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# WAVELET TRANSFORM AND DAMPED RECURSIVE LEAST SQUARES METHOD FOR EVALUATION OF MEASUREMENT UNCERTAINTY IN EV CHARGING PILE METERS

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**Abstract**

To solve the problem of inaccurate estimation of relative errors in real-time monitoring of charging pile meters, a model is proposed based on the wavelet transform and damped recursive least squares (WT-DRLS) method to assess the measurement error and uncertainty of electric meters. An energy conservation equation for the charging pile power system is established, along with two variables representing energy conversion efficiency and measurement error. The estimated value of the energy conversion efficiency is obtained by using wavelet transform for noise reduction. Subsequently, a damped recursive least square method with a sliding window is developed to exclude disturbances from circuit load flow and external environmental factors, which enables the calculation of the measurement uncertainty of electric meters. The proposed method supports online monitoring of charging pile meter performance. Data from an actual DC charging station are collected for validation. The experimental results show that the proposed method is effective and stable and outperforms the state-of-the-art methods.

Keywords: electric vehicle charging piles, electric meters, wavelet transform, damped recursive least squares method, measurement uncertainty.

## 1. Introduction

Over time, the internal electronic components of *electric vehicle* (EV) charging pile meters undergo degradation due to thermal, electromagnetic, mechanical, and aging effects. This degradation compromises the reliability of their measurement results, which impacts the fairness and integrity of billing and affects the interests of numerous charging users [1, 2]. According to the prevailing electric meter rotation standards in various countries, at the end of their operational cycle charging pile meters are expected to be replaced [3]. However, this practice can lead to the unnecessary disposal of meters that are still functioning accurately, causing a considerable



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waste of hardware resources. Moreover, it places a substantial burden on electrical grid metering centres for verification, which leads to significant human and material resource expenditure. Given the uncertainty of actual on-site operating conditions, the measurement error of electric meters is susceptible to temperature, harmonics, voltage changes, and frequency fluctuations [4]. Consequently, determining the deviation status of smart meter measurements and controlling their performance becomes a critical concern.

Presently, the overall operation status of charging piles is generally inferred based on a certain proportion of sampling inspection, which decides whether to replace the entire group or to maintain their usage [5]. Yet, the constrained scope of random sampling carries the risk of omitting meters that have surpassed error thresholds. Additionally, the error status of functioning smart meters remains undetected between sampling intervals. As a result, meters exceeding their limits might operate for prolonged durations [6, 7]. Consequently, leveraging existing electricity measurement data to devise an efficient and precise method to detect measurement errors in smart meters is important.

Recently, the proliferation of smart grids has enhanced the availability of data for power companies, which has facilitated the adoption of online monitoring methods to evaluate the measurement performance of charging facilities. Such methods primarily involve the development of energy conservation models and the application of relevant algorithms to assess the relative error of electric meters [8, 9]. Yip *et al.* [10] designed two linear regression-based algorithms to analyse users' energy usage behaviour and determine their anomalous coefficients. This allows for the detection of defective smart meters in substations and identification of faulty ones. However, such method does not provide a specific error estimation for smart meters. Kong *et al.* [11] proposed an online estimation method for determining the operational error of meters. This method uses clustering to screen similar measurement data of each meter, and then establishes relationships between the master meter, submeters, and line losses. Finally, the parameters are estimated by a dual-parameter recursive least squares algorithm. However, the model is susceptible to ill-conditioned problems. Liu *et al.* [12] employed decision trees to filter abnormal data and classify data based on estimated line loss rates. They created an operational error analysis matrix for electric meters to remotely estimate the operational error of smart meters. Ma *et al.* [13] considered severe measurement errors in electric meters operating under extreme natural conditions. They developed an improved kernel support vector regression and optimized adaptive genetic algorithm to propose a new multisource feature fusion framework for error prediction. However, the method only has a monthly temporal resolution and cannot achieve real-time prediction. Additionally, the error-prone voltage method is used to construct a network loss parameter model, which leaves room for improvement in applicability and accuracy.

With the ongoing advancements in deep learning, researchers have started using neural networks to analyse the measurement performance of smart electric meters [14, 15]. Duan *et al.* [16] proposed a novel recursive neural network prediction algorithm that incorporates data decomposition techniques and error decomposition correction methods, although it does not address hyperparameter tuning. Sehovac *et al.* [17] developed a sequence-to-sequence neural network prediction model to improve the accuracy of long time series prediction. Liu *et al.* [18] proposed a method based on long short-term memory networks and improved convolutional neural networks to detect faulty smart electric meters. However, this approach requires additional information such as meter voltage and current, which imposes higher requirements for data collection and storage devices and limits its widespread application.

