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# A hybrid model based on stacking and multi-correction mechanisms for urban water demand prediction ⋆

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**Abstract:** Water demand prediction is the key link for the effective operation of urban intelligent water supply system. Since the non-linearity and complex variability of water consumption, it is difficult for traditional water demand prediction models to guarantee high accuracy for a long period. Different holiday types and even tiny changes in temperatures can affect urban water demand seriously. This paper proposes a Stacking-based hybrid model which integrates multi-correction mechanisms to address these problems. A better stacking model is proposed to minimize the generalization error. The stability and reliability of predictions are improved through the design of multi-correction mechanisms such as high temperature weather compensation feature, holiday-type correction model and water quantity fluctuation correction model. Comparing different models before and after stacking also before and after correcting, the prediction accuracy of the proposed hybrid model is much higher and the predictions are more stable and reliable.

*Keywords:* Water supply system, Prediction methods, Hybrid models, Stacking methods, Multi-correction mechanisms, Neural-network models, Time-series analysis.

## 1. INTRODUCTION

With the rapid growth of urban water consumption and the shortage of water resources, the optimal planning of water resources and water use systems has become more and more important, see Zhang et al. (2012). At present, the shortage of water resource has been emerging as one of the urgent problems that many cities in China are faced with due to the rapid urbanization, see Yin et al. (2018). Water demand forecasting provides valuable trigger in determining the time and the capacity for new water resources development, see Mohamed and Al-Mualla (2010). Therefore, as the premise and basis of water supply management, the short-term water demand forecast has been greatly developed.

There are quantities factors leading to the variation in urban water demand, such as climatic factors (temperature, humidity, and rainfall), see Firat et al. (2009), public policy factors(pricing, conservation programs, and education), see Babel et al. (2007), efficiency and techonology, see Kayaga et al. (2011). To predict the short-term urban water demand, the traditional models such as Grey model(GM), see Xie and Liu (2009) and Kumar and Jain (2010), support vector machine(SVM), see Ji et al. (2014) and Wang et al. (2015), and neural network(NN), see Tiwari and Adamowski (2013) , and Long and Qian (2010). However, the limited generalization ability of a single model could leads to the instability of the prediction. Also, it is unsuitable to use single model to solve practical prediction problems. Besides, the urban water demand is greatly affected by high temperature weather and national statutory holidays, which makes it difficult to maintain the high prediction accuracy of the traditional models. To address these problems, therefore, it is necessary to design

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comprehensive stacked model and reasonable correction models with reference to the prior knowledges.

Combining impact factors modeling-based machine learning models and time series modeling-based deep learning models, this paper proposes a hybrid model based on muti-correction mechanisms and a better stacking method. Compared with pure time series model, the introduction of impact factor-based model enables the model to capture valuable information not only dependent on time series. In addition, compared with the pure impact factors-based model, the introduction of time series model enables the model to make more effective use of historical information. This combination, through the verification of water demand data from a city of China, significantly improves the prediction accuracy of urban water demand and contributes to higher practical value. Moreover, the water demand prediction accuracy during high temperature weather and national statutory holidays are also well improved after being corrected by the muti-correction models. The major contributions of this paper are listed as follows:

- A better stacking model is proposed to strengthen the generalization ability of the hybrid model.
- High temperature compensation correction is introduced to improve the prediction accuracy.
- Holiday-type correction model is designed to enhance the prediction ability during national statutory holidays.
- Water quantity fluctuation correction model is constructed to reduce prediction instability.

The remainder of the paper is organized as follows. Prediction methods is mainly introduced in Sec.2. Then the data flow and the whole construct of proposed model are described in Sec.3. In Sec.4, the model prediction results are evaluated and compared with different models. Finally the conclusion is drew in Sec.5.

## 2. PREDICTION METHODS

### 2.1 Analysis of impact factors

To achieve high accuracy of prediction, the key is to make the optimal combination of multiple independent features that highly relevant with urban water demand. The features' datatype would be numerical as well as categorical. For numerical features, correlation analysis of numerical features is carried out to determine the most relevant factors for the prediction. $T_{cpt}$, $T_{max}$ and $T_{min}$ are the high temperature compensation feature, the daily maximum and minimum temperature. $D_{max}$ and $D_{min}$ are the daily maximum and minimum dew points. $H_{max}$ and $H_{min}$ are the daily maximum and minimum humidity. $W_{max}$ and $W_{min}$ are the daily maximum and minimum wind speed. $P_{max}$ and $P_{min}$ are the daily maximum and minimum atmosphere pressure.

