Real-Time Identification of Power Fluctuations based on LSTM Recurrent Neural Network: A Case Study on Singapore Power System

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***Abstract*—Fast and stochastic power fluctuations caused by renewable energy sources and flexible loads have significantly deteriorated the frequency performance of modern power systems. Power system frequency control aims to achieve real-time power balance between generations and loads. In practice, it is much more difficult to exactly acquire the values of unbalance power in both transmission and distribution systems, especially when there is a high penetration level of renewable energies. This paper explores a deep learning approach to identify active power fluctuations in real-time, which is based on a long short-term memory (LSTM) recurrent neural network (RNN). The developed method provides a more accurate and faster estimation of the value of power fluctuations from the real-time measured frequency signal. The identified power fluctuations can serve as control reference so that the system frequency can be better maintained by automatic generation control, as well as emerging frequency control elements such as energy storage system. A detailed model of Singapore power system integrated with distributed energy storage systems is used to verify the proposed method and to compare with various classical methods. The simulation results clearly demonstrate the necessity for power fluctuation identification, and the advantages of the proposed method.**

***Index Terms*— Power fluctuation identification, deep learning, recurrent neural network, long short-term memory, Singapore power system.**

I. Introduction

With the large-scale penetration of renewable energy sources, modern power systems are facing operational challenges due to the uncertainties and intermittent nature of renewables [1]. In order to compensate the fast power fluctuations caused by the stochastic renewable energy, more effective load frequency control (LFC) methodologies are needed. However, the power mismatch between inter-connected areas, the uncertainties of distributed generators, model parameters and load demands have significantly increased the complexity of the LFC problem [2].

In the traditional LFC, the area control error (ACE) is formed as a control signal by weighted frequency and tie-line power exchanges. To ensure the dynamic stability of a power system, proportional-integral (PI) controllers are extensively utilized to regulate the ACE and frequency deviations of a power system [3]. Even though several intelligent optimization methods are explored to tune PI parameters [4]-[6], the optimal PI parameters for the traditional LFC are still difficult to be determined and may vary when the system operating condition changes.

To improve the controller performance, the method of disturbance observer has been employed to estimate the power fluctuations for LFC. Liao et al. [7] proposed a novel robust load frequency control framework for multi-area power systems based on a second-order sliding mode control and an extended disturbance observer. Ma et al. [8] developed a fuzzy model predictive control scheme for a hypersonic vehicle system, which was based upon an adaptive neural network disturbance observer. Wang et al. [9] designed a new frequency control method based on a disturbance observer and double sliding mode controllers for a hybrid isolated microgrid. Kurita et al. [10] utilized a disturbance observer to obtain the amount of fluctuation and the control of an energy storage system was realized herein. Some other approaches such as distributed control [11], robust control [12], and model predictive control [13] are also developed to improve the performance of the LFC, but the efficiency and response speed of these methods heavily depend on the estimated unbalance power.

In recent years, deep learning has shown the promising capability to solve complex nonlinear engineering problems. Kong et al. [14] proposed a prediction framework based on the long short-term memory (LSTM) recurrent neural network (RNN) to solve the short-term load forecasting problem for individual residential households. A radial basis function neural network was employed for the short-term load demand prediction in [15]. Yu et al. [16] developed a transient stability

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assessment system based on the LSTM network to balance the trade-off between assessment accuracy and response time. Yao et al. [17] presented a semi-supervised deep learning model for soft sensor development based on the hierarchical extreme learning machine. The deep network structure of auto-encoder was first implemented for unsupervised feature extraction and the prediction performance was greatly improved.

To the best of the authors' knowledge, the on-line identification for power fluctuations through a data driven method has rarely been reported. Existing research works on power fluctuations estimation in LFC are mostly based on disturbance observers [7]-[10]. However, owing to the increased penetration of renewable energy sources and controllable loads, the fast and stochastic power fluctuations can significantly deteriorate the power system's frequency performance. This paper aims to make full use of deep learning techniques for accurately estimating real-time power unbalance from frequency measurements. The main contribution of this paper can be concluded as follows.

1) A real-time power fluctuation identification tool based on a long short-term memory recurrent neural network is designed to provide an accurate control reference for the LFC to regulate the power system frequency.
2) The well-trained LSTM is applied online to identify the real-time power fluctuations from the measured frequency. With the help of the identified power fluctuations, the frequency can be maintained within a stable state by the control elements such as synchronous generators and ESSs.
3) A model of the Singapore power system is developed with realistic data of power and frequency fluctuations, which comprises combined cycle gas turbines (CCGT), a photovoltaic (PV) generation, distributed energy storage systems (DESSs) and loads. The proposed algorithm is tested on this platform and compared with various classical algorithms.

The rest of this paper is organized as follows: Section II puts forward with an explorative data analysis to visualize the necessity of the power fluctuation identification. Section III proposes the method of LSTM RNN. Section IV conducts serval case studies to demonstrate the efficiency of the proposed algorithm. Section V verifies the tuned neural network and introduces a real application into the frequency disturbance recorder. Section VI draws the conclusion.

II. PROBLEM STATEMENT

A. Power System LFC

The goals of the LFC are to mitigate power fluctuations and to control the frequency of each area back to its nominal value (e.g. 50Hz). A typical configuration of a LFC model in the non-reheated power system is described by Fig. 1.

