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Predication of Ocean Wave Height for Ocean Wave Energy Conversion System

Yingjie Cui [1], Fei Zhang [1,*] and Zhongxian Chen [1,2]

[1] School of Intelligence Manufacturing, Huanghuai University, Zhumadian 463000, China; cuiyingjie@huanghuai.edu.cn (Y.C.)
[2] Henan Key Laboratory of Smart Lighting, Huanghuai University, Zhumadian 463000, China
* Correspondence: zhangfei@huanghuai.edu.cn

Abstract: Ocean wave height is one of the critical factors to decide the efficiency of the ocean wave energy conversion system. Usually, only when the resonate occurs between the ocean wave height (ocean wave speed in the vertical direction) and ocean wave energy conversion system, can the conversion efficiency from ocean wave energy into electric energy be maximized. Therefore, this paper proposes two predication methods to predict the future ocean wave height in 1.5–2.5 s. Firstly, the data fitting of real ocean wave height is achieved by the polynomial method, which is beneficial to the predication of ocean wave height. Secondly, the models of the moving average (MA) predication method and auto regressive (AR) predication method are presented by the time series analysis process. Lastly, after the predication of ocean wave height by the MA method and AR method, and compared with the data fitting result of real ocean wave height, it can be found that the AR method is more accurate for the predication of ocean wave height. In addition, the predication results also indicated that the error between the predication value and true value in the future 2.5 s is considered acceptable, which provides enough time to optimize the operation process of the ocean wave energy conversion system by a suitable control method.

Keywords: ocean wave height; data fitting; predication method; ocean wave energy conversion

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1. Introduction

With the popularization and application of new energy developments, ocean wave energy extraction has become a popular research direction for converting this renewable energy into electric energy [1,2]. However, during the research process of ocean wave energy extraction, the conversion efficiency from ocean wave energy into electric energy is low, which is analyzed and verified by many experts [3–5]. For example, reference [3] has estimated that the power efficiency of ocean wave energy to electric energy is 11.97%, and reference [4] has calculated that the operation efficiency and power translation of the wave energy converter is 23% (without operation control). Moreover, reference [5] has obtained that the natural efficiency of the wave energy conversion system is 1.4%, and the experimental test process was implemented in the Yellow Sea near Lianyungang port.

In order to improve the operation efficiency of the ocean wave energy conversion system, some control methods have been proposed and researched. With the certain structure of the ocean wave energy conversion system, the field weakening (FW) control of the linear generator [6], second order sliding mode control [7–9], model-predictive control (MPC) [10,11], sliding mode control [12] and other control methods have been investigated one after another. Actually, the real-time motion situation of ocean waves is one crucial factor to improve the operation efficiency of the ocean wave energy conversion system, except for the optimized control of the ocean wave energy conversion system. The reason for this statement is that only the resonate occurs between the ocean wave and ocean wave energy conversion system, and the conversion efficiency from ocean wave energy into electric energy is maximum [13]. Therefore, real-time monitoring or predicting of the motion situation of the ocean wave is beneficial to the optimization control and efficiency improvement of the ocean wave energy conversion system.

At present, the focus of research on ocean wave height predication is mostly based on empirical equations and numerical simulation. In 2021 and 2022, Jrges et al. and Lou et al. proposed a long short-term memory (LSTM) neural network model to forecast ocean wave height [14,15]. The LSTM neural network model is suitable for high and low ocean wave height predication, and its predication accuracy in the short-term period and long-term period of ocean waves was improved by 7.4–11.7% and 8.8–9.1%, respectively. Moreover, some other kinds of ocean wave height predication with the LSTM neural network have been proposed in recent years. Fan et al. proposed a simulating waves nearshore LSTM model to make a single-point predication of ocean wave height, and its performance was outperformed by the standard SWAN model with an over 65% improvement in accuracy [16]. For the higher lead times of ocean wave height, the recurrent neural networks (RNN) based on the correlation coefficient and Root Mean Square Error of the LSTM model perform better than the persistence model [17]. Moreover, ocean wave height predication is beneficial for the wave power density estimate; for example, a modified gamma spectrum method is presented and revised to estimate the wave energy density in a desired geographic area [18], and a series of wave energy estimation methods with the linear wave theory are achieved in the Gulf of Mexico [19].

However, the predication of ocean wave height using empirical equations and numerical simulation is complicated and needs a long calculation time. If the predication time is too long, it will be detrimental to implement the optimal operation control and efficiency improvement of the ocean wave energy conversion system. For the predication of ocean wave height quickly and effectively, this paper proposes two predication methods (the MA and AR predication methods) to predict the future ocean wave height. After the modeling and simulation calculation, it found that both the two predication methods are time-saving, and the AR predication method is more accurate than the MA predication method. It can also accurately predict the future ocean wave height in the next 2.5 s.

This paper was arranged as follows: Section 2 describes the data fitting of real ocean wave height by the polynomial method, which is beneficial to the predication of ocean wave height. Section 3 presents the predication models of the MA method and AR method by the time series analysis processes. Section 4 compares the predication results with the data fitting result of real ocean wave height, and analyzes the predication accuracy of the MA method and AR method. Finally, the discussions and conclusions are drawn in Sections 5 and 6.