Although the aforementioned researchers have proposed valuable ideas for the online detection of electric meter measurement performance, there are still several limitations:

1. Estimating line losses often requires certain structural parameters of the distribution network, without which reliable results cannot be obtained.

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2. Directly incorporating line losses into the energy conservation model often leads to significant errors due to the frequent and intense variations in line losses, which greatly affects the estimation of meter relative error.
3. Due to the influence of circuit load flow and network operating conditions, each estimation of meter relative error experiences substantial fluctuations, reducing the stability, accuracy, and applicability of traditional models.

To address these issues, this paper proposes an online monitoring method to measure the performance of charging pile electric meters based on *wavelet transform and damping recursive least squares* (WT-DRLS). This method offers several main contributions. First, the electric grid system structure of charging piles, characterized by its simplicity with short circuit lengths and absence of additional appliances, permits the neglect of line losses. However, in the case of measurement uncertainty estimation of charging piles, unlike traditional distribution network systems, there exists the problem of calculating energy conversion efficiency. In response, this paper adopts a system identification approach and applies wavelet transform to deal with the observed values of energy conversion efficiency. Second, the damped recursive least squares method is employed to address noise disturbances in relative error. Last, a sliding window design is incorporated to calculate measurement uncertainty in electric meters, facilitating the online monitoring of charging pile meter performance.

## 2. Estimation of Energy Conversion Efficiency Based on Wavelet Transform

### *2.1. Establishment of Energy Conservation Equation for Charging Pile Electric Grid System*

Compared to traditional distribution network systems [19–21], charging stations have simpler electric grid lines. The topology structure, as shown in Fig. 1, demonstrates that each charging pile is equipped with a submeter to monitor electric energy consumption while charging electric vehicles. The master meter is connected to all charging piles, transmitting data collected from the submeters and master meter to the information collection platform through a local area network. Unlike household electric grids, the electric grid system of charging piles does not have complex transmission lines, which results in negligible line loss. However, the submeters at charging piles record electric energy consumption during vehicle charging, where again conversion efficiency is crucial. Therefore, the relative error of the submeter is expressed as follows:

$$\varepsilon = \frac{W_o - \eta_t w_t}{\eta_t w_t}, \tag{1}$$

where $W_o$ is the observed value of consumed energy, $w_t$ is the true value of consumed energy, and $\eta_t$ is the conversion efficiency.

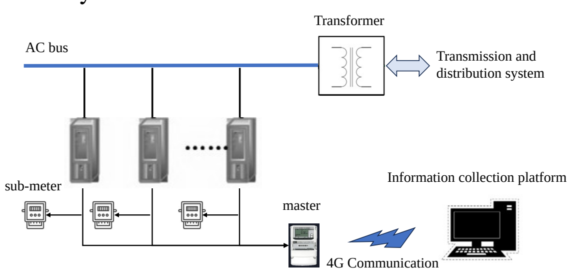


Fig. 1. Topology of electric vehicle charging pile.

For electric energy data, since electric meters measure the cumulative electricity consumption on their branch, it is necessary to perform first-order differencing to obtain the observed value of energy consumption at the charging piles:

$$w_o = w_{i+1} - w_i, \tag{2}$$

where $w_i$ is the energy reading of the electric meter at the $i$-th sampling moment.

From this, the error coefficient for the $m$−th submeter is constructed as follows:

$$\xi_m = \frac{1}{(1 + \varepsilon_m)}, \tag{3}$$

Finally, the equation describing the process of the energy conservation for the electric grid system composed of charging piles is as follows:

$$\begin{bmatrix} y^1 \\ y^2 \\ \vdots \\ y^t \end{bmatrix} = \begin{bmatrix} w_1^1 & w_2^1 & \cdots & w_m^1 \\ w_1^2 & w_2^2 & \cdots & w_m^2 \\ \vdots & \vdots & \vdots & \vdots \\ w_1^t & w_2^t & \cdots & w_m^t \end{bmatrix} \begin{bmatrix} \xi_1/\eta_1 \\ \xi_2/\eta_2 \\ \vdots \\ \xi_m/\eta_m \end{bmatrix}, \tag{4}$$

where $y^t$ is the total energy consumed by all charging piles during the $t$ sampling period and $w_m^t$ is the energy consumed by the $m$−th charging pile during the t sampling period.