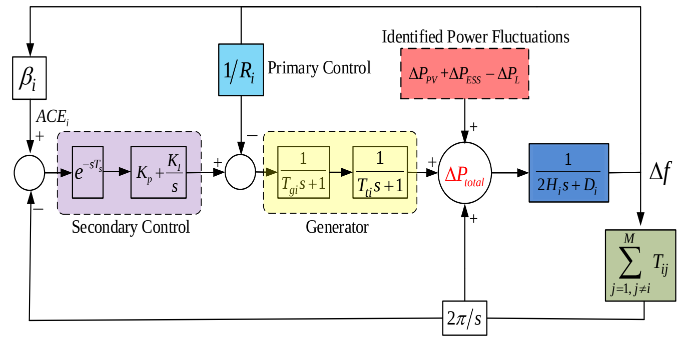

Fig. 1. The configuration of the LFC model in power system

The frequency dynamics of the LFC model can be represented by the differential equations shown in (1)-(4).

$$\Delta\dot{f}_i = \frac{1}{2H_i}\Delta P_{mi} - \frac{1}{2H_i}\Delta P_{Li} - \frac{D_i}{2H_i}\Delta f_i - \frac{1}{2H_i}\Delta P_{tie,i} \tag{1}$$

$$\Delta\dot{P}_{mi} = \frac{1}{T_{ti}}\Delta P_{gi} - \frac{1}{T_{ti}}\Delta P_{mi} \tag{2}$$

$$\Delta\dot{P}_{gi} = \frac{1}{T_{gi}}\Delta P_{ci} - \frac{1}{R_i T_{gi}}\Delta f_i - \frac{1}{T_{gi}}\Delta P_{gi} \tag{3}$$

$$\Delta\dot{P}_{tie,i} = 2\pi \sum_{j=1,\, j\neq i}^{N} T_{ij}(\Delta f_i - \Delta f_j) \tag{4}$$

where i is the area number; Δf_i , ΔP_{mi} , ΔP_{gi} denote the frequency deviation, mechanical output of the synchronous machine, and valve position, respectively; ΔP_{ci} , $\Delta P_{L,i}$, and $\Delta P_{tie,i}$ are the output of controller, the load variations, and the mismatch between the actual and the scheduled power flows respectively; T_{ij} is the tie-line synchronization coefficient between area i and area j; H_i , D_i , T_{gi} , T_{ti} , R_i denote the inertia of the synchronous machine, machine damping coefficient, time constant of the governor, time constant of the turbine, and speed drop, respectively.

Note that the power interchange (ΔP_{totali}) plays a critical role in the performance of LFC and (5) presents its effect on system frequency.

$$\Delta P_{totali} = \Delta P_{Gi} - \Delta P_{Li} + \Delta P_{ESSi} + \Delta P_{PVi} = 2H_i\frac{d\Delta f_i}{dt} + D\Delta f_i \tag{5}$$

The LFC in a power system should ensure zero steady state error for frequency and tie-line power deviations when power fluctuations occur. However, in fact, the values of power fluctuations are difficult to be estimated because of the increasing integration of renewable energy sources, electric vehicles and responsive loads [18].

B. General Idea

Owing to the high dependency on the frequency deviation and net power interchange, LFC models can hardly exhibit a good dynamic performance without an accurate reference. Furthermore, traditional LFC models cannot capture the fast frequency deviation especially in the presence of other destabilizing effects, such as parameter variations and system nonlinearities.

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In order to accurately identify the real-time power fluctuations in the power system, this paper proposes a data-driven method, which provides a more accurate reference for LFC to enhance the power system frequency performance.

In this regard, a machine learning algorithm is crucial to realizing a better identifying performance since frequency and power fluctuations show strong diversity and complexity in a super short-term level. Since the frequency fluctuations essentially result from the power fluctuations, the present frequency fluctuation may have a hidden relationship with previous power fluctuations in a very short term. In other words, a fast small power fluctuation and a slowly large power change may lead to similar frequency fluctuations. For instance, as shown in Fig. 2, even though there is only a 0.026 Hz frequency fluctuation happened in 136 seconds, the power fluctuation is increased dramatically by 69.65 MW. Moreover, there is the same frequency fluctuation of 0.026 Hz occurred in 30252 seconds, but the power fluctuation rises to 152.34 MW, indicating that the present frequency fluctuation depends on the previous variations. Additionally, the power and frequency fluctuations vary differently in different time periods, which requires the algorithm to accurately abstract previous features from fluctuation variations and to establish a correlation between the abstraction and identification target. The LSTM algorithm is regarded as an effective solution because of its higher accuracy and ideal capability of feature abstraction of input and output patterns no matter these patterns are linear or nonlinear [14], [16]. In the identification problem, the LSTM recurrent neural network is expected to be able to identify power fluctuations in very short term (e.g., second) from the various patterns of historical frequency data. Based on the identified power fluctuations, the system frequency can be rapidly regulated within a specified limit.

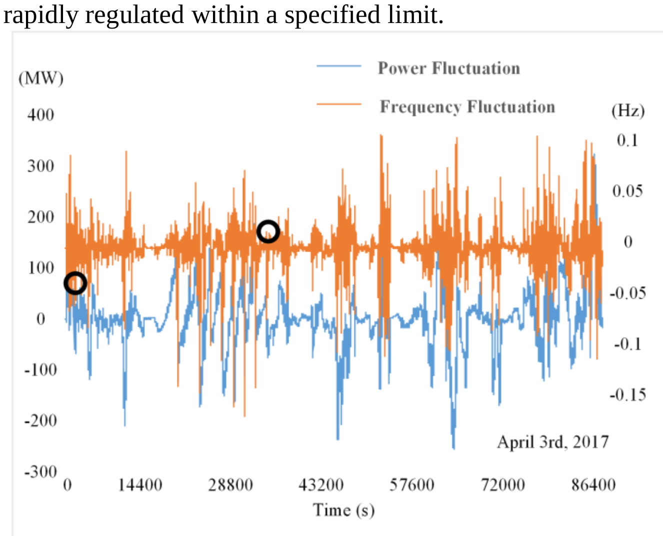

Fig. 2. Identification of power fluctuations from frequency fluctuations in second

III. Proposed Method

A. Long Short Term Memory Network

A recurrent neural network is an improved class of artificial neural network making use of temporal information of input data, which is different from the traditional conventional neural network that only has connections between layers. Consequently, RNN has a better performance in tackling time-series learning problem. To possess the vanishing gradient problem behind RNNs, the LSTM network was first put forward by Hochreiter *et al*. [19] with a memory cell and further improved by Gers *et al*. [20] with an extra forget gate. In this paper, the structure of the LSTM cell comprising the input gate, forget gate and output gate is shown in Fig.3.