2. Data Fitting of Real Ocean Wave Height

Actually, the motion process of real ocean waves is irregular [20]. Figure 1 shows the real ocean waves near the ocean wave energy conversion system. From Figure 1, it can be seen that the real ocean waves are irregular, including the period and height of the ocean waves. Without predicting or measuring such kinds of ocean wave height, it is difficult to maximize the conversion efficiency of ocean wave energy into electrical energy. If the ocean wave height is measured by instruments, many difficulties will occur, such as the installation position of instruments, high-cost investment and so on. Therefore, this paper adopts the time series analysis method to predict the future ocean wave height. In addition, the operational principle of the ocean wave energy conversion system in Figure 1 can be found in the reference [5].

If research is conducted on the height predication of real ocean waves directly, then the actual optimization control of the ocean wave energy conversion system will become complex and even difficult to achieve. Thus, the method of data fitting is introduced in this paper, which aims to find the physical and mathematical significance of ocean wave motion, and provide less but effective data information for the predication of ocean wave height.

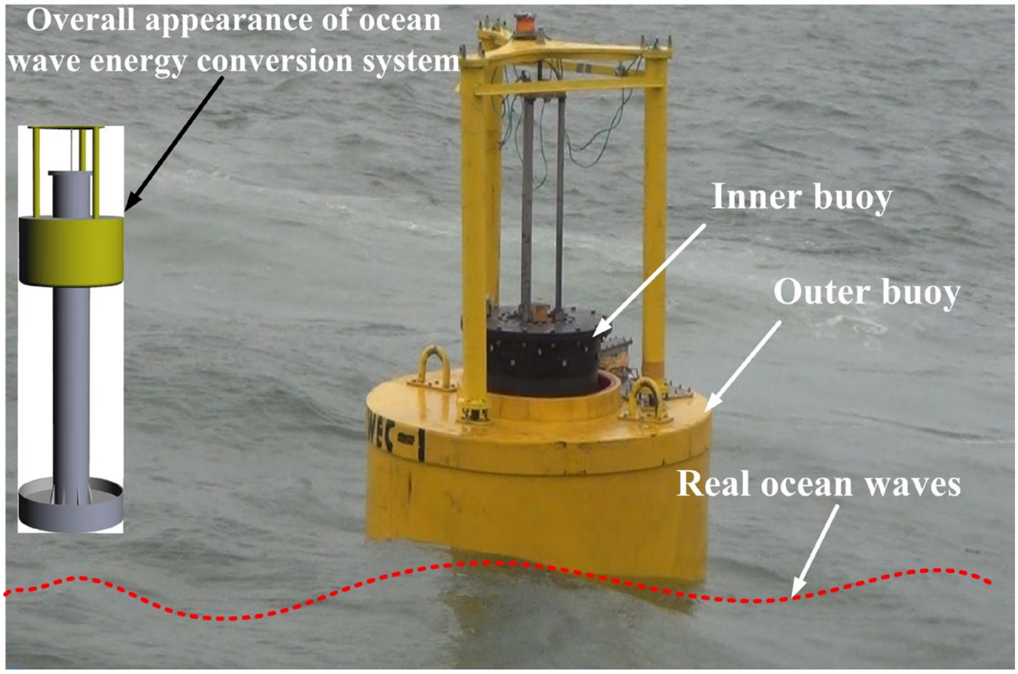


Figure 1. The real ocean waves near the ocean wave energy conversion system.

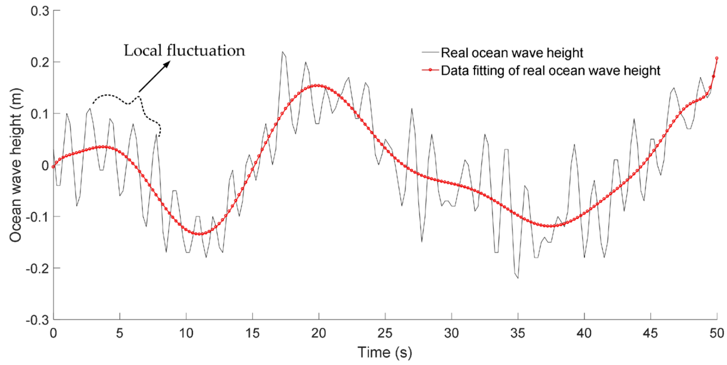
In some papers or books, data fitting is also called curve fitting [21]. Through the method of data fitting, the date series (data in chronological order) can be described by smooth curves or mathematical expressions. Usually, there are five mathematical methods to achieve data fitting, such as the least square method, stepwise regression method, polynomial method, logarithmic method and gamma adjustment method. This paper adopts the polynomial method to process ocean wave height variation with time. The representation of the polynomial function can be written as

$$f(x,w) = w_0 + w_1 x + w_2 x^2 + w_3 x^3 + \cdots + w_m x^m = \sum_{i=0}^{m} w_i x^i \tag{1}$$

where x is the input variables, $f(x,w)$ is the output variables, w is the coefficient and m is the order of polynomial function.

Using the polynomial method, Figure 2 shows the example of data fitting of real ocean wave height, where the time series of ocean wave height is collected in the Yellow Sea near Lianyungang port, on 1 November 2017. From Figure 2, it can be concluded that the real ocean wave height is nonlinear and irregular, which makes it difficult to predict the future ocean wave height, and the subsequent operation control of the ocean wave energy conversion system will become complex and even difficult. However, after the data fitting of real ocean wave height, the variation of ocean wave height is smooth (the small area oscillations are eliminated), which is beneficial to the predication of ocean wave height, and the conversion of ocean wave energy into electric energy will be improved by a suitable operation control method.

