Data-driven mode for the performance of hundreds megawatt wave energy converter in China: A case study

Chenhua Ni

Abstract—**The increasing development of wave and tidal energy technologies in China lead to huge open sea testing demands after experienced kind of laboratory experiments and small-scale model. More WECs (wave energy converter) and tidal devices owners put the devices into testing stations spontaneously and endured strict sea testing in order to improve the TRL (technology readiness level) and reliability. The paper introduces a data-driven model using deep learning algorithm associate with resource and testing data to evaluate performance of device. The result which jointed with model and sensors data shows the specific relationship between resource and power output and the deep learning algorithm was confirmed to be a considerable method to do power predict based on testing data.**

Keywords—**Deep learning, Long Short Term Memory, marine energy, power prediction, wave energy converter**

I. Introduction

MARINE energy (ME), also known as ocean energy (OE), has considered being one resource of renewable energy and remains widely untapped [1]. It is estimated that the potential of OE can generate electrical power almost 80,000 TWh per year by converting ocean temperatures, salt content, movements of tides, currents, waves and swells [2]. Wave energy, as one of the OE resource, represents the vast majority of the resource potential and has reached the relatively mature technology among these OE technologies. Despite the technology readiness level (TRL) of WEC achieved level eight by some converters, it still needs to be improved to running as a commercial stage [3]-[4]. The increasing development of wave energy technologies leads to huge open sea testing demands after experienced kind of laboratory experiments and small-scale model. Electrical power prediction from wave energy plants plays an important role in control the gird balance and consumption, as well as manage the energy usage and shortage. Besides, the accurate prediction of power from WECs is able to well organize the operation and reduce the costs from maintenance because of the unpredictable resource and harsh sea condition [5].

The traditional way to predict wave energy power usually consists of two steps. Firstly, wave parameters (wave height, period and direction) can be forecast by either statistical algorithms or physical models. Then specific regression methods are produced to take the responsibility to do the prediction from wave parameter to electrical power generation through historical data[6].

Long short-term memory (LSTM), which represents one kind of DL methods is an artificial recurrent neural network (RNN) architecture [10] used in the field of deep learning, as Fg.1 shown. Its networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series [11]. Convolutional neural network (CNN), a kind of deep learning model, has achieved significant success for image and video recognition, recommender systems and natural language processing due to the independence from prior knowledge and human effort in feature design [12].

The contribution of this paper is the experience of deep learning methods used in the WEC testing data processing. For this purpose, the paper is organized as follow: Section 2 gives the methodology of LSTM and Methodology

A. CNNs

As one of the deep learning algorithms, CNN method has been considered one of the most appropriate methods to address predicting problems because it has shown potential to solve a range of problems involving CNN

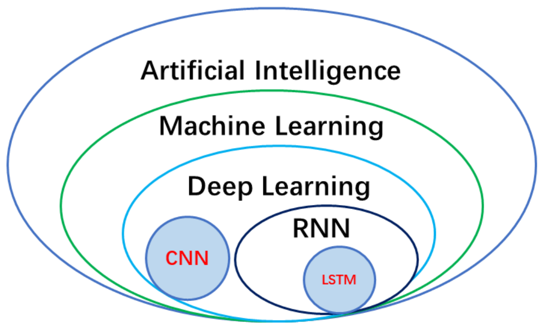

Fig. 1. The relationship between CNN and LSTM algorithms.

This paper was first submitted in the conference EWTEC2019 in Mar 2019, the ID number of submission is #1734 and the Conference Track is selected as Wave device development and testing. Some of the work received support from SFMRE (Special Funds for Marine Renewable Energy) from MNR (No. GHME2018ZC01).

C. Ni. Author is with Department of Marine Renewable Energy, National Ocean Technology Center, 211 Jieyuanxi Rd. Nankai District, Tianjin China 300112 (e-mail: jeff_ni@126.com).