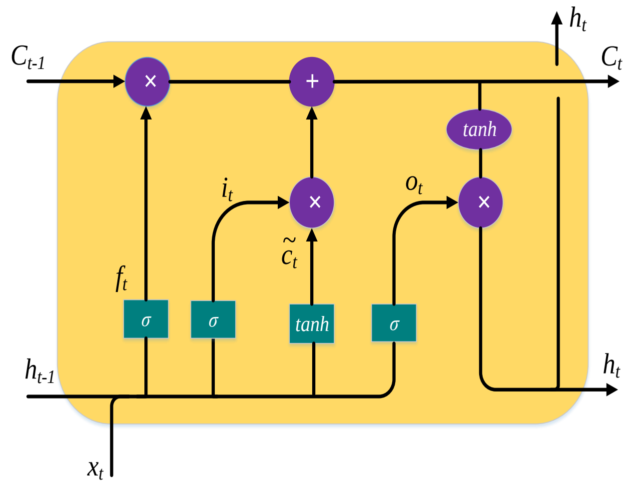

Fig. 3. Structure of the LSTM

In order to capture long-term temporal dependences, the LSTM defines and maintains the cell state to regulate the information flow, which is an important mechanism in the LSTM framework [21]. The memory cell state C_{t-1} interacts with the intermediate output h_{t-1} and the subsequent input x_t to determine which elements of the internal state vector should be updated, maintained or vanished based on the outputs of the previous time steps and inputs of the present time step. The compact formulations of an LSTM network with a forget gate are described as follows.

$$i_t = \sigma(x_t U^i + h_{t-1} W^i) \tag{6}$$

$$f_t = \sigma(x_t U^f + h_{t-1} W^f) \tag{7}$$

$$o_t = \sigma(x_t U^o + h_{t-1} W^o) \tag{8}$$

$$\tilde{C}_t = tanh(x_t U^g + h_{t-1} W^g) \tag{9}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{10}$$

$$h_t = tanh(C_t) * o_t \tag{11}$$

where the operator $*$ represents element-wise multiplication, and σ represents the sigmoid activation function; *i*, *f*, and *o* denote the input, forget and output gates, respectively; W^i, W^f, W^o, and W^g represent the weight matrices that need to be learned during training; U^i, U^f, U^o, and U^g are coefficient matrixes; $\tilde{C}_t$ is a "candidate" hidden state which is calculated based on the current input and the previous hidden state; C_t is the internal memory of the unit; h_t represents the final output of the memory unit. Via the function of various gates, LSTM memory units can capture the complicated correlation features within time series in both short and long terms, which are a remarkable improvement compared with other RNNs.

B. LSTM Network for Power Identification

This paper proposes an online identification method of the real power fluctuations based on LSTM recurrent neural network, which provides a new accurate reference for automatic generation control (AGC) to maintain the system frequency. By incorporating the Adam optimization method [22], the LSTM network is developed to classify the unbalance power between generation and load demand. The proposed algorithm can be separated into two parts: 1) offline training and 2) online application of the LSTM, and the whole procedure is illustrated as Fig. 4.

1) *Offline Training Progress*

For a specific identification point in a power system, the historical data of frequency fluctuations can be regarded as prior knowledge, which serves as the input for the LSTM training. The real power fluctuations are the target (i.e., the output) and the training procedures are detailed as follows.

Step 1: Collect the data of frequency and active power fluctuations.

Step 2: Normalize the data and initialize weight matrices and bias vectors including W^i, W^f, W^o, W^g, U^i, U^f, U^o, and U^g.

Step 3: Train the neural network by using the backward propagation method with the gradient-based optimizer, to minimize the cost function by updating the weight coefficients and bias vectors.

Step 4: Inverse the identified power fluctuations from normalized values into real values and output the identification results.

The whole procedure for power fluctuation identification by the LSTM is illustrated in Fig. 4.

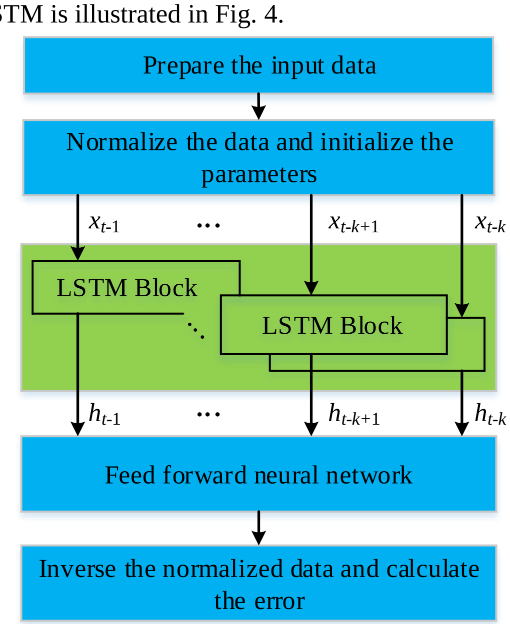

Fig. 4. The LSTM based power fluctuation identification framework

2) *Online Application*

The proposed LSTM network is trained in offline by the historical data and generated by power and frequency fluctuations. Once the LSTM network is well-trained, it can be applied in online to estimate the power fluctuation from the online measured frequency. Note that during the offline training state, different system operating conditions can be considered for training database generation. Besides, the model can also be periodically updated if new online measurement data and generated data are available or unforeseen system condition changes. The identified real-time power fluctuations form a control signal for AGC to be smoothed out by the frequency control resources, such as synchronous generators and ESSs.