Moreover, for the reason of the additional mass and damping coefficient of the ocean wave energy conversion system (device) in the ocean waves, the local fluctuation of ocean waves will not affect the motion of the ocean wave energy conversion system significantly. Therefore, the data fitting of real ocean wave height is reasonable.



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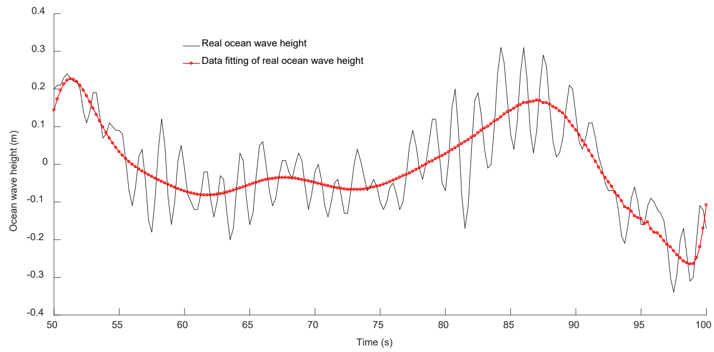

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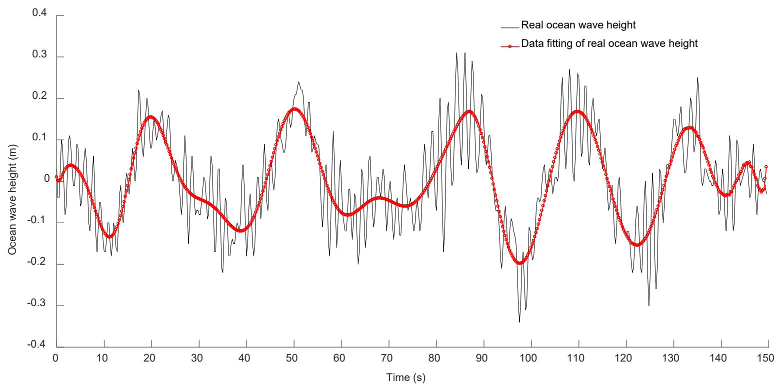


(**c**)

Figure 2. The data fitting of real ocean wave height. (**a**) The time series is 0–50 s. (**b**) The time series is 50–100 s. (**c**) The time series is 0–150 s.

3. Predication Model of Ocean Wave Weight

After the data fitting of real ocean wave height, the future ocean wave height in the next few seconds can be predicted. This paper creates two models to predict the future ocean wave height.

3.1. Moving Average (MA) Model

For the time series x_t, its qth-order MA model can be written as [22]

$$x_t = \mu + \varepsilon_t - b_1\varepsilon_{t-1} - b_2\varepsilon_{t-2} - \cdots - b_q\varepsilon_{t-q} \tag{2}$$

where $b = \left(b_1, b_2, \cdots b_q\right)^T$ is the coefficient of the MA model, μ is the invariant constant and $\{\varepsilon_t\}$ is the white noise sequences with $WN\left(0, \sigma^2\right)$.

Considering the relationship between predication step l and order q, the future predicted time series x_{t+l} can be written as

$$\begin{aligned} x_{t+l} &= \mu + \varepsilon_{t+l} - b_1\varepsilon_{t+l-1} - b_2\varepsilon_{t+l-2} - \cdots - b_q\varepsilon_{t+l-q} \\ &= (\varepsilon_{t+l} - b_1\varepsilon_{t+l-1} - \cdots b_{l-1}\varepsilon_{t+1}) + \left(\mu - b_l\varepsilon_t - \cdots b_q\varepsilon_{t+l-q}\right) \end{aligned} \quad (l \leq q) \tag{3}$$

$$\begin{aligned} x_{t+l} &= \mu + \varepsilon_{t+l} - b_1\varepsilon_{t+l-1} - b_2\varepsilon_{t+l-2} - \cdots - b_q\varepsilon_{t+l-q} \\ &= \left(\varepsilon_{t+l} - b_1\varepsilon_{t+l-1} - b_2\varepsilon_{t+l-2} - \cdots b_q\varepsilon_{t+l-q}\right) + \mu \end{aligned} \quad (l > q) \tag{4}$$

At the right of the last equal sign of Formulas (3) and (4), the first part is the predication error, and the second part is the predication value. By comparing Formulas (3) and (4), it can be obtained that the predicted value is practical only when the predication step l is smaller than the order q.