During the initial and final phases of charging, the charging efficiency significantly changes and does not adequately reflect the current measurement performance of the smart meter. However, during the stable charging process, the energy conversion efficiency should remain constant. Therefore, the data from each entry into stable charging are used for calculation, assuming a constant conversion efficiency $\eta$. To prevent coupling of the two variables in the calculation process, the energy loss can be extracted from the error coefficient because it is related to the total energy consumption. Hence, the energy conservation equation can be reformulated as follows:

$$\mathbf{Y} = \frac{\mathbf{W}_o \times \xi_m}{\eta} + \sigma, \tag{5}$$

where $\mathbf{Y}$ is the column vector composed of $y^t$, $\mathbf{W}_o$ is the matrix composed of $w_m^t$, and $\sigma$ is the system error term.

### *2.2. Estimation of Energy Conversion Efficiency*

As energy loss is directly related to the total consumed energy of all charging piles, (4) cannot be solved directly using the least squares method. It is necessary to first calculate the energy conversion efficiency, which is associated with the energy conversion loss. The observed value of the energy conversion loss $\zeta_0$ is given by:

$$\zeta_o = y - \sum_{i=1}^{m} w_i, \tag{6}$$

where $y$ is the total energy consumed by all charging piles and $w_i$ is the energy consumed by the $i$−th charging pile.

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It is assumed that the energy conversion efficiency $\eta$ comprises the true value of the energy loss, the noise in the energy conversion loss, and the error noise:

$$\eta = \left(1 - \frac{\zeta_o}{y}\right) + \sigma_{\text{loss}} + \sigma_{\text{error}}, \tag{7}$$

where $\sigma_{\text{loss}}$ is the noise in the energy conversion loss and $\sigma_{\text{error}}$ is the error noise, both of which have zero means but different variances.

Therefore, this paper utilizes the wavelet transform to denoise the energy conversion efficiency obtained from (7). After wavelet decomposition, the wavelet coefficients with larger amplitudes are considered useful signals, while those with smaller amplitudes are generally noise. It is assumed that the wavelet coefficients of useful signals are greater than those of noise. The selection of a threshold value is crucial in wavelet denoising. Thus, a heuristic threshold rule is applied. When the signal-to-noise ratio is large, the unbiased risk estimation rule is utilized:

$$\lambda'(t) = \frac{n - 2t + \sum\limits_{i=1}^{t} \eta(i) + (n-t)\eta(t)}{n}, \tag{8}$$

$$\lambda_1 = \sqrt{\min\left(\lambda'(t)\right)}, \tag{9}$$

where $n$ is the length of the energy conversion efficiency series.

When the signal-to-noise ratio is low, a universal threshold rule is used:

$$\lambda_2 = \sigma\sqrt{2\ln N}, \tag{10}$$

where $\sigma$ is the standard deviation of the noise signal and $N$ is the total number of wavelet coefficients.

The heuristic threshold rule used in this article is calculated as follows [22, 23]:

$$e = \frac{\sum\limits_{i} x_i^2 - n}{n}, \tag{11}$$

$$c = \frac{[\log(n)/\log 2]^{3/2}}{\sqrt{n}}, \tag{12}$$

$$\lambda = \left\{ \begin{array}{cc} \lambda_2, & e < c \\ \min(\lambda_1, \lambda_2), & e \geq c \end{array} \right., \tag{13}$$

where $\lambda_1$ is the threshold obtained from the unbiased risk estimation rule and $\lambda_2$ is the threshold obtained from the universal threshold rule.

After determining the threshold rule, the wavelet denoising process for the energy conversion efficiency series can be conducted in three steps:

1. An appropriate wavelet base function and decomposition level are selected to perform a wavelet orthogonal transform on the series, decomposing it into different frequency subbands.
2. Nonlinear threshold processing is applied to the high-frequency wavelet transform coefficients obtained at each decomposition level, while the low-frequency coefficients are left unchanged.
3. The wavelet inverse transform is performed using the low-frequency coefficients of the final layer of decomposition and all the processed high-frequency coefficients to obtain the estimated value of the energy conversion efficiency.