The correlation coefficients between water demand and climatic impact factors are shown in table 1. It can be concluded that $T_{cpt}$, $T_{max}$ and $T_{min}$ are the most relevant factors for the urban water demand. Therefore, the selected numerical features consist of $T_{cpt}$, $T_{max}$ and $T_{min}$. As for the categorical feature, climate types(sunny, cloudy, rainy, etc.) are selected to be transformed into one-hot vector with 17 dimensions($V_{0\sim16}$). Then the input vector is obtained from combining the numerical features and the categorical feature as described in (1).

Table 1. Correlation coefficient ($r$) of factors and Water demand

| Impact factor | $r$ | Impact factor | $r$ |
|---|---|---|---|
| $T_{cpt}$ | 0.613 | $T_{max}$ | 0.580 |
| $T_{min}$ | 0.556 | $D_{max}$ | 0.532 |
| $D_{min}$ | 0.535 | $H_{max}$ | 0.032 |
| $H_{min}$ | -0.148 | $W_{max}$ | -0.062 |
| $W_{min}$ | -0.114 | $P_{max}$ | -0.472 |
| $P_{min}$ | -0.437 | – | – |

$$Input = [T_{cpt}, T_{max}, T_{min}, V_0, V_1, V_2, ..., V_{16}] \quad (1)$$

### 2.2 Design of stacking

Stacking is a technique whose purpose is to achieve a generalization accuracy(as opposed to learning accuracy) which is as high as possible. A set of base models are constructed from bootstrap samples of a dataset, then their outputs on a hold-out dataset are used as input to a meta-model. For the two layers stacking process, the set of base models are called first layer, and the meta-model are called second layer, see H.Wolpert (1992). However, the nonnegligible shortcoming of bootstrap samples, that is, when the amount of data is small(especially for short-term water demand forecast), it will repeatedly pick the same samples, which makes it easy to over-fitting. Therefore, this paper designs a better stacking models combined with $k$-fold cross validation. $K$-fold cross validation divides all samples into $k$ sample subsets with equal size, then traverse these k subsets in turn, taking the current subset as the validation set, and the rest subsets as the training set to train and evaluate the model. Thus, combined with cross validation and model stacking, the model can obtain as much effective information as possible from a limited amount of data, and reduce the probability of overfitting to some extent.

For the process of two layers stacking, supposing that there are $n$ models in the first layer and the amount of training data and testing data are denoted as j and k. In the training stage, stacking the output of $k \times n$ models in the first layer as the training input(with the shape of [j,n]) of the second layer model, then trains the models in the second layer. In the testing stage, because each model in the first layer makes $k$ predictions, averaging the $k$ predictions of each model and stacking them as the prediction input(with the shape of [k,n]) of the models in the second layer. At last, the final predictions are output by the second layer's model. This hybrid model makes Linear Regression(LR), see Quinlan (1986), which can effectively capture linear features that affect water demand consumptions, Decision Tree Regression(DT), see Quinlan (1986), which can choose features that are highly correlated with water demand as impact factors, Random Forest(RF), see Strobl et al. (2007), which can combine predictions into a better one, and Support Vector Regression(SVR), see Schölkopf (2003), which can find a properly hyperplane in high-dimensional space to make resonnable predictions, as the first layer models. The predictions made by first layer's models are stacked to create the training set to

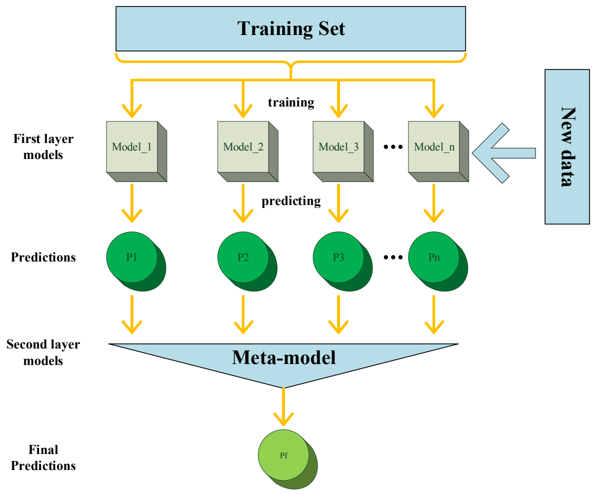


Fig. 1. Model Stacking procedure

train the second layer's model XGBoost, see Chen and Guestrin (2016). The whole Stacking procedure should be seen in Fig. 1. To be more specific, every model at first layer will be trained by five-fold cross validation, as shown in Fig. ??.