In order to improve the accuracy of the MA model, the double moving average method is adopted to process the results of the MA model further, which is described as follows:

$$M_t^{(1)} = \frac{x_t + x_{t-1} + \cdots + x_{t-N+1}}{N} \tag{5}$$

$$M_t^{(2)} = \frac{M_t^{(1)} + M_{t-1}^{(1)} + \cdots + M_{t-N+1}^{(1)}}{N} \tag{6}$$

$$a_t = 2M_t^{(1)} - M_t^{(2)} \tag{7}$$

$$b_t = \frac{2\left(M_t^{(1)} - M_t^{(2)}\right)}{N-1} \tag{8}$$

$$x_{t+l} = a_t + b_t l \tag{9}$$

3.2. Auto Regressive (AR) Model

The pth-order AR model can be described as [23]

$$x_t = a_0 + a_1x_{t-1} + a_2x_{t-2} + \cdots + a_px_{t-p} + \varepsilon_t \tag{10}$$

where $a = \left(a_0, a_1, a_2 \cdots, a_p\right)^T$ is the autoregressive coefficient of the AR model, $\{\varepsilon_t\}$ is the white noise sequences with $WN\left(0,\ \sigma^2\right)$. In the Formula (10), if the autoregressive coefficient $a_0 = 0$, then the pth-order AR model is named as zero mean sequence. Formula (10) indicates that future value with k steps can be predicted by the history time series $\mathrm{x}_t = (x_1, x_2 \cdots, x_t)$. However, in order to improve the feasibility and accuracy of the predication result, some data analyses and processing should be achieved. Figure 3 shows the data analysis and processing of the AR model.

Step 1: White noise test. The aim of the white noise test is to check the feasibility of future ocean wave height predication by the AR model. If the time series data (ocean wave height) is white noise, then the modeling of the AR model (the ocean wave height cannot be predicted) stops, or else converts to Step 2.

Step 2: Stable test of time series data. If the time series data (ocean wave height) are unstable, then a stable process, such as the differential processing method, should be implemented on the time series data. After the stable process, the white noise test of Step 1 will check the feasibility of the time series data again. When the time series data are stable, then converts to Step 3.

The method of the stable test of time series data in this paper is the Phillips-Perron test [24].

Step 3: Model order. Normally, the order of the AR model can be determined by the autocorrelation coefficient and partial correlation coefficient of the time series data. However, in order to create an AR model with optimal order and optimal residual series variance, the model order selection should be further considered.

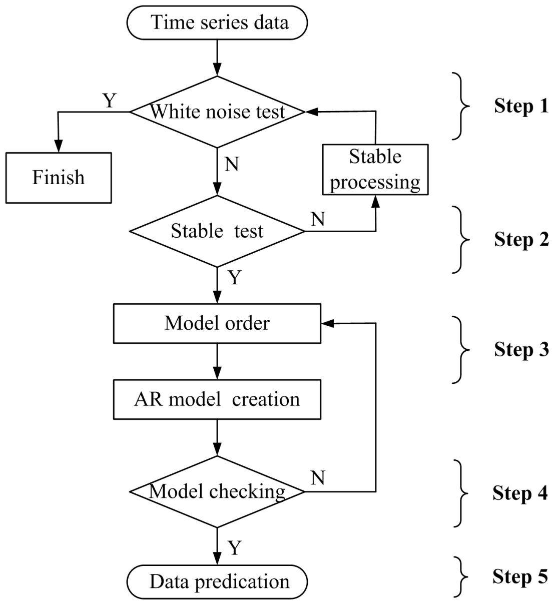


Figure 3. Data analysis and processing of AR model.

This paper adopts the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) to determine the optimal order of the AR model [25].

The AIC criterion can be described as

$$\mathrm{AIC}(p) = \mathrm{Ln}\sigma^2 + \frac{2(p+1)}{N} \tag{11}$$

where $p + 1$ is the number of data that will be predicted, σ^2 is the random error variance and N is the number of time series data. When the predicted data $p + 1$ increases, the logarithm of random error variance $\mathrm{Ln}\sigma^2$ decreases, but the second term $\frac{2(p+1)}{N}$ in Formula (11) increases. Therefore, under the condition of $p + 1$ increases, the value of $\mathrm{AIC}(p)$ can be minimum. After the process of data analysis and comparison, the minimum value of $\mathrm{AIC}(p)$ means the optimal order of the AR model.

The analytic expression of BIC criterion is

$$\mathrm{BIC}(p) = \mathrm{Ln}\sigma^2 + \frac{\mathrm{Ln}2(p+1)}{N} \tag{12}$$

Compared with Formula (11) of the AIC criterion, the last item of Formula (12) of the BIC criterion is Ln2. When the number of time series data N is larger, then Ln2 $>>$ 2; thus, the really suitable orders of the BIC criterion are lower than the orders of the AIC criterion.

Actually, the purpose of the AIC criterion and BIC criterion is to compare the balance point between the data fitting residuals and the number of data, which can provide some choices for us to concentrate on the data fitting error or model complexity.

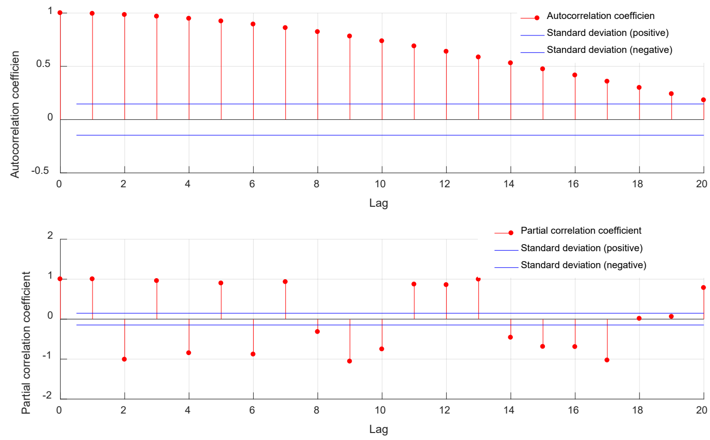
Normally, the AR model creation is based on the minimum order of the AIC criterion and BIC criterion.