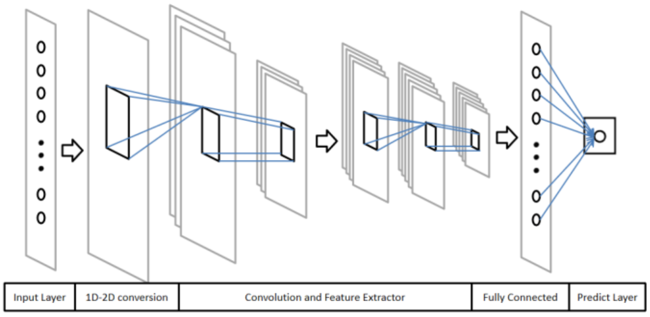

Fig. 2. The architecture of CNN.

algorithm in detail. Section 3 gives the results and performance of applying LSTM and CNN in details, the competition of CNN and LSTM also be presented as well. Finally, Section 4 summarizes the conclusions from the study.

sequential learning in recent years [13]. There are many advantages to applying CNNs: (1) the neurons inside a convolution layer are connected to only a small region of the convolution layer before it, called a receptive field, which could reduce plenty of parameters; (2) each filter is replicated across the entire visual field. These replicated units share the same parameters (weight vector and bias) and form a feature map; (3) pooling layer is usually used to generate translation invariant features by computing statistics of the convolution activations from different positions along specific windows [14][15].

In terms of model architecture, as Fig.2 shows, the CNN applied here include convolution layer, pooling layer, fully connected layer and prediction layer. The convolution layer is a two-layer feed-forward neural network that adopts a convolution operation to map the low-level maps with local features into several high-level maps with global features. the convolution layer calculated as follows,

$$a_{i,j} = \mathrm{f}\left(\sum_{m=0}^{2}\sum_{n=0}^{2} w_{m,n}x_{i+m,j+n} + w_b\right) \tag{1}$$

where, $x_{i,j}$ denotes a specific element in the input image, $w_{m,n}$ denotes the weight in m[th] row nth column, w_b represents bias of filter, $a_{i,j}$ as the element the feature map. In addition, the output activation function f is chosen to be the ReLU function.

Pooling layers are typically used immediately after convolution layers to simplify the information. Different pooling methods were used max pooling and average pooling. Fully connection is a linear operation, which concentrates all representations at the highest order into a single vector. This vector can be seen as the features extracted from the original input. Finally, the linear predict layers are used to forecast the final results after obtaining the features.

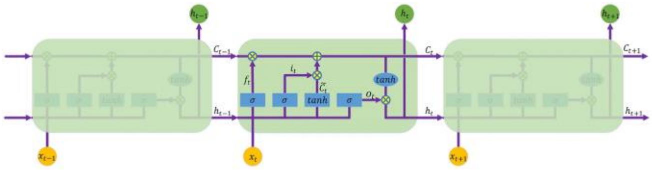

Fig. 3. The repeating module in an LSTM contains four interacting

B. LSTMs

RNN networks can theoretically use their feedback connections store representations of recent input events in forms of activations, mostly by changing weights for short-term memory and long-term memory. As a family member of RNN, LSTM network architecture also includes input layer, hidden layers, and output layer. Each hidden layer of a traditional RNN contains one short-term memory vector.

The LSTM does have the ability to remove or add information to the cell state, carefully regulated by structures called gates. As Fig.3 shows, the gates are: a forget gate (f) means how many memories will be reserved from c_{t-1} to c_t; an output gate (o) decides how many memories will be output to hi; an input gate (i) means how many memories will be reserved from c'_t.

The proposed LSTM network (illustrated in Fig.4) sets out with a multi-variants time-series input layer followed by an LSTM layer. An LSTM layer learns long-term dependencies between time steps in time series and sequence data. Then, a fully connected layer connects every neuron in LSTM layer to every neuron in next layer. For a regression prediction, this network ends with regression output layer.

