hazards will be caused in applications due to an ineffective battery. On the other hand, the consuming life of VRLA will easily decrease because of excessive internal temperature [7]. Thus, extra cost will be generated for maintenance or replacement [8]. Besides, thermal runaway, an unstoppable self-heating reaction, will happen if the battery keeps working at an inappropriate internal temperature. This self-heating reaction always causes serious consequences such as fires, electrolyte leakage and venting if insufficient attention is paid [9]. To prevent potential hazards from internal temperature, two main kinds of algorithms are developed to measure internal temperature. One of the methods is to measure the internal temperature directly by relative device. The other is to predict the internal temperature based on several external parameters using an established thermal model.

One of the traditional battery internal temperature estimation methods is direct measurement. To measure the internal temperature directly, researchers installed thermocouples inside the battery [10]. An obvious demerit of this method is that the cost of manufacturing a battery will increase a lot. Also, a potential safety problem may exist if a redundant component is added and thus destroy the original structure of the battery. In conclusion, it is not an appropriate method to directly measure internal temperature unless the mentioned issues can be solved. Another familiar method is to estimate internal temperature by a thermal model. In previous years, a large number of researches have been done on this topic. However, most of them concentrate on the temperature prediction models of Lithium-ion but no one about VRLA battery [11]. The methodology of Lithium-ion battery using an external parameter for prediction provides inspirations for the internal temperature prediction of VRLA battery. However, instead of a thermal model, neural networks based model is involved in our algorithm.

In this research, a NB-IoT connected VRLA battery internal temperature prediction (VBITP) algorithm is developed. NB-IoT is one of the most suitable mobile network technologies for IoT applications which need exceptionally deep coverage and extremely low power consumption. These applications usually require low data rates and moderate reaction times of a few seconds, such as smart metering. The first network deployments began back in late 2017 and global commercial deployment started in 2018. NB-IoT can be deployed inside Long-term Evolution (LTE) carrier, in the LTE guard band and as a standalone solution. In March 2019, the Global Mobile Suppliers Association announced that over 100 operators have deployed/launched either NB-IoT or LTE-M networks [12]. The VBITP, utilizing neural network and NB-IoT, does not fall into either of the mentioned categories. It consists of three parts: measurement of input parameters, data transmission by NB-IoT network and establishment of a prediction model. Two external parameters, namely ambient temperature (AT) and input current (IC), are measured and saved as the input. The output of the prediction model, internal temperature (IT) is measured at the same time. A dataset including the two inputs and the output is thus established.

Then a recurrent neural network, called nonlinear autoregressive exogenous (NARX) neural network, is applied to find the potential relationship between the input and the output. As a category of the recurrent neural network, NARX considers the continuous change in time series of the input. In this research, the value changes of ET and IC are both associated with the time. Thus, taking advantage of this, NARX is applied for training the prediction model in this paper. In application, the measured data will be transmitted to the backend server for decision making. The details of NB-IoT infrastructure will be explained in the later section.

The contributions of this paper can be summarized as follows:

1. A VRLA battery internal temperature prediction (VBITP) algorithm is developed to effectively monitor the internal temperature of the VRLA battery.

2. NARX neural network is involved in the proposed model as a novel method to find the relationship between the input parameters and internal temperature.

3. NB-IoT system has been implemented.

The rest of this paper is organized as follows. In Section 2, relative researches on VRLA temperature prediction is reviewed and the proposed VBITP algorithm is introduced. In Section 3, the NB-IoT system will be described. Section 4 describes the implemented experiments and the results are analyzed and discussed. In Section 5, a conclusion is made.

2. METHODOLOGY

2.1 Overview

The diagram of the proposed methodology in this study is shown in Fig. 1. This section consists of three parts: NARX neural network, model establishment and model validation. In part one, the basic structure of NARX neural network will be described. In the second part, the extraction of the input feature and the establishment of