Step 4: Model checking. After AR model creation, the parameter estimation of the AR model and the test of white noise residuals should be established. Firstly, the parameter estimation of the AR model is to estimate the parameters $a = \left(a_0, a_1, a_2 \cdots, a_p\right)^T$ of Formula (10) and the random error variance σ^2. Secondly, the test of white noise residuals is to check the feasibility of time series data, which is based on the model order of Step 3.

Step 5: In this step, the future time series data are predicted, and the error between the predication value and real value is compared, which verify the feasibility and accuracy of the AR model in the predication of future ocean wave height.

3.3. An Example of Ocean Wave Height Predication by AR Model

According to the steps of data analysis and processing of the AR model (see Figure 3), an example of ocean wave height predication is investigated, as shown in Figure 4. In Figure 4d, the historical time series (data of ocean wave height) is 0–46.25 s.



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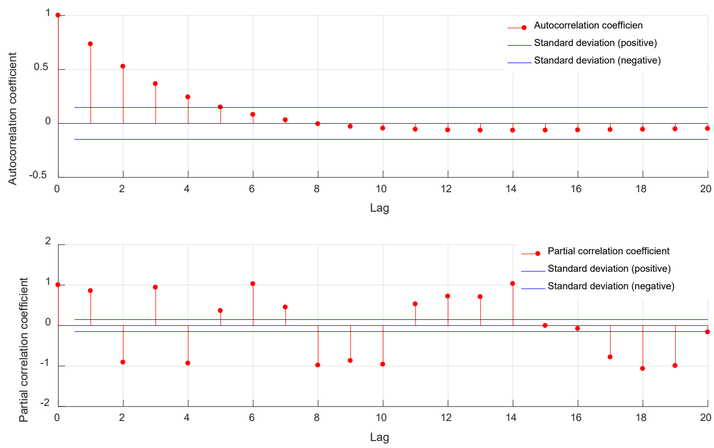

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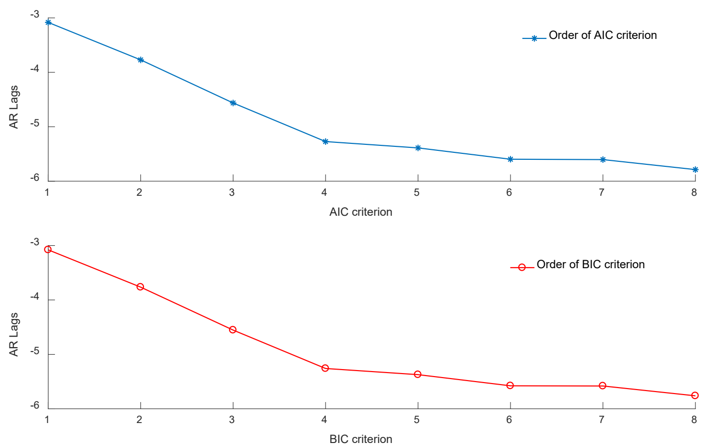

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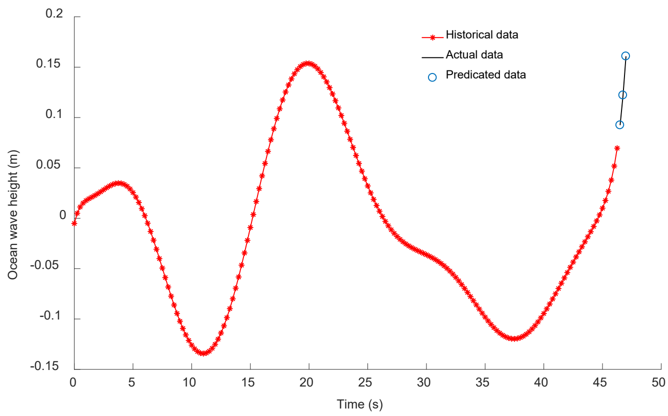
Figure 4. *Cont.*



(**d**)

Figure 4. An example of ocean wave height predication by AR model. (**a**) Autocorrelation coefficient and partial correlation coefficient (before the data are stable). (**b**) Autocorrelation coefficient and partial correlation coefficient (after the data are stable). (**c**) AIC criterion and BIC criterion. (**d**) Ocean wave height predication (three future data are predicated).

As the historical time series of ocean wave height is not the white noise, then the stable test of historical time series is implemented, and the autocorrelation coefficient and partial correlation coefficient are calculated before and after time series stable processing. Compared with Figure 4a, the decay rate of the autocorrelation coefficient of Figure 4b is higher, which suggests that after the time series stable processing, the autocorrelation coefficient of the historical time series of ocean wave height is truncation. However, after the time series stable processing, the partial correlation coefficient is not within the range of two times standard deviation. Therefore, in order to determine the optimal order of the AR model, the AIC criterion and BIC criterion of historical time series are achieved, as shown in Figure 4c. From Figure 4c, it can be concluded that the optimal order range of the AR model is about 4–8, as the variation rate of the Lags value is small in this order range.

After the optimal order of the AR model is determined by the AIC criterion and BIC criterion, an AR model is created, and the predication result of the three future data of ocean wave height is described in Figure 4d. The comparison between the actual data and predicated data means that the created AR model is correct.