## 3. Estimation of Measurement Uncertainty Based on Damped Recursive Least Squares and the Sliding Window Algorithm

### 3.1. Estimation of Relative Error

After applying wavelet denoising, the energy conversion efficiency from (5) can be utilized to solve for the error coefficients. To account for the influence of the power system load flow and current disturbances, the *damped recursive least squares* (DRLS) method is employed to determine these error coefficients.

The model input matrix consists of the observed matrix $\mathbf{W}_o$ of the energy consumed by the charging piles and the total consumed energy matrix $\mathbf{Y}$. The model parameter matrix is set as follows:

$$\boldsymbol{\theta} = \frac{1}{1+\boldsymbol{\varepsilon}}. \tag{14}$$

The energy conservation equation can be rewritten as follows:

$$\eta\mathbf{Y}(t) = \mathbf{W}_o(t) \times \boldsymbol{\theta} + \sigma, \tag{15}$$

where $\sigma$ represents the undetectable noise term with a mean of 0 and is unaffected by the model parameters.

Equation (15) can be solved using the DRLS method [7]. The purpose of adding a damping coefficient is to penalize the objective function when the difference between the estimates at times t and (t – 1) increases, thus limiting the range of parameter estimation changes, reducing environmental disturbances, and suppressing the volatility of the solution. The objective function $J(t)$ is:

$$J(t) = (\mathbf{Y}(t) - \mathbf{W}_o(t)\hat{\theta}(t))\mathbf{\Psi}(t)(\mathbf{Y}(t) - \mathbf{W}_o(t)\hat{\theta}(t))^T + \lambda(\hat{\theta}(t) - \hat{\theta}(t-1))^T(\hat{\theta}(t) - \hat{\theta}(t-1)), \tag{16}$$

$$\mathbf{\Psi}(t) = \begin{bmatrix} \rho\mathbf{\Psi}(t-1) & 0 \\ 0 & 1 \end{bmatrix}, \tag{17}$$

where $\mathbf{\Psi}(t)$ is the weight matrix and $\rho$ is the weight factor. When $\rho < 1$, the weight of the historical data decays exponentially. $\hat{\theta}(t)$ represents the estimated model parameters, and $\lambda$ is the damping factor.

Setting the first derivative of $J(t)$ with respect to $\hat{\theta}$ to zero minimizes the objective function. The final parameter estimation process for the DRLS method is as follows:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + \rho\lambda\mathbf{P}(t)\left[\hat{\theta}(t-1) - \hat{\theta}(t-2)\right] + \mathbf{P}(t)\mathbf{W}_o(t)^T[\mathbf{Y}(t) - \mathbf{W}_o(t)\hat{\theta}(t-1)], \tag{18}$$

where $\mathbf{P}(t)$ is the covariance matrix, defined as:

$$\mathbf{P}(t) = [(1-\rho)\lambda\mathbf{I} + \rho\mathbf{P}(t-1)^{-1} + \mathbf{W}_o(t)^T\mathbf{W}_o(t)]^{-1}, \tag{19}$$

### 3.2. Calculation of Measurement Uncertainty

The solution $\hat{\theta}(t)$ from (18) provides the current moment parameter estimates. However, the relative error of electric meters fluctuates during actual measurement. Thus, it is necessary to calculate the measurement uncertainty of the meter to assess its stability.

Assuming that the measurement performance of the electric meter does not change in a short period, the measurement uncertainty evaluation method can be applied to a sliding window of length $m$ [24, 25], which can be as follows:

$$\overline{\varepsilon} = \mathrm{mean}\,(\hat{\varepsilon}), \tag{20}$$

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$$u_A = k \times \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}(\hat{\varepsilon}_i - \overline{\varepsilon})^2}, \tag{21}$$

where $\hat{\varepsilon}$ is the matrix of estimated relative errors for a submeter, $\overline{\varepsilon}$ is the mean relative error for the current sliding window, and $u_A$ is the measurement uncertainty, and $k$ is the expansion coefficient related to the confidence level.

Finally, the measurement uncertainty of the meter is represented as $\overline{\varepsilon} \pm u_k$. The operational performance of the meter can be assessed based on whether the limits of measurement uncertainty exceed national standards. If the meter is within normal limits, the monitoring continues. However, if the limits are exceeded, the operation and maintenance department should be alerted for onsite verification to determine whether the charging pile meter needs to be replaced. The complete process of online monitoring of charging pile measurement performance is depicted in Fig. 2.