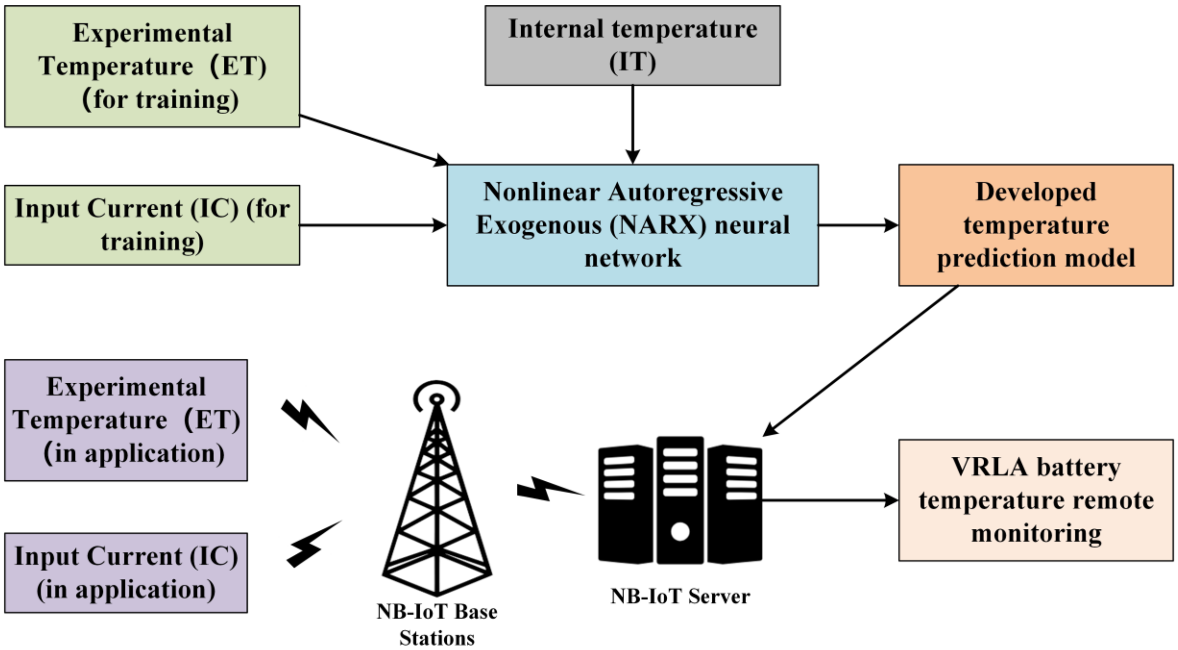

Fig. 1. The diagram of VBITP algorithm.

the prediction model will be introduced. Finally, in part three the validation method will be defined to verify the effectiveness of the developed model.

2.2 Nonlinear autoregressive exogenous (NARX) neural network

NARX is an extension of Autoregressive Exogenous (ARX), which is widely used in linear system analyzing [13] and generally utilized to model a variety of non-linear systems. It is a kind of nonlinear dynamic neural network used in the prediction. Neural networks are mathematical tools stimulated to the biological neural system, which have powerful capacity in learning, storing and recalling information. They are black-box modeling tools that map the low dimensional input space to the high dimensional output space for nonlinear mapping when the relationship between the input space and the output space is unknown. The nonlinear problems in low dimension become linear in high dimension, which decreases the complexity and difficulty. To be specific, NARX belongs to recurrent neural network (RNN), a typical kind of neural network. RNN considers the relationship between current input and previous one and thus good at dealing with prediction problem of time series; composed of input layer, output layer, feedback layer and multiple hidden layers. In the NARX neural network model, the function of the feedback layer node is to store the output value of the output layer node at the previous moment.

The structure of NARX could be formulated as equations (1)-(4) as follows [14]:

$$x_1(k) = f\left[w^1 u(k) + w^c x_c(k)\right] \tag{1}$$

$$x_i(k) = f\left[w^i x_{i-1}(k)\right],\ i=1,2,\ldots,s \tag{2}$$

$$x_c(k) = y(k-1) \tag{3}$$

$$y(k) = g\left[w^{s+1} x_s(k)\right] \tag{4}$$

In (1), w^i is the weight matrix of connections between hidden layers. w^c is the weight matrix connecting the feedback layer and the hidden layer. $u(k)$ is the input of the neural network at time k. In (1) and (2), $x_i(k)$ and $x_c(k)$ are the outputs of the feedback layer and the hidden layer. In (3), $y(k)$ is the output of the output layer. In (2) and (4), s is the hidden layer.

2.3 Model establishment and validation

To validate the performance of the developed prediction model, Mean Absolute Percentage Error (MAPE) is selected as an indicator for the model. It can be formulated as equation (5):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_{t,i} - y_{p,i}\right|}{y_{t,i}} \times 100\% \tag{5}$$

In (5), $y_{t,i}$ represents the true value of output (internal temperature) and $y_{p,i}$ represents the predictive value given by the model. The MAPE reflects the relative error in the prediction process to measure the performance of the model.

In the model training phase, 10-fold cross-validation is applied. The dataset is divided into ten equal groups randomly. In each turn, nine groups are utilized as the training data and the other one is used for validation. The choice of training and validation data in each turn should not be repeated. The average MAPE in these ten turns will be identified as the final result and reflect the performance of the model.

3. NB-IOT SYSTEM

NB-IoT is developed under the specification of LTE. The bandwidth of NB-IoT is about 180 kHz, and the coverage is less than 10Km in practical. NB-IoT protocol can be deployed in not just LTE, but also GSM or UMTS, whose downlink speed is from 160 kbps to 250 kbps and uplink speed is from 160 kbps to 200 kbps. Moreover, NB-IoT communication protocol is half-duplex. The maximum transport block size in downlink is 680 bits, and uplink is 1000 bits.