4. Predication Results and Analysis

Based on the data fitting of real ocean wave height in Section 2 and the predication model in Section 3, this section compares the predication results of the MA model and AR model and analyzes their predication accuracy.

With the predication cycle as 1.5 s (three predication data in one cycle), Figure 5 shows the predication results of the MA model and AR model, where the continue predication time is 46–140 s. From Figure 5a, it can be seen that the predication accuracy of the MA model is lower in the areas of wave crest (point a1, b1, c1 and d1) and wave trough (x1 and y1). However, compared with the predication results of the MA model, the predication results of the AR model are higher and smoother, which are shown in Figure 5b.

The predication cycle of Figure 5 is 1.5 s, and this short time will not benefit the optimization control technology implementation of the ocean wave energy conversion system. Therefore, the longer predication time of ocean wave height is investigated in this section, as shown in Figure 6. In Figure 6, the continue predication time is also 46–140 s, the predication cycle is 2.5 s and the predicated data are five in one predication cycle. Figure 6a indicates that as the predication cycle increases, the predication accuracy of the MA model is lower than Figure 5a, especially in the wave crest area (point a2, b2, c2 and d2) and wave trough area (x2, y2 and z2). However, under the same condition of the predication cycle (2.5 s), the predication accuracy of the AR model is higher than the MA model, as shown in Figure 6b. Although the predication cycle increases, the predication results' comparison between Figures 5b and 6b show that the predication accuracy of the AR model is nearly constant.

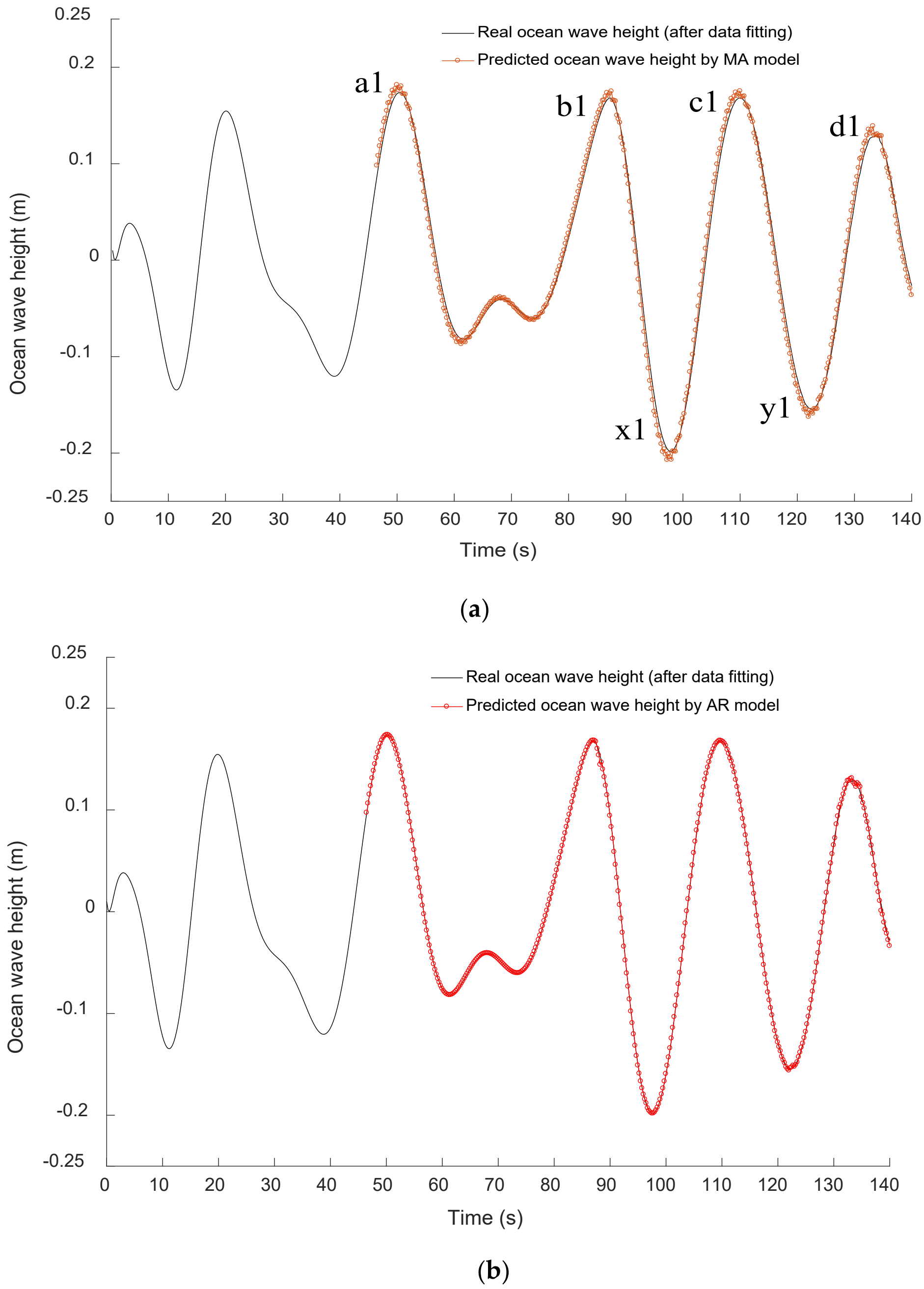
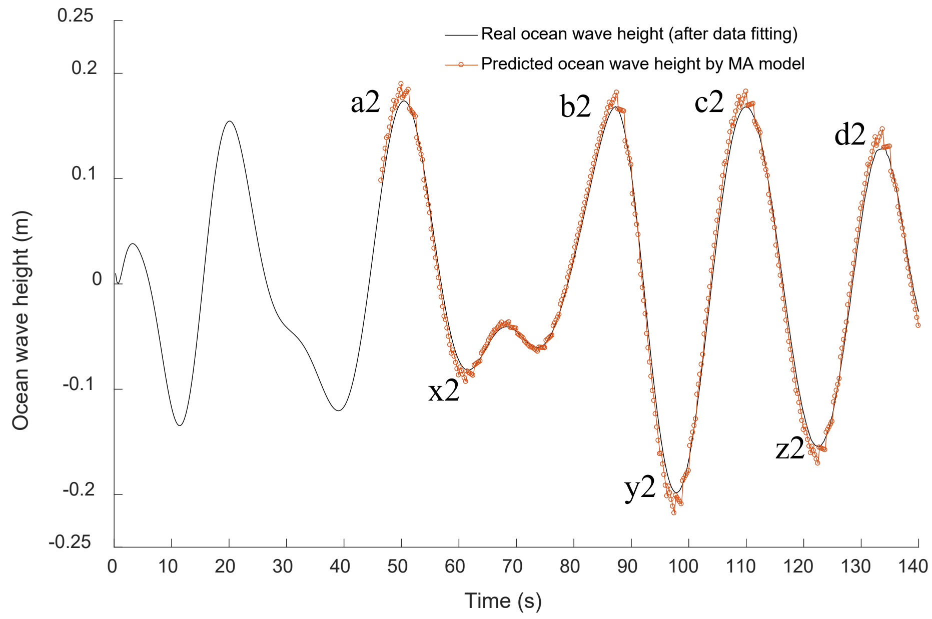