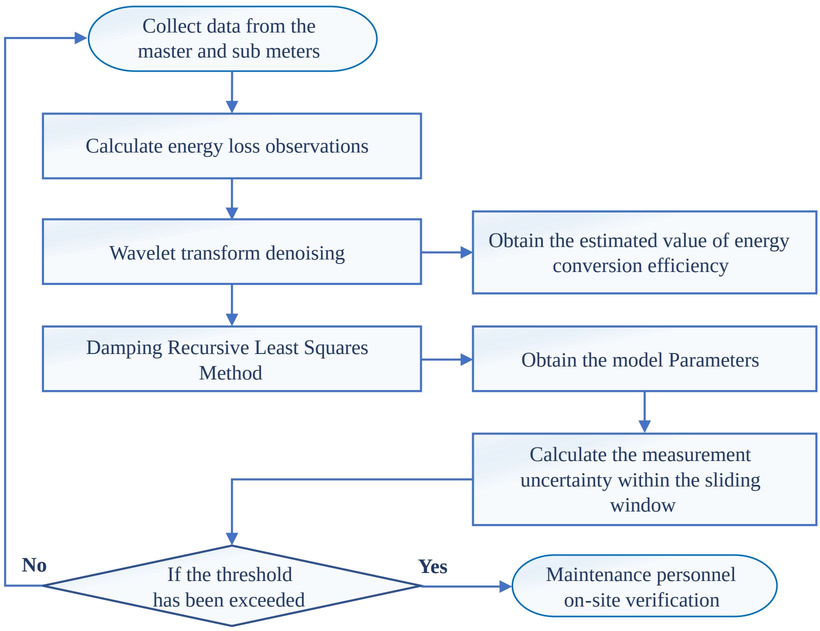


Fig. 2. Charging pile measurement performance analysis flowchart.

## 4. Experimental Case Study

### *4.1. Calculation of Energy Conversion Efficiency*

This model is focused on conducting a measurement error and uncertainty analysis of DC charging piles. To verify the effectiveness of the proposed method, data collected from a DC charging station in 2022 is utilized for experimentation. The measurement and acquisition system is shown in Fig. 3. The setup consists of one DC energy metering collection device (Master) with six DC charging piles situated beneath it, with a sampling period of 15 min. There is a communication unit in every meter that transfers necessary electric parameters to the concentrator via a Lora wireless module. Then, the concentrator transmits all connected data to the information acquisition platform with the 4G technique. A total of 60 data points for the charging piles are collected for validation.

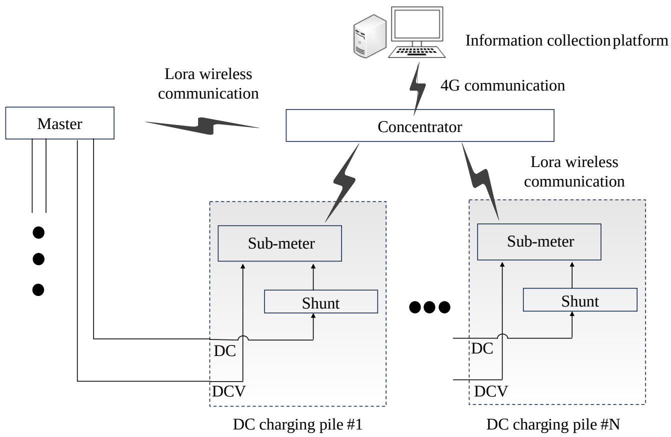


Fig. 3. Measurement and acquisition system.

Initially, data for 672 sampling periods, equivalent to 7 days, were collected. Given that electricity is a cumulative measurement, a preprocessing step involving first-order differencing was carried out. Additionally, any randomly encountered missing or outlier values during data collection and transmission were removed prior to inputting the data into the model. Subsequently, the observed values of energy conversion efficiency for the charging piles were calculated as presented in Section 2 and depicted in Fig. 4. The red dotted lines are the upper and lower limits of 3-sigma, indicating that the observed data contains a large amount of random noise and unreasonable observed nonsense values. For example, the energy conversion efficiency at point 1 reaches 100.536%, which exceeds 100%. To address this, wavelet denoising was performed, resulting in estimated energy conversion efficiency values for the charging piles, as shown in Fig. 5. The estimated values are largely stable at 94.04%. This aligns with the assumption in Section 2 that the energy conversion efficiency during steady charging remains constant. If the filtered curve shows obvious fluctuations, it indicates that the charging system has problems and requires timely maintenance by the staff. Furthermore, laboratory field tests conducted on this type of DC charging pile demonstrated an energy conversion efficiency of 94.69%, which is close to the results calculated in this study. This validates the feasibility of the constructed model.