### *2.3 Design of Multi-correction mechanisms*

*High temperature compensation correction* Urban water demand is very sensitive to temperature changes, especially for hot weather condition(From the historical data of water demand, when the temperature is higher than 30 °C, there is obvious positive correlation between temperature and water demand). Under this condition, even 1 °C changes of temperature can cause a serious change in water demand. In order to capture the pattern between hot weather and urban water demand, this paper designs a high temperature compensation feature based on a logistic function which is introduced as (2), where $c$ denotes the maximum progressive value of the curve, $k$ denotes the growth rate of curve and $m$ denotes the median value of curve, respectively. This function has a saturation characteristic that fits the intrinsic mode, from the analysis of historical data, the increment of urban water demand is nearly saturated after the temperature exceeds a certain threshold. Also, the squashing property(it takes any real value and squashes it into the range between 0 and $c$) allows one to interpret outputs as probabilities of high temperature weather. Because the daily maximum temperature and the daily minimum temperature can roughly reflect the daily temperature, the high temperature comensation feature $T_{cpt}$ is obtained from the arithmatical average combination of $L(T_{max})$ and $L(T_{min})$ as described in (3).

$$L(T) = c/\left(1 + e^{-k(T-m)}\right) \tag{2}$$

$$T_{cpt} = 1/2 \times [L(T_{max}) + L(T_{min})] \tag{3}$$

*Remark 1.* In different regions, the intrinsic mode of high temperature weather and water demand is slightly different, and the corresponding three parameters in the function need to be adjusted appropriately according to the actual situation.

*Holiday-type correction* Special time periods such as rare weather, natural disasters, and national statutory holidays have a significant impact on urban water demand. Due to the randomness and unpredictability of the previous two cases, this paper designs a holiday-type water demand correction model based on interval division. In China, important national statutory holidays include National Day, New Year's Day, Spring Festival, Mid-Autumn Festival, etc. According to the change rule of water demand during holidays, this correction model divides the holiday into two sub-intervals such that the demand for water in the first interval is continuously decreasing, and the demand for water in the second interval is gradually increasing. Obtained from the historical data, the turning date(intersection of two subintervals) of the National Day is on the third day, which is October 3 of each year. For the other national statutory holidays, the turning date is on the day of the holiday. The division of interval of these holidays is shown in table 2. $T_{Holiday}$ is the date of the holiday. $T_{Holiday-n}$ is the first n days of the holiday and $T_{Holiday+n}$ is the after n days of the holiday.

In Decreasing/Increasing subinterval, the water demand decreases/increases gradually till the end. Using (4), water demand decrement of day t $\left(\delta_t^{decrement}\right)$ is obtained by the product of the average reduction ratio and the water demand of dat $t-1$. Water demand increment of day t $\left(\delta_t^{increment}\right)$ is obtained by the product of the average increase ratio and the water demand of day $t-1$ by using (5). The value of $N$ determines how many years' historical data are coverd and $L$ is the length of the decresing/increasing subinterval. $W_{t-1}$ is the water demand of day $t-1$ and $W_{td}$ is the water demand of the day on turning date.

$$\delta_t^{decrement} = \frac{W_{t-1}}{N \times L} \times \sum_{i=1}^{N} \left(W_{td-L}^i - W_{td}^i\right) \tag{4}$$

$$\delta_t^{increment} = \frac{W_{t-1}}{N \times L} \times \sum_{i=1}^{N} \left(W_{td}^i - W_{td+L}^i\right) \tag{5}$$

Using (6), the final prediction $\left(\hat{W}_t\right)$ of day t is obtained by combining the prediction $\left(\tilde{W}_t\right)$ of the stacked model and the empirical forecast $(W_{t-1} + \delta_t)$ of holiday-type correction model. $\bar{\epsilon_n}$ is the average prediction accuracy of the n days before day t. Thus, when the prediction accuracy of the stacked model at a low level, the holiday-type correction model will play a leading predictive role. On the other hand, when the accuracy of the stacked model at a high level, the correction model will play a reasonable auxiliary part of predicting.