Figure 5. Predication results by MA model and AR model (three future data are a predication cycle). (**a**) Predication result of MA model (predication cycle is 1.5 s). (**b**) Predication result of AR model (predication cycle is 1.5 s).

Figure 7 shows the predication error of the MA model and AR model, where the predication error is the difference value between the real ocean wave height (after data fitting) and the predicted ocean wave height. For the MA model, its predication error is higher in the area of wave crest and wave trough of ocean wave height, which is expressed in Figure 7a. Figure 7a also shows that as the predication cycle increases (from 1.5 s to 2.5 s), the whole predication error is higher.



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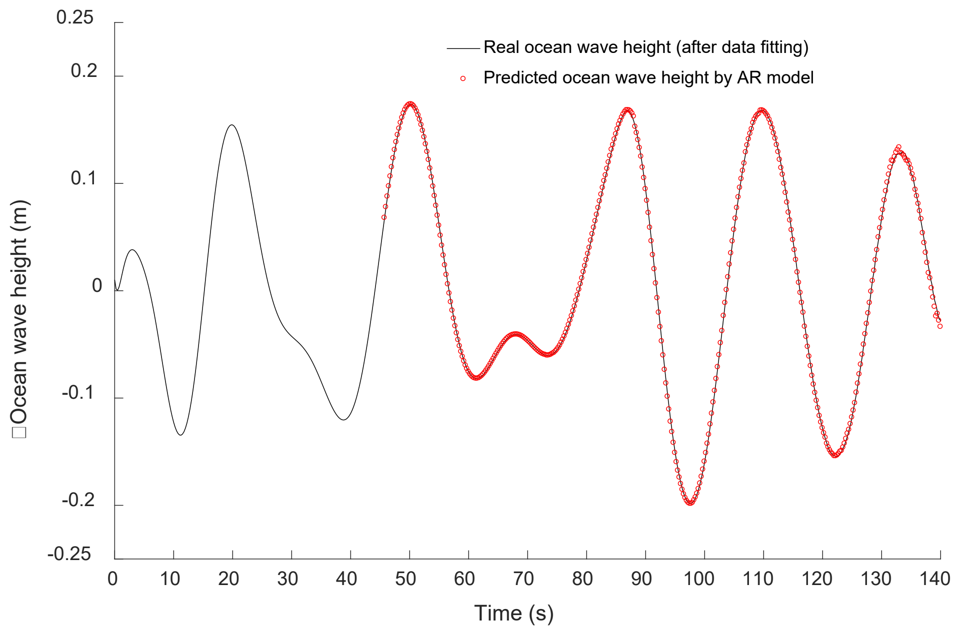

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Figure 6. Predication results by MA model and AR model (five future data are a predication cycle). (**a**) Predication result of MA model (predication cycle is 2.5 s). (**b**) Predication result of AR model (predication cycle is 2.5 s).

Figure 7b describes the predication error of the AR model. Compared with the predication error of the MA model, the predication error of the AR model is very small. However, the error distortion occurred at the time of 85–90 s and 130–140 s. The reason for this phenomenon is that in these time intervals, the ocean wave height variation is not smooth, especially in its wave crest area, as shown in Figures 5b and 6b.