The mathematical representation of LSTM can be obtained as follow [14-15]:

Input gate (i_t) decides the information which will be added to the cell:

$$i_t = \sigma(\omega_i * x_t + U_i * S_{t-1} + V_i^0 c_{t-1} + b_i) \tag{2}$$

Forget gate (f_t) decides the information which will be abandoned from the cell:

$$f_t = \sigma_g(\omega_f * x_t + U_f * s_{t-1} + V_f^0 c_{t-1} + b_f) \tag{3}$$

Output gate (o_t) decides the information which will be exported from the cell:

$$o_t = \sigma_g(\omega_0 * x_t + U_0 * s_{t-1} + V_0^0 c_{t-1} + b_0) \tag{4}$$

From the equations above, x_t represents the input vector, W, U, V and b denote the hyper-parameters for weights and biases. ˚ represents the scalar product of two vectors. σ_g is the sigmoid function, and σ_h and σ_c are the hyperbolic tangent functions [14-16].

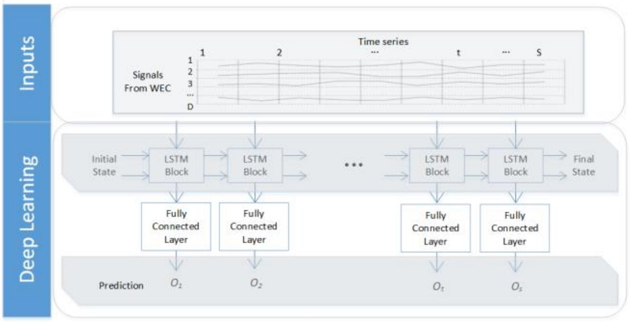

Fig. 4. The architecture of deep-learning load forecasting.

C. Performance Evaluation Index

Here we choose three mainstream performance evaluation indexes to measure the accuracy of prediction, these include the coefficient of determination (R-squared), root mean square error (RMSE) and the mean absolute error (MAE). R-squared value provides a measure of how well observed outcomes are replicated by the model, based on the proportion of total variation of outcomes explained by the model [17]-[18]. RMSE is more sensitive to a large deviation between the predicted values and the actual outcomes. In addition to that, the MAE measures the absolute difference value between the forecasts and the actual values. MAE is also the average difference between each value and the identity base [19-20]. They are calculated as follow equations:

$$R_T^2 = 1 - \frac{\sigma_e^2}{\sigma_y^2} \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(e_{t+k/t}\right)^2} \tag{6}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{t=1}^{N}\left|e_{t+k/t}\right| \tag{7}$$

II. PREDICTION RESULTS

D. Data acquisition

WECs which convert the ocean wave energy to electrical power achieved magnificent progression due to the energy shortage and environmental pollution. So far, the WECs designed mainly divided into three categories: oscillating water column devices, oscillating body systems and overtopping converters [21]. There are typically convert kinetic energy into electricity through three procedures: energy capture, power take-off (PTO) and electrical energy generating system. So far, three alternative PTO mechanisms were widely used globally which include turbine, hydraulic and electrical linear generators respectively shown in Fig.5.

The modelling data used in this study were collected from a testing WEC which deployed in near-shore condition. The capacity of the WEC is ten kW and the data collected from Feb. to Apr. 2017 at SanYa, Hainan Province, China. The ten kW WEC prototype was first invented in 2016 and this is the first time for sea testing after plenty of laboratory testing and simulating. The numerical model associated with real observation data show that the wave condition changes vary during seasons here. More than 20 crucial parameters during operation and testing were collected and recorded in the SCADA system with 10 Hz frequency include oil pressure and flow, rotor speed and torque, current and voltage, cylinder angles, mechanical power, inverse power et al.

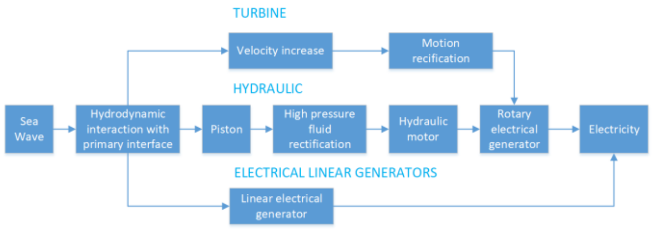

Fig. 5. Alternative PTO mechanisms.

