations into the present. In other words, GARCH includes the past variances in the explanation of future variances and allows users to model the serial dependence of volatility.

As stated in our previous work [9], in order to decrease the effect of volatility clustering on time series prediction, a nonlinear version of GARCH, nonlinear generalized autoregressive conditional heteroscedasticity (NGARCH) [10,11], is included in this study, bring the resolution to the volatility clustering problem. That is, we incorporate NGARCH into BWGC model so that a composite model BWGC/NGATCH, denoted BWGC/NGATCH, is built to deal with the crucial problem just mentioned above. For the purpose of simplicity the linear composite for BWGC/NGARCH is designed and subsequently a powerful optimization—quantum-based minimization (QM) [12]—is introduced to regularize this composite to best fit time series, denoted QM-BWGC/NGARCH model [13]. Our objective is to construct a composite model that is capable of overcoming the overshoot and volatility clustering at the same time upon time series forecast and hopefully obtains the satisfactory results as well. Although this generic framework has been mentioned early in [9], this paper herewith gives an extensive study on three aspects: a variety of performance evaluations based on several criteria to judge the predictive accuracy (e.g., mean absolute deviation, MAD; mean absolute percent error, MAPE; mean squared error, MSE; Theil'U inequality coefficient, Theil'U), an effective model validation on the basis of hypothesis tests (e.g., Engle's test and Q-test), and a comparison between a particular class of composite models (e.g., QM-ASVR/NGARCH model versus QM-BWGC/NGARCH model where ASVR stands for adaptive support vector regression that is a special regression approach as described in paper [9]).

In the following sections, a composite model BWGC, which is used for tackling the problem of the overshoot, was described in Section 2. In Section 3, a NGARCH was introduced to combine BWGC for resolving the volatility clustering effect. Section 4 will present QM technology that is an optimization algorithm employed to search the optimal parameters. A follow-up in Section 5 described how QM is employed to regularize the composite model BWGC/NGARCH. Experimental results and discussion were given in Section 6 to show their performance evaluation upon time series prediction. Finally, we drew the conclusion in Section 7.

2. Models for tackling the overshoot problem

In order to overcome the crucial problem of the overshoot effect occurred in time series prediction, a GM combined with a cumulated 3-point least square polynomial (C3LSP) will be described based on their modeling in detail in the following subsections. Besides, a backpropagation neural network has been applied to tuning the coefficients between GM and C3LSP such that linear combination of GM and C3LSP can lead to the predicted results without big residual errors caused by the overshoot effect.

2.1. Grey model (GM)

Let $x_{gm}^{(0)}(k)$ denote an initial sequence of given data. The following steps briefly describe GM $(1,1|\alpha)$ [1] modeling.