$$\hat{W}_t = (1 - \bar{\epsilon_n}) \times (W_{t-1} + \delta_t) + \bar{\epsilon_n} \times \tilde{W}_t \tag{6}$$

*Water quantity fluctuation correction* As time goes by, the inherent laws of daily water demand will change, which will lead to over-predicted or under-predicted. And due to the unaviodable sporadic data anomalies, the model predictions will also be severely affected. These problems will further multiplies the difficulty of dispatching the urban water supply system.

In addition to the closely related impact factors aforementioned, urban water demand is also related to historical

Table 2. The division of interval of national statutory holidays

| National Statutory Holidays | Decreasing subinterval | Increasing subinterval | Turning date |
|---|---|---|---|
| Spring Festival | $[T_{SF-9}, T_{SF-8}, ..., T_{SF-1}, T_{SF}]$ | $[T_{SF}, T_{SF+1}, ..., T_{SF+8}, T_{SF+9}]$ | $T_{SF}$ |
| National Day | $[T_{ND-4}, T_{ND-3}, T_{ND-2}, ..., T_{ND+2}, T_{ND+3}]$ | $[T_{ND+3}, T_{ND+4}, ..., T_{ND+9}]$ | $T_{ND}$ |
| Tomb Sweeping Day | $[T_{TSD-3}, T_{TSD-2}, T_{TSD-1}, T_{TSD}]$ | $[T_{TSD}, T_{TSD+1}, T_{TSD+2}, T_{TSD+3}]$ | $T_{TSD}$ |
| Dragon Boat Festival | $[T_{DBF-3}, T_{DBF-2}, T_{DBF-1}, T_{DBF}]$ | $[T_{DBF}, T_{DBF+1}, T_{DBF+2}, T_{DBF+3}]$ | $T_{DBF}$ |
| New Year's Day | $[T_{NYD-2}, T_{NYD-1}, T_{NYD}]$ | $[T_{NYD}, T_{NYD+1}, T_{NYD+2}]$ | $T_{NYD}$ |
| Labor Day | $[T_{LD-2}, T_{LD-1}, T_{LD}]$ | $[T_{LD}, T_{LD+1}, T_{LD+2}]$ | $T_{LD}$ |
| Mid-Autumn Festival | $[T_{MAF-2}, T_{MAF-1}, T_{MAF}]$ | $[T_{MAF}, T_{MAF+1}, T_{MAF+2}]$ | $T_{MAF}$ |

sequences because of the urban water supply system has the characteristics of long-term circulation, and the urban water demand sequence has a strong autocorrelation, which means that the difference of water demand between the adjacent days are predictable. To avoid unresonable predictions, Water quantity fluctuation correction model is designed to predict difference sequence of water demand. Then the predicted difference is used to correct the water demand forecast, which not only solves the sporadic data anomaly problem, but also further improves the stability of the model prediction. The method of prediction is based on Long-Short Term Memory(LSTM), see Gers et al. (2000). The prediction of the difference $\left(\varepsilon_t^{t-1}\right)$ between day $t$ and day $t-1$ is obtained from feeding the Difference sequence of day $t-n$ to day $t-1$ into correction model. The difference sequence is described in (7). In LSTM model, Tanh function is used as the hidden update activation function. The hidden state of recurrent units at time t is computed by using (8∼13).

$$\mathbf{x}_t = \left[\varepsilon_{t-n}^{t-n-1}, \varepsilon_{t-n+1}^{t-n}, ..., \varepsilon_{t-1}^{t-2}\right] \tag{7}$$

$$\mathbf{i}_t = \sigma\left(\mathbf{W}_{xi}^T \cdot \mathbf{x}_t + \mathbf{W}_{hi}^T \cdot \mathbf{h}_{t-1} + \mathbf{b}_i\right) \tag{8}$$

$$\mathbf{f}_t = \sigma\left(\mathbf{W}_{xf}^T \cdot \mathbf{x}_t + \mathbf{W}_{hf}^T \cdot \mathbf{h}_{t-1} + \mathbf{b}_f\right) \tag{9}$$