E. CNN results

Obviously, the purposed CNN performed significant results compared with traditional data driven methods which shown in Table 1. The four signals recorded from the WEC which include hydraulic pressure, hydraulic flow, motor speed and motor torque were applied as inputs of the network and the wave resource information was considered. The indicators of difference between actuals and forecasts become quite small if CNN model was used. SVM and RLR produces worst performance as the MAE value was much higher (more than twice than others) among the five models which means the results were much bigger of an error we can expect from the forecast on average. The R^2 value of ANN, MT and BT revealed general fitting results. It is worth mentioning that the training of ANN and CNN take a little longer time (more than 43 s in this situation) and the time greatly depends on hidden layers, epochs and break time of networks.

Fig. 6 illustrates the CNN model fit to a section of the validation data set for the power output of WEC. The

TABLE I
THE PERFORMANCE OF CNN COMPARED WITH DIFFERENT SUPERVISED MODELLING APPROACHES

Approaches	RMSE	MAE	R2	TIMES(S)
Artificial Neural Network(ANN)	*2144.83*	*11.38*	*0.83*	*39.19*
Support Vector Machine(SVM)	*34.88*	*27.10*	*0.69*	*583*
Robust Linear Regression(RLR)	*35.15*	*27.30*	*0.69*	*4.68*
Medium Tree(MT)	*23.36*	*12.92*	*0.86*	*7.21*
Boosted Tree(BT)	*20.83*	*12.49*	*0.89*	*11.26*
CNN	*3.11*	*1.92*	*0.96*	*42.85*

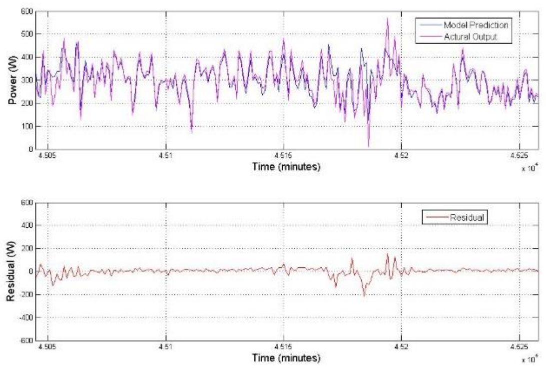

Fig. 6. The residual between CNN prediction and actual output.

residual between the model prediction and the actual active power output is shown in the lower plot. It can be seen that the model is able to estimate successfully the output signal. However, few peaks in the signals are over estimated.

F. LSTM predicting results

In order to improve the performance of predicting accuracy between time sequence signals, the single sequence forecasting method was used [22]. Here, the oil pressure, rotor torque, voltage and generator power input as single time-series sequence to the model separately. The Fig.7 illustrates the predicting performance resulted by individual sequence. The oil pressure, rotor torque and generator power output forecasted the significant results compared with the voltage result among these signal sequences both in tendency and magnitude. The red forecasting dots matched the blue observed line much better compared with the result made by sequence to sequence mode. This phenomenon illustrates that the LSTM response quite different predictions if individual signal sequence imported into the model possibly because the observed data in the left below figure features complicated tendency and kept oscillating in almost timespan. Nevertheless, the LSTM model was false to control the long-term and short term memory gates and got the unacceptable results.

The predicting scores from the four features were collected which shown variety of tendencies. The R^2 value from oil pressure, rotor torque and generator power acquired considerable results which up to 0.9. By contrast, the score of voltage performed much worse during the four prediction, 0.243, shown in left below figure of Fig. 7.

G. Methods comparison

For comparison, other AI methods were taken to make forecasting using the same collected signals in order to test prove the performance of the data-driven model in this paper. In term of validation and accuracy, the support vector machine (SVM), regression tree (RT), Gaussian Process Regression (GPR) and Ensembles of Trees (ET) were applied and the average metrics of performance as listed in Table 2.