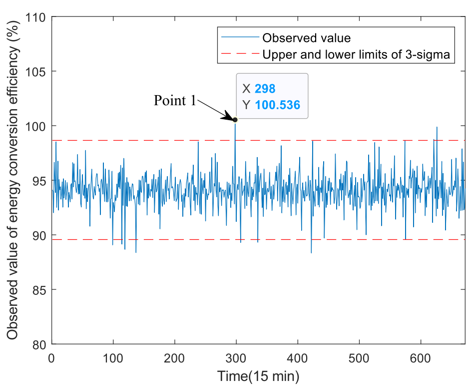


Fig. 4. Observation of energy conversion efficiency of the charging pile.

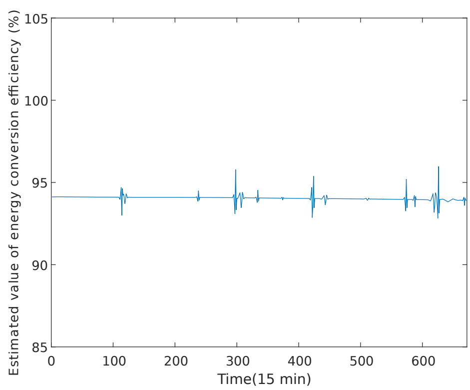


Fig. 5. Estimation of the energy conversion efficiency of the charging pile.

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### *4.2. Comparative Analysis of Experimental Results*

The calculated energy conversion efficiency was incorporated into (5), and the DRLS method was utilized to solve for the estimated relative errors. The model parameters are presented in Table 1. The *root mean square error* (RMSE) and *mean absolute error* (MAE) are utilized as evaluation metrics. These metrics are defined as follows [26]:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - f(i))^2}, \tag{22}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - f(i)|, \tag{23}$$

where $n$ is the number of samples, $y_i$ is the actual value, and $f(i)$ is the predicted value.

Table 1. Parameters of WT-DRLS.

| **Type** | **Parameters** |
|---|---|
| Wavelet transform level | 9 |
| Wavelet base | Daubechies 3 |
| DRLS sliding window length | 672 |
| Measurement uncertainty sliding window length | 96 |
| Damping factor | 0.005 |
| Weight factors | 0.7 |

To validate the effectiveness of the proposed model, comparisons were made with the *limit memory recursive least squares method* (LMRLS), *damping recursive least squares method* (DRLS), and K-means-BP models. As shown in Fig. 6, the LMRLS and K-means-BP models demonstrated significant deviations between their estimated and actual values, with some estimates surpassing the error limit of 2%. This can lead to misjudgement of how electric meters function normally. The DRLS model also exhibited lower accuracy. Based on the evaluation metrics presented in Table 2, the proposed model achieved an RMSE of 0.3392% and an MAE of 0.2478%, outperforming the comparative models.

Table 2. Comparison of performance evaluation indicators of different models.

| **Model** | **RMSE (%)** | **MAE (%)** |
|---|---|---|
| WT-DRLS | 0.3392 | 0.2478 |
| LMRLS | 0.8554 | 0.6664 |
| DRLS | 1.0053 | 0.8589 |
| K-means-BP | 1.0421 | 0.9277 |

Considering that Fig. 6 represents a single calculation of average relative error, it was observed that the calculation results for each meter varied significantly. Given the unlikelihood of an actual electric meter's performance changing within a short period, it is necessary to calculate the meter's uncertainty to accurately represent its measurement performance. To this end, the sliding window size was set to 96 relative errors, and calculations were conducted for Meter number 1 using