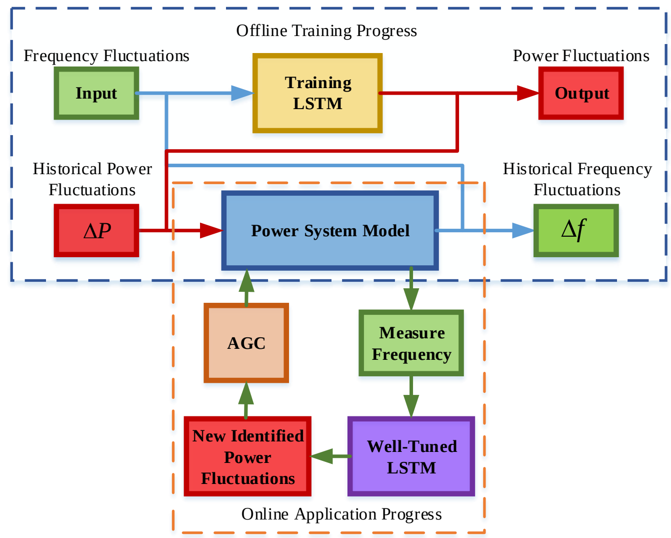

Fig. 5. Flowchart of the identification work

C. Performance Evaluation

To evaluate the identification accuracy of the proposed approach, the mean absolute normalized error (MAE), mean absolute percentage error (MAPE), and mean squared normalized error (MSE) are introduced as the performance indices. Three criteria are defined as follows.

$$\begin{cases} MAE = \dfrac{1}{n}\sum_{i=1}^{n} |\,\tilde{h}_i - h_i\,| \\ MAPE = \dfrac{1}{n}\sum_{i=1}^{n} \left|\dfrac{\tilde{h}_i - h_i}{h_i}\right| \times 100\% \\ MSE = \dfrac{1}{n}\sum_{i=1}^{n} (\tilde{h}_i - h_i)^2 \end{cases} \tag{12}$$

where $\tilde{h}$ is the identified data, and h is the target value.

The whole algorithm, as shown in Fig. 4, is programmed and implemented in Keras [23] with TensorFlow backend [24] on a desktop computer with a 3.8 GHz Intel i7600 processor and 16GB of memory.

IV. Simulation Results

A. Singapore Power System

Singapore locates closely to the equator, and accordingly air conditioners occupy more penetration in total load demand than

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that in other places. The high penetration of solar power and flexible loads will lead to dramatic frequency fluctuations, which challenges the frequency performance of Singapore power system [25]. In order to study its characteristics, a detailed LFC model of Singapore power system was built to generate the training and testing data for the proposed method, which is depicted in Fig. 6. The simplified Singapore power system comprises a centralized combined cycle gas turbine, a PV power plant, distributed energy storage systems and loads, whose parameters are shown in Table I.

TABLE I
PARAMETERS OF LFC POWER SYSTEM

Peak Load (MW)	Rated Frequency (Hz)	DESS (MW)
7000	50	100
$2H$ (p.u./Hz)	D (p.u./Hz)	R (Hz/p.u.)
0.1667	0.0015	3
B (p.u./Hz)	T_{ij} (p.u./Hz)	Power Plant
0.8675	0.25	CCGT

Due to the fact that 95% of electricity in Singapore is supplied by CCGT, the system frequency model of Singapore based on CCGT is established [26]. The primary reserve and secondary control are triggered when the frequency drops to 49.7 Hz and 49.4 Hz, respectively. In addition, the Singapore power system is connected to the Malaysia power system by 230 kV submarine cables with the transmission capacity of 400 MW.

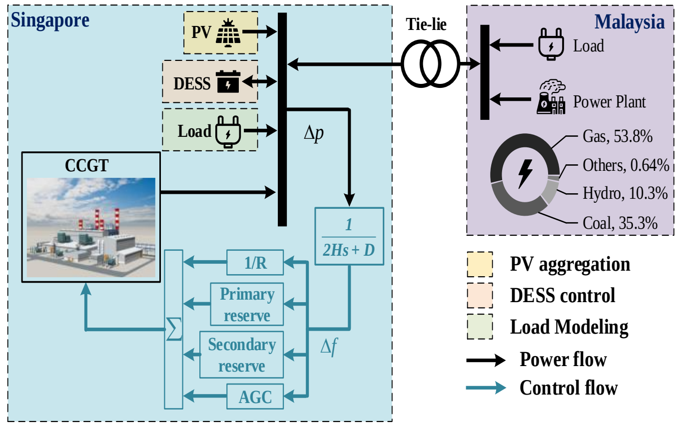

Fig. 6. A configuration of the Singapore power system LFC model

B. Dataset Generation

The accuracy of an artificial neural network highly depends on the training data. Based on the data supplied by Energy Market Company of Singapore [27], the hourly real power fluctuations are sampled every second by a linear interpolation