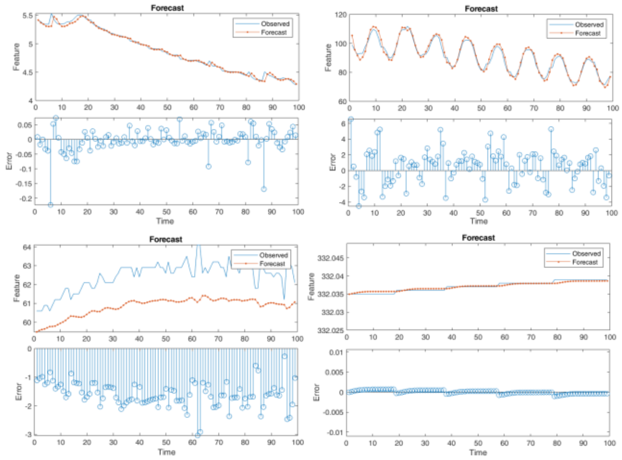

Fig. 7. The errors between actual and predicting data presented by LSTM forecasting model.

Furthermore, the predicting features of CNN and LSTM also mentioned in this study. It can be found from Table 1 and Table 3, the LSTM model take the remarkable advantages in single signal prediction than CNN network, but the running the LSTM model took more time than CNN. The performance of LSTM method largely depended on the individual signals. For instance, the purposed LSTM cannot predicting voltage signal well in this case. The experience also found that the advantage of CNN is multiple signals processing mostly because CNN addresses data in the form of a dimensional 2D matrix and is widely applied in the field of image. In other words, the more feature captured from training images, the better performance provided by the model. All in all, both the CNN and LSTM network acquired considerable results compared with ML network and traditional predicting methods, and the deep learning methods show the great potential in power prediction and some other fields [24-25].

III. CONCLUSIONS AND DISCUSSIONS

This study proposed creative two highlighted deep learning networks to deal with wave power forecasting by training and testing various signals collected from an open sea testing WEC. The LSTM adopted to avoid long term independences during the forecasting and CNN method was used to prediction based on 2 dimensional signals.

The result shows the proposed both LSTM and CNN network perform accurate predicting on wave power signals and condition signals, the R-squared value reached highest at 0.988 by LSTM, meaning that the predicting results well matched the actual output. For

TABLE II
THE METRICS OF PERFORMANCE THOUGH KIND OF PREDICTION METHODS

Methods	RMSE	MAE	R2	Times(s)
SVM	*17.679*	*12.748*	*0.86*	*426.9*
RT	*20.681*	*15.460*	*0.81*	*6.9*
RPG	*16.366*	*11.974*	*0.88*	*653.4*
ET	*17.444*	*13.417*	*0.87*	*11.9*

comparison, traditional machine learning algorithms such as SVM, RT, RPG and ET also adopted and the result reveals the proposed network outperform these machine learning algorithms and typically time saving. Theoretically, the CNN used to process 2 dimensional signals while LSTM charged for time series signals, and the results acquired from modelling gave the evidence of this theory.

Besides, there are plenty of challenges that cannot be ignored. We got the results from the experiment that the large size of images contains more feature than small size ones. The prediction was affected by not only the current inputs but also the connections in one input series and series in between. In other words, the current inputs combined with adjacent pixels could provide more information than a single input. In LSTM modelling, the longer predicting term makes less accuracy during same sequence if the timespan is extended longer. The LSTM seems to adapt gentle and regular data more than tremble data. To take the signal property into account, the voltage signals always irregularly and doesn't building close connections in time dimension compared with the oil pressure and rotor torque signals.

REFERENCES

[1] Saadat, Y.; Fernandez, N.; Samimi, A.; Alam, M.R.; Shakeri, M.; Ghorbani, R. Investigating of helmholtz wave energy converter. Renew. Energy 2016, 87, 67–76.

[2] Ocean-potential. International Energy Agency (IEA). Archived from the original on 2015-05-22. Retrieved 2016-08-08.

[3] Ni, C.; Ma, X. Prediction of Wave Power Generation Using a Convolutional Neural Network with Multiple Inputs. Energies 2018, 11, 2097.

[4] International Energy Agency. Implementing Agreement on Ocean Energy Systems, Annual Report 2007. Jochen Bard ISET. 2007. 1 July 2015.