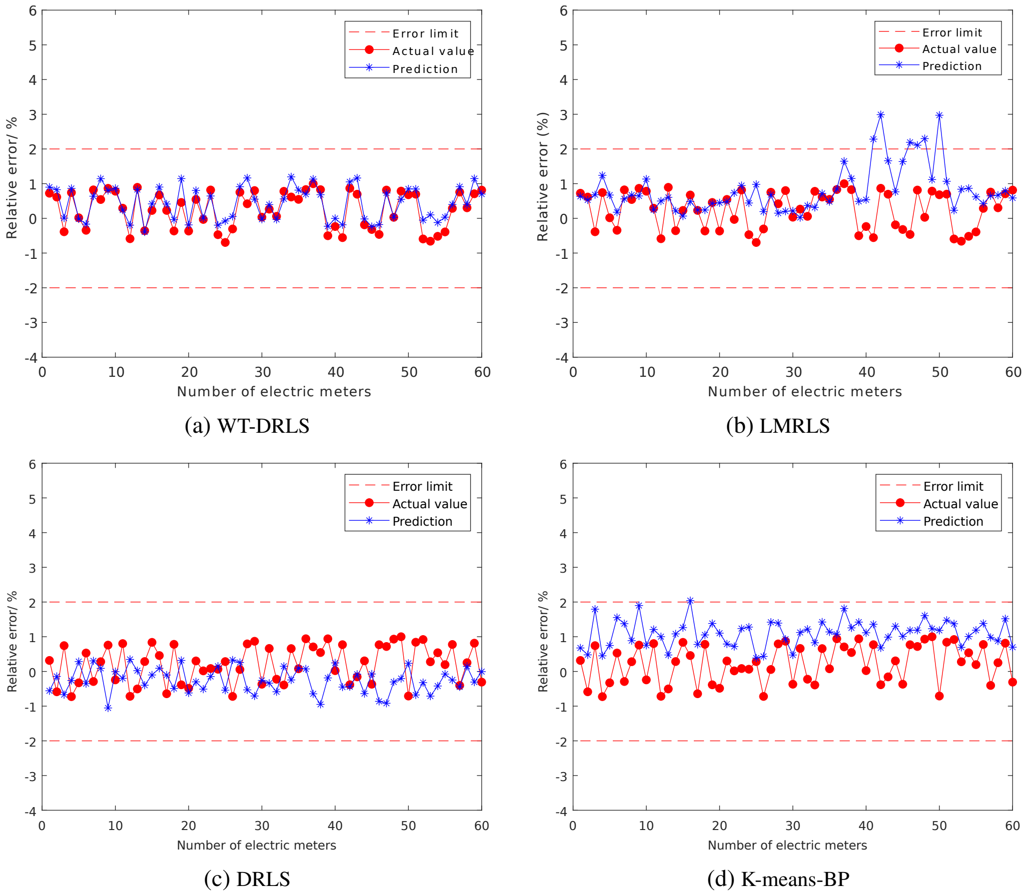


Fig. 6. Relative error estimation results for different models.

various models, as shown in Table 3. The LMRLS and K-means-BP models resulted in larger uncertainty intervals, indicating poor model stability. In contrast, the proposed model produced a smaller uncertainty interval that closely aligned with the actual measured uncertainty. This demonstrates the model's strong resistance to power system load flow and external environmental disturbances and robustness and reduced likelihood of misjudging or missing the measurement performance of electric meters.

Table 3. Comparison of measurement uncertainty between different models.

| **Model** | **Measurement uncertainty (%)** |
|---|---|
| True value | 0.78140.1374 |
| WT-DRLS | 0.73590.1759 |
| LMRLS | 0.91610.8372 |
| DRLS | –0.42270.2887 |
| K-means-BP | 1.23610.6083 |

## 5. Conclusions

Online monitoring of the measurement performance of charging piles plays a crucial role in safeguarding the interests of both charging users and operational and maintenance departments. However, the state-of-the-art methods fail to fully meet practical application requirements as they are susceptible to power system load flow and environmental factors,. As a result, this paper proposes a WT-DRLS method to monitor the measurement performance of electric meters. The proposed method first removes system noise and error noise using wavelet transform from the perspective of system identification, in order to solve the energy conversion efficiency of DC charging piles during charging and determine whether they are in a normal charging state. Secondly, DRLS is used to solve the energy conservation equation for accurate identification of error parameters. Finally, the relative error and measurement uncertainties are calculated to assess the operating status of electric meters, thereby enhancing the accuracy of evaluating meter measurement performance. Through comparisons with the state-of-the-art methods in practical applications, the proposed method demonstrates its successful monitoring capability.

However, it is important to note that the proposed model has only been verified using DC charging piles in one region. The effectiveness of model in monitoring the measurement performance of AC charging piles and charging piles under different environmental conditions remains unknown. Moreover, this study primarily focuses on a typical charging station topology structure. Further research is needed to explore other types of topological structures and increase model versatility.

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