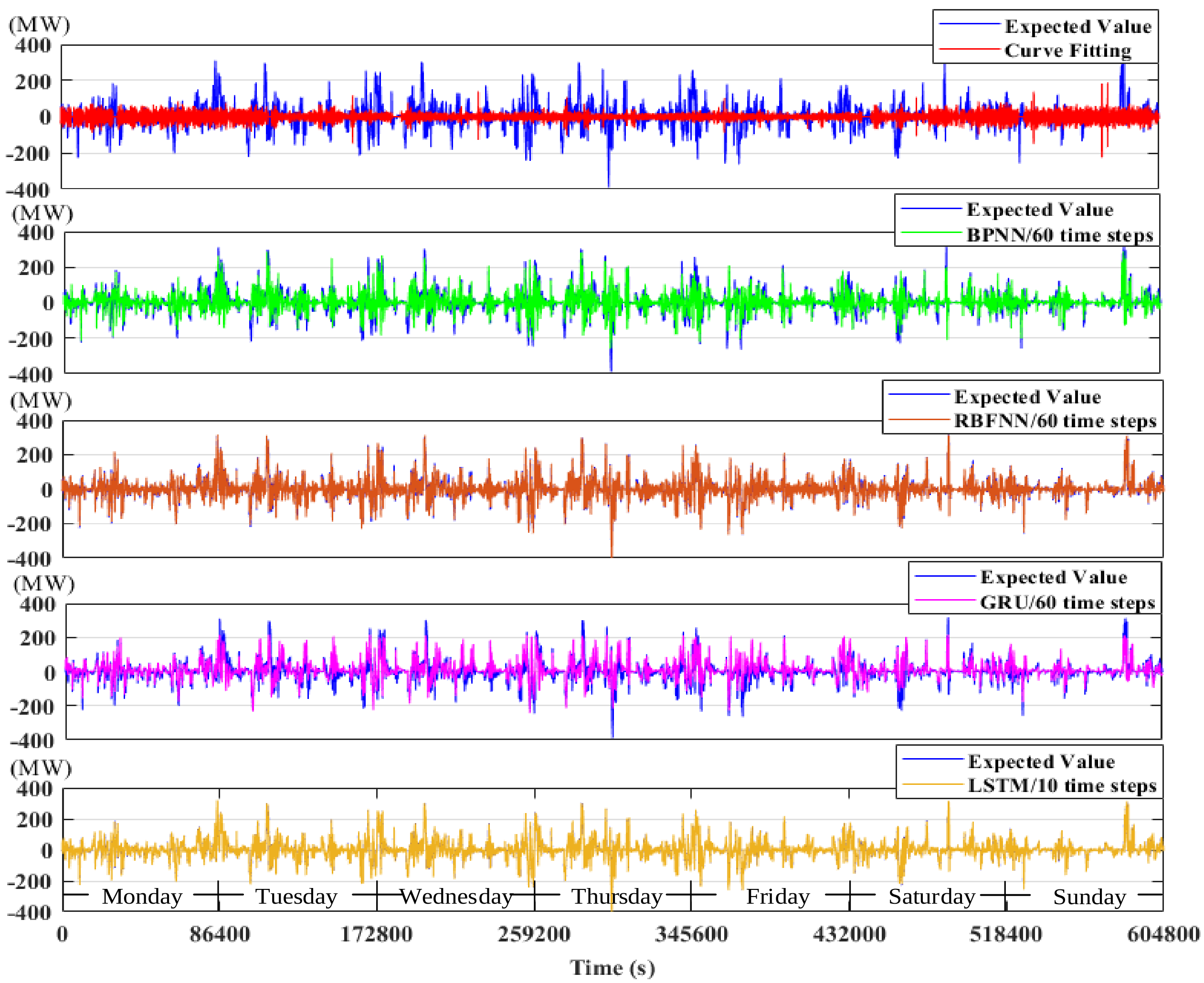

Fig. 7. Identified results for comparison

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method. To obtain the data of frequency fluctuations, the second-level power fluctuations are applied to build the LFC power system model. The training data of frequency fluctuations in second for the input and real power fluctuations for the output are prepared herein, which considers the various patterns including high frequency, medium frequency, and low frequency patterns. More specifically, a 3-month period hourly data from April 01, 2017 to June 30, 2017 are selected to sample into secondly data and then be introduced to the proposed Singapore power system to obtain the frequency data. The period spans over 91 days (7,862,400 seconds), which is separated in two subsets for training (from April 01, 2017 to June 18, 2017) and testing (from June 19, 2017 to June 30, 2017).

C. *Case Study*

In this paper, various methods for identifying the real power fluctuations by frequency measurements are compared to demonstrate the high accuracy and efficiency of the proposed LSTM scheme.

Case 1: A curve fitting method for identification work.
Case 2: Back propagation neural network (BPNN) with different time steps.
Case 3: Radial basis function neural network (RBFNN) with different time steps.
Case 4: Gated recurrent unit (GRU) recurrent network with various time steps.
Case 5: LSTM network with different time steps.

The parameters and conditions follow the data sheet, which are presented in Table II.

TABLE II
PARAMETER SUMMARY

Method	Orders	Layers	Neurons	Epochs
Curve fitting	10	n/a	n/a	n/a
BPNN	n/a	3	20	300
RBFNN	n/a	3	varied	100
GRU	n/a	3	15	100
LSTM	n/a	3	10	100

Case 1

The curve fitting method is a basic algorithm for time-series estimation and its performance is shown in Table III and Fig. 7.