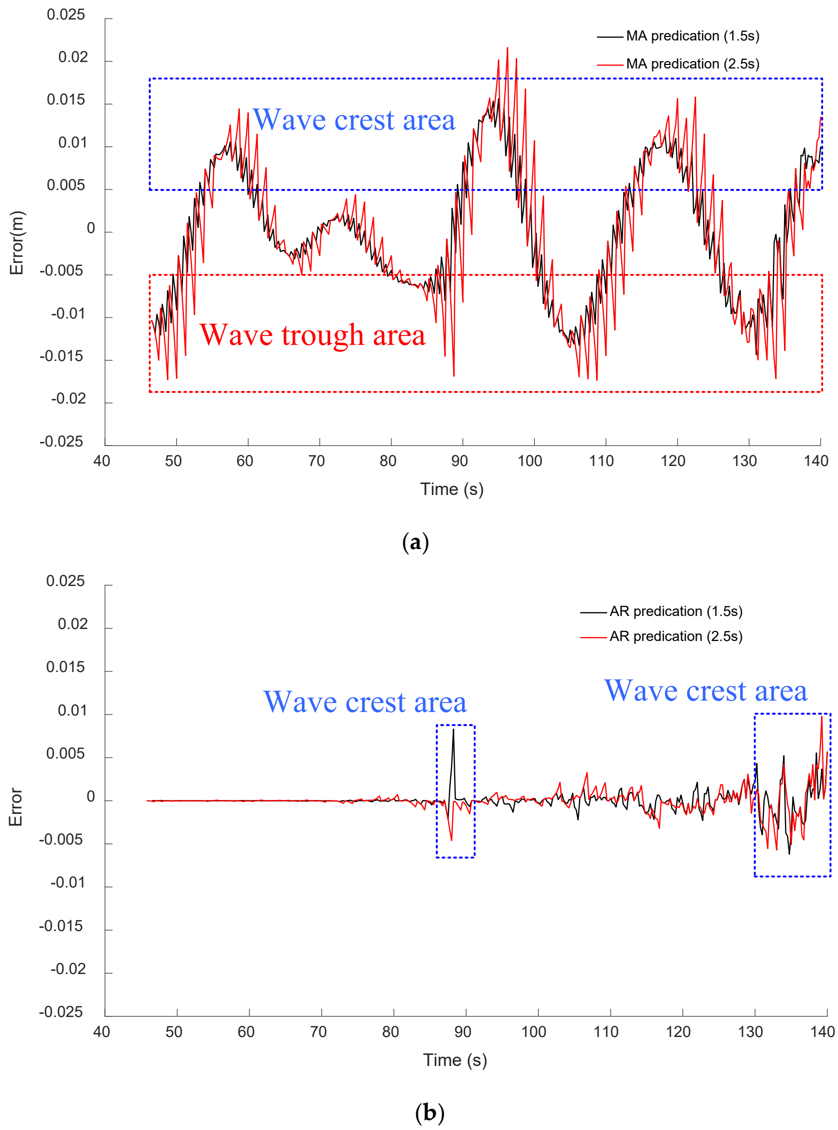

Figure 7. Predication error of MA model and AR model. (**a**) Predication error of MA model. (**b**) Predication error of AR model.

5. Discussion

This paper proposed a data fitting method and two predication methods to increase the predication accuracy of future ocean wave height. Before the conclusion of this paper, some discussions are necessary to be presented.

As shown in Figure 2, the real ocean wave height in one cycle is irregular and displays small-area fluctuation. Therefore, the first discussion concerns the specific impact of this data fitting method on the follow-up optimization control and efficiency of the ocean wave energy conversion system. In order to conduct profound research on this issue, the relationship between ocean waves and wind and the characteristics (period and spectrum et al.) of ocean waves should be investigated. As there are many similarities between the wind and waves (ocean waves), some numerical simulation and analysis methods of wind waves may be beneficial for the predication and research of ocean waves [26–30].

Secondly, although the predication accuracy of the AR model is higher than the MA model, some aberrant error distortions may occasionally occur, as shown in Figure 7b. Thus, a suitable method to avoid or eliminate the aberrant error distortions should be investigated in the next research, which aim is to improve the practicability of the AR model in the predication of ocean wave height.

Lastly, for the structure type of the ocean wave energy conversion system proposed in this paper, the real ocean wave height (historical data and current data) can be measured by the relative motion between the outer buoy and inner buoy, which is beneficial to the real time correction of data fitting, and can also increase the scientific method of the AR model in ocean wave height predication.

In addition, if the predication time is more than 2.5 s, then the white noise sequences and coefficients will be magnified by the calculation process and the predication error will be larger (especially for the ocean waves with both a short wave period and larger wave height), and this phenomenon is not beneficial to the optimization control and efficiency improvement of the ocean wave energy conversion system. However, based on the operational speed of the current controller, 2.5 s is sufficient for the controller to accomplish the optimization control of the ocean wave energy conversion system.

6. Conclusions

In order to improve the efficiency of the ocean wave energy conversion system by a suitable optimization control method, and reduce the complexity and calculation time of ocean wave height predication, this paper proposed two predication methods (the MA and AR predication methods) to predict the future ocean wave height. After the data fitting, modeling and calculation, it found that the AR predication method is more accurate than the MA predication method. It can also accurately predict the future ocean wave height in the next 2.5 s by the AR predication method, which provides enough time to optimize the operation process of the ocean wave energy conversion system by a suitable optimization control method.

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Conflicts of Interest: The authors declare no conflict of interest.

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