$$\mathbf{o}_t = \sigma\left(\mathbf{W}_{xo}^T \cdot \mathbf{x}_t + \mathbf{W}_{ho}^T \cdot \mathbf{h}_{t-1} + \mathbf{b}_o\right) \tag{10}$$

$$\mathbf{g}_t = \tanh\left(\mathbf{W}_{xg}^T \cdot \mathbf{x}_t + \mathbf{W}_{hg}^T \cdot \mathbf{h}_{t-1} + \mathbf{b}_g\right) \tag{11}$$

$$\mathbf{c}_t = \mathbf{f}_t \otimes \mathbf{c}_{t-1} + \mathbf{i}_t \otimes \mathbf{g}_t \tag{12}$$

$$\mathbf{y}_t = \mathbf{h}_t = \mathbf{o}_t \otimes \tanh\left(\mathbf{c}_t\right) \tag{13}$$

$\otimes$ is the element-wise product and $\sigma$ is the sigmoid function. $\mathbf{W}_{xi}, \mathbf{W}_{xf}, \mathbf{W}_{x0}, \mathbf{W}_{xg}$ are the weight matrices of each of the four layers for their connection to the input vector $\mathbf{x}_t$. $\mathbf{W}_{hi}, \mathbf{W}_{hf}, \mathbf{W}_{h0}, \mathbf{W}_{hg}$ are the weight matrices of each of the four layers for their connection to the previous short-term state $\mathbf{h}_{t-1}$.$\mathbf{b}_i, \mathbf{b}_f, \mathbf{b}_o, \mathbf{b}_g$ are the bias terms for each of the four layers.

Due to the nonlinear nature of the Recurrent component, one of the main disadvantages of neural networks is that the scale of the output is not sensitive to the scale of the input. To overcome this drawback, the final difference prediction is decomposed into non-linear part and linear part, which are calculated by using (14) and (15). Autoregressive moving average(ARMA), see Brockwell and Davis (1987), is adopted as the linear part. Denote $v_t^R$ as the output of non-linear part(LSTM) and $v_t^L$ as the output of linear part(ARMA). $\gamma$ and $\theta$ are the coefficients of model ARMA. $\mu$ is a constant and $\xi$ is the errors. $\varepsilon_t$ is the final prediction of water quantity fluctuation correction model calculated by using (16).

$$v_t^R = \mathbf{W} \cdot \mathbf{h_t} + b \tag{14}$$

$$v_t^L = \mu + \sum_{i=1}^{p} \gamma_i v_{t-i}^L + \xi_t + \sum_{i=1}^{q} \theta_i \xi_{t-i} \tag{15}$$

$$\varepsilon_t = v_t^R + v_t^L \tag{16}$$

## 3. MODEL EVALUATION

### *3.1 Evaluation Metrics*

To evaluate the results of model prediction, two evaluation indicators are selected. Using (17) and (18), mean absolute percent error(MAPE) and mean squared error(RMSE) are obtained. $y_i$ denotes the real data of water demand and $\widehat{y}_i$ is the predicted value. The smaller the calculated values of these two indicators are, the more stable the prediction ability of the model is, and the better the prediction curve can fit the real curve.

$$\text{MAPE} = \sum_{i=1}^{n} \frac{|y_i - \widehat{y}_i|}{y_i} \frac{100}{n} \tag{17}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - \widehat{y}_i\right)^2} \tag{18}$$

### *3.2 Accuracy analysis of water demand forecasting with high temperature compensation*

To illustrate the effectiveness of the high temperature compensation, the prediction accuracy of different models before and after the introduction of high temperature compensation is compared in table 3 and table 4. The two data sets used for evaluation are taken from March 15, 2019 to April 15, 2019 and July 13, 2019 to August 13, 2019.

*Remark 2.* Since all the input features need to be standardized, the default value of parameter $c$ could be set to 1 and based on the analysis of the historical data, parameter $k$ and $m$ are set to be 0.6 and 30.