TABLE III
IDENTIFICATION ERROR SUMMARY

Method/Scenario	MAE (MW)	MAPE (%)	MSE
Curve fitting	2.791	138.22%	3679.10
BPNN / 1 time step	0.218	34.98%	272.65
BPNN / 10 time steps	0.182	28.63%	220.18
BPNN /60 time steps	0.039	25.38%	181.19
RBFNN/10 time steps	0.076	158.72%	704.32
RBFNN/60 time steps	0.038	105.72%	504.62
GRU/10 time steps	0.162	18.39%	84.32
GRU/60 time steps	0.15	15.39%	72.25
LSTM / 1 time step	0.014	24.27%	143.69
LSTM / 10 time steps	0.002	6.23%	54.85

It can be seen from Table III that the method of curve fitting can capture the main characteristic of power fluctuations with the mean absolute error of 2.791 MW.

However, it is difficult to follow the peak when the active power varies dramatically since the method of curve fitting is not suitable to model non-linear systems but the established Singapore power system is a complicated system with many non-linear components associated with non-linear control, which indicated that more accurate approaches are necessary for identification work.

Case 2

1) *BPNN/1 time step*: In this case, BPNN under one time step is implemented to estimate the power fluctuations. It can be seen that the performance of BPNN is much better than the curve fitting method. In particular, both MAE and MAPE scores are significantly reduced from 2.791 MW to 0.218 MW and from 138.22% to 34.98%, respectively.

2) *BPNN/10 and 60 time steps*: Even though there is a one-to-one match between frequency and real power, the present real power fluctuations have a hidden relationship with the previous frequency fluctuations because the past load demand is related to the present load due to the continuous load demand behavior pattern. Therefore, 60 time steps are used to take into account previous frequency fluctuations. Totally, the BPNN with 10 and 60 time steps has smaller errors than that with one time step. The MAE scores are reduced by 0.036 MW and 0.179 MW, respectively but the MSE score is still as high as 181.19.

Case 3

The RBFNN under different time steps is utilized in this case to realize the identification work because of its good generalization and easy design [28]. Compared to the methods of curve fitting and the BPNN with 10 time steps, the MAE of RBFNN under 10 time steps is reduced to 0.076 MW. To improve the identification performance, the RBFNN under 60 time steps is also invested in this case and the MAE drops to 0.038 MW. The scores of MAPE and MSE, however, rise to be 105.72% and 504.62, respectively, implying that the power fluctuation identification is a complicated non-linear problem and one more efficient method is needed for achieving better performance.

Case 4

In this case, the GRU under various time steps is employed to identify the power fluctuations due to its strong capability in capturing the dependency among input and output sequences [29]. As shown in Fig. 7, the GRU achieves a better identifying performance than other three methods that are curving fitting, BPNN, and RBFNN. Compared to the BPNN and the RBFNN with 10 time steps, both the MAPE and MSE of the GRU under 10 time steps are reduced dramatically, which are 18.39% and

84.32 respectively. However, the MAE is increased to be 0.162 MW and even the MAE of the RBFNN under 60 time steps is high as 0.15 MW, which indicates that the robustness of the identified model need to be further enhanced.

Case 5

As mentioned in Section II, the real power identification is essentially a non-linear time series problem and even a minor frequency oscillation will lead to a large identifying error, which increases the complexity of the identifying problem. Owing to the better capability to capture the non-linear relationship between frequency and active power fluctuations, this paper proposes a LSTM-based method for real power fluctuations. In general, the LSTM network outperforms all other approaches.

1) *LSTM/1 time step*: In this case, LSTM under 1 time step is utilized to identify the power fluctuations from the changing frequency patterns, and the MAPE is 24.27%, which is 113.95% less than curve fitting and 71.45% less than RBFNN. Compared to the method of curving fitting and BPNN, the MAE and MSE scores of LSTM with one time step are also dramatically decreased.

Since the time scale of this work is second, which means that the LSTM network has to identify 86400 frequency data for each day and the different periods own different fluctuations. Thus, the amount of the training data is so enormous that LSTM with only one time step cannot recall all the “memory” of the variations, and LSTM with more time steps should be applied to achieve better performance.

2) *LSTM/10 time steps*: Generally, the LSTM network with 10 time steps has the best identification performance among all the proposed approaches. It can be observed from Fig. 7 that the LSTM network under 10 time steps can completely capture the peak of frequency fluctuations, with the minimum MAE, MAPE and MSE scores being 0.002 MW, 6.23%, and 54.85, respectively.

As the comparison results reveal, the BPNN and the GRU have to sacrifice more input parameters and time steps to obtain a good result, while the LSTM can follow the peak better under the condition of less neurons and time steps. To further verify the LSTM network to identify the fluctuations, the convergence speed is also taken into account, which is depicted in Fig. 8.

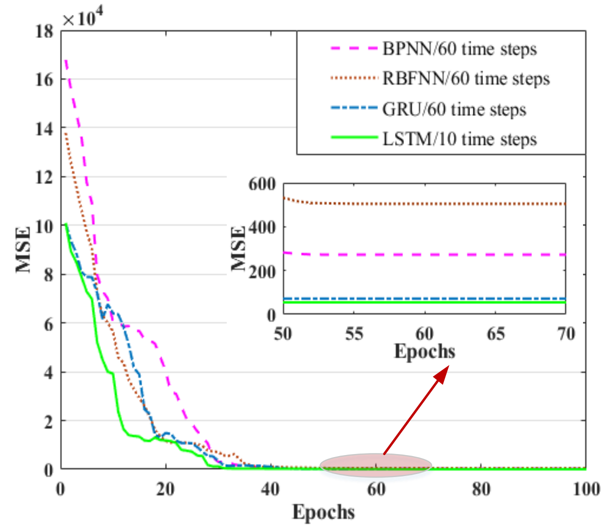

Fig. 8. Convergence of different algorithms

As seen in Fig. 8, it takes 28 epochs for the LSTM network with ten time steps to converge with a high descending speed at the beginning, implying the high training quality and efficiency of the LSTM network. Furthermore, even though the GRU has the fastest converging speed, the LSTM has the minimum training error with the MSE score of 54.85, compared with other neural networks. In order to examine the training process, the loss curve of the LSTM unit is displayed in Fig. 9.