NB-IoT has three deployment methods, Independent Deployment, Guard-band Deployment and In-band Deployment. Independent Deployment is that the 180 kHz frequency band is located out of LTE carrier. Guard-band Deployment is that the 180 kHz frequency is in the edge of LTE carrier. From the name, In-band Deployment's frequency band is located in LTE carrier [15]. Communication operators define the deployment method. Hence, it is not considered in this paper.

In this investigation, the battery temperature data will be carried back to the backend server through NB-IoT. NB-IoT data delivery is shown in Fig. 2.

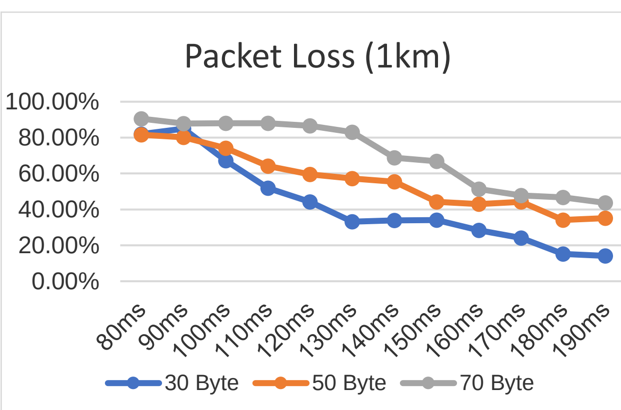

Fig. 2. NB-IoT data characteristics.

4. EXPERIMENTS AND RESULTS

In the experiments, the scope of input data, AT and IC are limited to simulate the real situation in the VRLA application. Considering the normal range of VRLA temperature, four typical ambient temperature value, 15°C, 25°C, 35°C, 45°C are considered in the experiments. The experiment will be conducted at these four ATs. In each AT phase, a repeatable current pulse set is introduced to act as pseudo-random frequency pulses. Three typical values of IC are also settled as 12.5 A, 15 A, 20 A. The output of IT is measured synchronously. The range of IT is corresponding to the ET of battery. In each phase, IC increases as the IC is floating and charging the battery. These three kinds of data are utilized for training the prediction model. 10-fold cross-validation is applied to validate the performance. As is shown in Fig. 3, the curve of target value and output is very close which can barely be distinguished. The curve below shows the error rate of the established model. The average error rate is about 0.04. Regarding the final example, we proceeded some real ex-

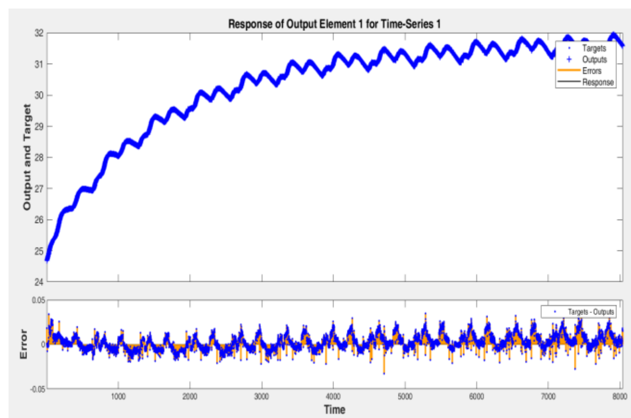

Fig. 3. The comparison between output and target (up) and the MAPE result (down).

periments to verify our proposed narrowband internet of thing connected VRLA battery internal temperature prediction algorithm to conclude all thermal reaction such as Joule heating effect, entropy changes due to H_2SO_4 reaction and the water cycle in VRLA battery. The uncontrollable self-heating problem, thermal runaway, can be easily avoided by using our prediction as the precaution. Our NB-IOT VBIPT is able to predict the battery's temperature without any thermal knowledge but simulates the thermal runaway. Regarding the temperature range, we all agree that 45°C ambient temperature is the highest temperature we should go on to prevent any danger from happening. Also, the battery's temperature rises to over 55°C after the experiment should be considered as the threshold of becoming thermal runaway. So that our

NB-IOT VBIPT is capable to prevent self-heating problem in great measure cases.

5. CONCLUSIONS AND FUTURE WORK

In this paper, a narrowband internet of thing (NB-IoT) connected valve-regulated lead-acid (VRLA) battery internal temperature prediction (VBITP) algorithm is developed to monitor the internal temperature of VRLA battery. VBITP could provide early warning of VRLA battery temperature and thus prevent potential hazards in applications. Different from traditional methods, IoT networks and neural networks are involved in VBITP to predict the internal battery temperature of VRLA battery based on two external parameters, namely, input current and ambient temperature. Taking advantage of NARX neural network, the prediction model in VBITP could predict internal battery temperature with excellent performance. The NB-IoT system sent the measured data back to the server and battery temperature is monitored and an alert will be activated when overheating occurs. The experimental results show that the error rate of the temperature prediction model is no more than 0.04. In the future, we are going to apply this algorithm to the study of lithium battery internal temperature. At the same time, a new training structure will be developed to improve the performance further.

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