Table 3. Comparison of different models of data set 1

| Type | without compensation | | with compensation | |
|---|---|---|---|---|
| Indicators | RMSE | MAPE | RMSE | MAPE |
| LR | 38.21 | 6.13% | 35.82 | 5.70% |
| DT | 47.61 | 7.84% | 46.53 | 7.64% |
| RF | 45.41 | 7.44% | 43.89 | 7.16% |
| SVR | 42.33 | 6.88% | 40.13 | 6.48% |
| XGBoost | 39.42 | 6.35% | 37.64 | 6.03% |
| Stacked model | **34.51** | **5.46%** | **33.17** | **5.21%** |

In tabel 3, the data set 1 was taken from the spring of 2019(from March 15, 2019 to April 15, 2019), during which time the average daily temperature of this city is lower than 25°C. From the results above, it can be seen that although the temperature is not high, the high temperature compensation can still slightly enhance the ability of the model prediction.

Table 4. Comparison of different models of data set 2

| Type | without compensation | | with compensation | |
|---|---|---|---|---|
| Indicators | RMSE | MAPE | RMSE | MAPE |
| LR | 44.01 | 8.10% | 37.00 | 6.76% |
| DT | 49.92 | 9.18% | 40.97 | 7.48% |
| RF | 47.14 | 8.66% | 38.80 | 7.09% |
| SVR | 43.02 | 7.86% | 39.98 | 7.30% |
| XGBoost | 40.91 | 7.47% | 33.76 | 6.17% |
| Stacked model | **35.24** | **6.78%** | **31.16** | **5.34%** |

In table 4, the data set 2 was taken from the summer of 2019(from July 13, 2019 to August 13, 2019), during which time the average temperature is higher than 30°C. Compared with the results in table 3, it is obvious that, without compensation, the prediction ability of each model is worse under the condition of higher temperature, but the introduction of high temperature compensation can effectively make up for this disadvantage and reduce the prediction bias.

### *3.3 Accuracy analysis of water demand forecasting with holiday-type correction*

Urban water demand has dramatically changes during national statutory holidays, especially for those festivals with longer holidays. It is difficult for traditional models to capture this special quantity change characteristic because of the historical data of holidays are a tiny part of training set, which probably leads to underfit. Moreover, there is almost no difference in climatic conditions between holidays and non-holidays, which makes the model based on impact factors hardly to distinguish holidays from non-holiday. Without correction model, the accuracy of prediction during holidays is much lower than the accuracy during non-holiday. Among these national statutory holidays mentioned before, Spring Festival has the longest holiday and Mid-Autumn Festival is one of the shortest. Therefore, in table 5, 6, the accuracy results of different models' predictions during Spring Festival and Mid-Autumn Festival are compared before and after the adoption of holiday-type correction model.

Table 5. Comparison of different models of data set 3 during Spring Festival

| Type | without correction | | with correction | |
|---|---|---|---|---|
| Indicators | RMSE | MAPE | RMSE | MAPE |
| LR | 81.80 | 17.64% | 31.64 | 6.82% |
| DT | 85.98 | 18.54% | 34.72 | 7.49% |
| RF | 81.57 | 17.59% | 33.15 | 7.15% |
| SVR | 87.88 | 18.97% | 33.98 | 7.33% |
| XGBoost | 82.78 | 17.84% | 32.26 | 6.95% |
| Stacked model | **77.21** | **16.65%** | **28.84** | **6.22%** |

In table 5, the data set 3 was taken from the real water demand data of Spring Festival of 2019. According to table 2, the range of decreasing subintervals is from January 27, 2019 to February 5, 2019 and the range of the increasing subinterval is from February 5, 2019 to February 14, 2019. After the correction, the forecasting ability of the model during the Spring Festival is greatly improved.

Table 6. Comparison of different models of data set 4 during Mid-Autumn Festival

| Type | without correction | | with correction | |
|---|---|---|---|---|
| Indicators | RMSE | MAPE | RMSE | MAPE |
| LR | 55.75 | 11.08% | 29.08 | 5.78% |
| DT | 66.62 | 13.35% | 35.77 | 7.23% |
| RF | 62.99 | 12.41% | 31.45 | 6.26% |
| SVR | 64.86 | 12.73% | 32.64 | 6.49% |
| XGBoost | 58.77 | 11.61% | 26.87 | 5.31% |
| Stacked model | **49.61** | **9.82%** | **23.80** | **4.74%** |

In table 6, the data set 4 was taken from the real water consumption data of Mid-Autumn Festival of 2019, then the range of decreasing subintervals is from September 11, 2019 to September 13, 2019 and the range of the increasing subinterval is from September 13, 2019 to September 15, 2019. Compared with the results in table 5, before correcting, it can be concluded that models are more capable of predicting water demand for festival with shorter holidays and weaker of predicting for those with longer holidays. After correcting, the models' ability of predicting for festival with shorter holidays also considerably improved.