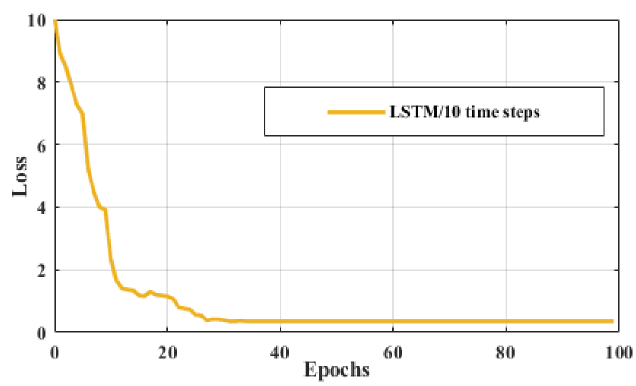

Fig. 9. Loss of the LSTM

Similar to the converging profile shown in Fig. 8, the loss of the LSTM drops from 10. 08 to 0.36 after 28 epochs, which indicates the parameters of the LSTM are well trained. Additionally, the proposed LSTM algorithm converges very fast with 289 CPU minutes, which is 56 minutes faster compared to BPNN with 60 time steps and 13 minutes less than RBFNN.

In general, the LSTM, the GRU and the BPNN approaches are the three best methods for real-time power identification. To be more specific, the LSTM network has the much better performance for identifying the on-line real power fluctuations than the GRU and the BPNN due to its capability of establishing a temporal relationship between inputs and outputs.

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V. Verification and Application

A. Verification of LSTM

In order to verify the trained LSTM model, the estimated power fluctuations from the model are applied back to the modeled Singapore power system to calculate the system frequency. To verify its accuracy, a frequency disturbance recorder (FDR) [30] is directly connected to the real Singapore power system to measure the real-world frequency. Fig. 8 shows the comparison between the measured frequency by FDR and calculated frequency by LSTM.

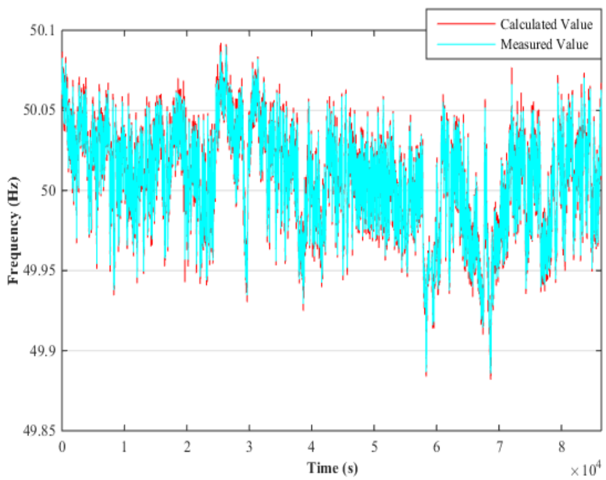

Fig. 10. Verification of the LSTM network

It can be seen from Fig. 10 that the calculated frequency through identified power is very close to the measured frequency with a very low MAPE score of 3.79%, which indicates that the LSTM network is well trained and it is able to identify the active power fluctuations through real-time frequency fluctuations.

B. Performance Evaluation

In this section, the performance of the proposed method is further compared with the disturbance observer approach. The disturbance observer is a widely used method to estimate the power fluctuations in LFC [7]-[9]. However, this method is highly relied on the system parameters, measurement accuracy and communication delays. Besides, the observer gains tuning can also largely influence its performance. Therefore, in practical, the performance of the disturbance observer is distorted. While for a well-trained LSTM, the identifying performance is independent of the previous system configuration and parameters.

With the help of the LSTM network, the power fluctuations occurred in the Singapore power system can be more rapidly identified than that by a disturbance observer, which is illustrated in Fig. 11. For instance, when the Singapore power system has to face a power change happened in 22 seconds, the LSTM algorithm can achieve the real-time identification of 40 MW power decrease but the power fluctuation estimated by the disturbance observer is 35 MW with almost one second delay. This delay and less accuracy will lead to a worse performance of the LFC.

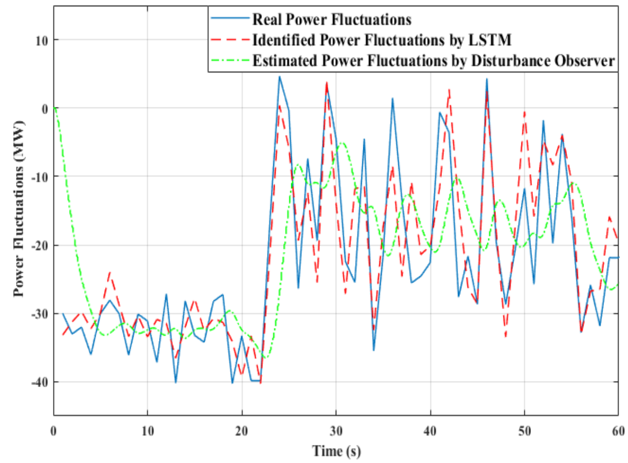

Fig. 11. Power fluctuations estimated by various methods

The system frequency can recover to a stable state if the unbalance power can be calculated more accurately and quickly. As the LSTM method has a faster and more accurate power identification performance, the system frequency response is also improved by the proposed approach, as depicted in Fig. 12. The frequency deviations can be maintained at a smaller variations range using the proposed approach.