[5] Ni, C; Ma,X.; Bai, Y. Convolutional Neural Network based power generation prediction of wave energy converter. the 24th International Conference on Automation & Computing, Newcastle University, Newcastle upon Tyne, UK, 6-7 September 2018

[6] Sun, Z.; Xue, L.; Xu, Y.; Wang, Z. Overview of deep learning. Application Research of Computers. Vol.29 No.8 Aug. 2012.

[7] Torres, J.M.; Aguilar, R.M.; niga-Meneses, K.V.Z. Deep learning to predict the generation of a wind farm.J. Renew. Sustain. Energy 2018, 10, 013305

[8] N. Krishna kumar; R. Savitha; Abdullah Al Mamun. Regional ocean wave height prediction using sequential learning neural networks. Ocean Engineering 129 (2017) 605-612

[9] Shikhar, S.; Stefan, L. A comparative study of LSTM neural networks in forecasting day-ahead global horizontal irradiance with satellite data. Solar Energy 162 (2018) 232-247

[10] Sepp Hochreiter, Jürgen Schmidhuber. Long short-term memory. Neural Computation. 9 (8): 1735–1780.

[11] Graves, A. Liwicki, M. Fernández, S. Bertolami, R. Bunke, H. Schmidhuber, J. A Novel Connectionist System for Unconstrained Handwriting Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence. 31 (5): 855–868.

[12] Collobert, Ronan; Weston, Jason. A Unified Architecture for Natural Language Processing: Deep Neural Networks with Multitask Learning. Proceedings of the 25th International Conference on Machine Learning. ICML '08. New York, NY, USA: ACM. pp. 160–167.

[13] Alberto Mozo, Bruno Ordozgoiti, Sandra GoÂmez-Canaval. Forecasting short-term data center network traffic load with convolutional neural networks.

[14] Anwen Zhu, Xiaohui Li, Zhiyong Mo, Huaren Wu. Wind Power Prediction Based on a Convolutional Neural Network. 2017 International Conference on Circuits, Devices and Systems. 978-1-5386-1871-4/17/

[15] H. Wang et al., Deep learning based ensemble approach for probabilistic wind power forecasting. Applied Energy 188 (2017) 56–70

[16] F. Shin et al., Wavelet Convolutional Neural Networks for Texture Classification. arXiv:1707.07394v1 [cs.CV] 24 Jul 2017

[17] Tian, Y.; Xu, Y.; et al. Integration of a Parsimonious Hydrological Model with Recurrent Neural Networks for Improved Streamflow Forecasting. Water 2018, 10, 1655; doi:10.3390/w10111655

[18] Hu, C.; Wu, Q. et al,. Deep Learning with a Long Short-Term Memory Networks Approach for Rainfall-Runoff Simulation. Water 2018, 10, 1543; doi:10.3390/w10111543

[19] K. Andrew et al,. Prediction, operations, and condition monitoring in wind energy. Energy 60 (2013) 1-12

[20] B. D. Phong et al,. Condition monitoring and fault detection in wind turbines based on cointegration analysis of SCADA data Renewable Energy xxx (2017) 1-16

[21] Steel, R. G. D.; Torrie, J. H. (1960). Principles and Procedures of Statistics with Special Reference to the Biological Sciences. McGraw Hill.

[22] Glantz, Stanton A.; Slinker, B. K. (1990). Primer of Applied Regression and Analysis of Variance. McGraw-Hill. ISBN 978-0-07-023407-9.

[23] Liu, J.; Zhang, T. et al. TD-LSTM: Temporal Dependence-Based LSTM Networks for Marine Temperature Prediction. Sensors 2018, 18, 3797; doi:10.3390/s18113797

[24] Md, J. H.; Kim J. M. Bearing Fault Diagnosis under Variable Rotational Speeds Using Stockwell Transform-Based Vibration Imaging and Transfer Learning. Appl. Sci. 2018, 8, 2357; doi:10.3390/app8122357

[25] Sproul, A.;Weise, N. Analysis of a wave front parallel WEC prototype. IEEE Trans. Sustain. Energy 2015, 6,1183–1189.