### *3.4 Accuracy analysis of water demand forecasting with water quantity fluctuation correction*

By introducing the water demand fluctuation correction model based on LSTM-ARMA, the difference sequence of water demand is modeled for difference prediction. The water quantity fluctuation correction model is the last correction mechanism, without loss of generality, choose the results corrected by aforementioned two correction mechanisms in table 4 and table 5, the final prediction results of different models are obtained and compared in table 7 and table 8.

*Remark 3.* The length of the sequence is set to be 7, which is to use the difference sequence of the first seven days to predict the water demand difference, then the predicted difference is used to correct the model predictions of water demand.

Table 7. Comparison of different models with/without quantity fluctuation correction model of data set 2

| Type | without correction | | with correction | |
|---|---|---|---|---|
| Indicators | RMSE | MAPE | RMSE | MAPE |
| LR | 37.00 | 6.76% | 13.93 | 2.09% |
| DT | 40.97 | 7.48% | 15.25 | 2.26% |
| RF | 38.80 | 7.09% | 14.60 | 2.15% |
| SVR | 39.98 | 7.30% | 15.24 | 2.25% |
| XGBoost | 33.76 | 6.17% | 14.05 | 2.10% |
| Stacked model | **31.46** | **5.75%** | **12.77** | **1.91%** |

From the results above, the water quantity fluctuation correction model significantly improves the generalization performance of all models.

### *3.5 Comparison between traditional models and proposed hybrid model*

After combining stacking method and muti-correction mechanisms, the prediction results of this hybrid model

Table 8. Comparison of different models with/without quantity fluctuation correction model of data set 3 during Spring Festival

| Type | without correction | | with correction | |
|---|---|---|---|---|
| Indicators | RMSE | MAPE | RMSE | MAPE |
| LR | 31.64 | 6.82% | 19.67 | 3.75% |
| DT | 34.72 | 7.49% | 20.42 | 4.09% |
| RF | 33.15 | 7.15% | 19.59 | 3.72% |
| SVR | 33.98 | 7.33% | 19.83 | 3.85% |
| XGBoost | 32.26 | 6.95% | 19.42 | 3.67% |
| Stacked model | **28.84** | **6.22%** | **18.44** | **3.38%** |

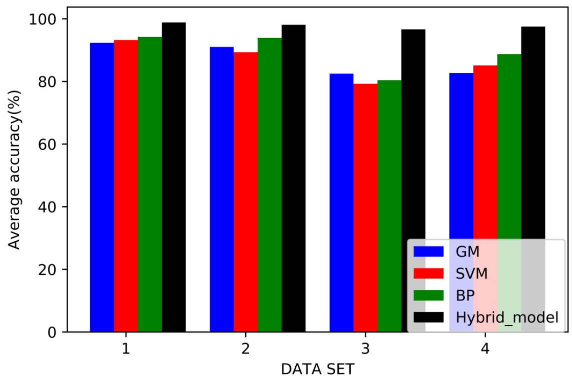


Fig. 2. Comparison between traditional models and hybrid model of four data sets

are compared with traditional models include GM, SVM, and BP(NN). See Fig. 2. Each model is evaluated by the four data sets mentioned previously.

From all the results in this section, it is evident that the proposed hybrid model has the best generalization performance, whether in a normal forecasting period or in a special forecasting period(high temperature weather period or during national statutory holidays).

## 4. CONCLUSION

In this paper, a better stacking model is proposed and it is examined to have the lowest generalization errors compared with other models. Moreover, multi-correction mechanisms are designed to solve the prediction problems that occur in different scenarios. The introduction of high temperature compensation feature effectively improves the prediction accuracy under high temperature condition. The construction of holiday-type correction model which combined prior knowledge and model predictions greatly reduce the prediction error during national statutory holidays. Finally, the LSTM-ARMA-based water demand fluctuation correction model is designed to mitigate unresonable changes of forecasting results caused by model itself and sporadic data anomaly. By combining these, the hybrid model has been tested to better solve the practical problems of urban water demand forecasting.

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