Based on the identified power fluctuations, the LFC has a more accurate control reference, which achieved the smallest frequency deviation. To be specific, when a power change of 5 MW appears in 27 seconds, the Singapore power system has to tolerate 0.026 Hz frequency deviation with traditional LFC, but with the help of the well-tuned LSTM network, the system frequency can be maintained within 0.008 Hz, which is 33.34% improvement compared to the LFC with disturbance observer.

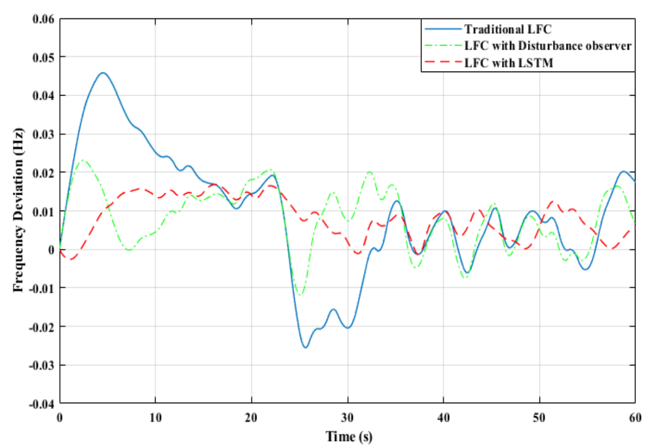

Fig. 12. Performance of various LFC models

C. Application for Frequency Control

The well-trained LSTM model is applied to an on-line frequency disturbance recorder to recognize the unbalance power for LFC through synchronous generators and DESSs.

Firstly, the FDR is used to collect the frequency of the Singapore power system. Secondly, the frequency fluctuations are calculated for the input of the proposed LSTM algorithm. Then the real power fluctuations are identified by the well-trained LSTM network, which send the signals to LFC.

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Finally, synchronous generators cooperate with DESSs to compensate the unbalance power by the identified power fluctuations and Fig. 13 shows the application procedure.

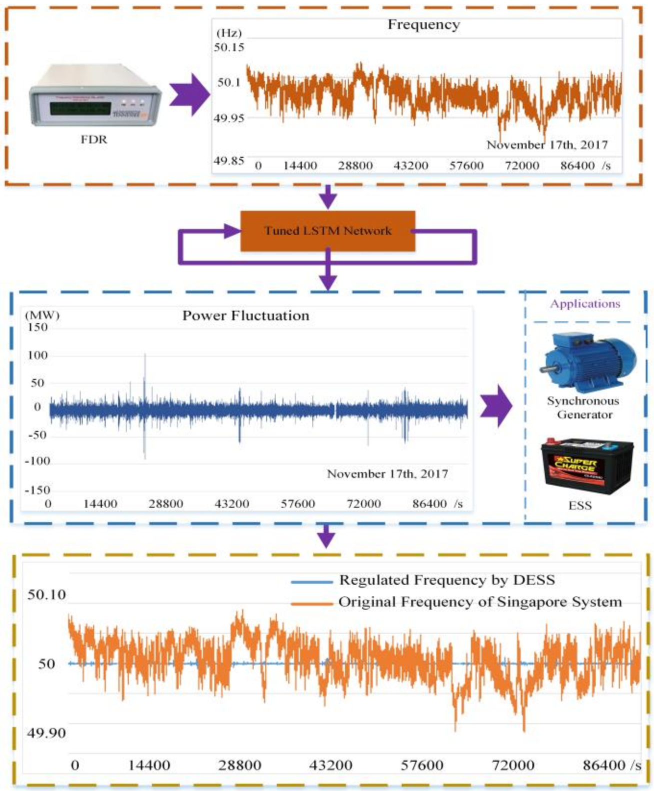

Fig. 13. Application procedure

As shown in Fig. 13, owing to the rapid power fluctuations caused by the renewable energy sources and load demand, the frequency of the Singapore power system fluctuates dramatically from 49.88 Hz to 50.09 Hz even under the traditional LFC and these high frequency deviations increase the risk of system instability. By employing the proposed method, the real-time power fluctuations are identified from the measured frequency, which provide an accurate reference for synchronous generators and DESSs to achieve the power sharing and the power balance. With the help of the well-trained LSTM network, the active power fluctuations can be accurately identified from the measured frequency within 0.86 seconds and, the system frequency can be maintained stable around 50 Hz by AGC. Moreover, the identified active power fluctuations also provide a guide for optimally allocating distributed energy storage systems in the network.

VI. Conclusion

As renewable energy sources and flexible loads continue to increase in power grids, it becomes significant to recognize the unbalanced power between various types of generations and loads. However, the load demand and energy consumption behavior are difficult to predict due to the uncertainties. In this paper, an LSTM network is proposed to identify real power fluctuations from frequency fluctuations. Unlike renewable energy and load forecasting, the focus of this paper is to realize the on-line identification of power fluctuations. The identified active power fluctuations provide a more accurate reference for frequency control and other applications such as the optimal allocation of energy storage systems, power-sharing, etc.

In addition, multiple benchmarks are comprehensively tested and compared to the proposed LSTM network on real power fluctuation identification task. A Singapore power system model is set up to collect the data for training and testing. Simulation results show that the proposed LSTM algorithm achieves the best performance compared with curve fitting, simple back-propagation neural network, radial basis function neural network, and gated recurrent unit.

Furthermore, a well-trained LSTM network is implemented to a frequency disturbance recorder to recognize the on-line real power fluctuations for real Singapore power system. The identified active power fluctuations provide a more accurate reference for automatic generation control to mitigate the frequency deviations and also supply a guideline for optimally planning distributed energy storage systems.

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